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ECONOMIC ORDER QUANTITY PREDICTIVE MODEL USING SUPERVISED MACHINE LEARNING FOR INVENTORY MANAGEMENT OF THE FAST-MOVING CONSUMER GOODS DISTRIBUTORS

By

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AUTHOR'S DECLARATION

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Doctoral College Quality Sub-Committee.

Work submitted for this research degree at the University of Plymouth has not formed part of any other degree either at the University of Plymouth or at another establishment.

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ABSTRACT

Economic Order Quantity Predictive Model Using Supervised Machine Learning For Inventory Management Of The Fast-Moving Consumer Goods Distributors

Nancy Mamdouh Tawfik Deraz

Due to the tough competition that exists today, most distribution companies are in a continuous effort to increase their profits and reduce their costs. An improvement in the distributors' forecasting process could have significant financial and organizational benefits. This requires decision-makers to have a fast, accurate, and efficient demand forecasting solution to be integrated into their business processes. One of the problems that face the distribution industry is how to control inventory levels by means of accurate demand and economic order quantity (EOQ) prediction. Due to some limitations, EOQ cannot be calculated by the formulas. In this situation, machine learning can help to determine the optimum EOQ. Thus, supervised regression models are chosen as the basic tools for EOQ prediction to reduce the uncertainty and enhance the efficiency, since most traditional statistical methods are incapable of modelling nonlinearities that exist in most real data. This research aimed to optimize fast moving consumer goods (FMCGs) inventory levels through investigating a suitable structure of supervised machine learning algorithms that can be used for predicting EOQ and then evaluating the performance of the selected algorithms.

The predictive model was developed through using four machine learning algorithms: linear regression (LR), random forest (RF), boosted decision tree (BDT) and artificial neural network (ANN). These algorithms are evaluated for predicting the distributor's weekly EOQ in two scenarios; parallel (data is certain and available) and sequential (data is predictable). It was found that BDT and ANN produced relatively accurate results in both scenarios. The research was considered as a single-case study to explore successful demand forecasting strategies that leaders of a small, retail, medical supply business used to increase profitability. Data collection is mainly through semi structured, face-to-face interviews with the top manager and other staff involved in inventory control operations. Sample data set was provided by the case company, which is the leading FMCGs distributors in Egypt, consisting of entries from January 2014 to December 2018. Microsoft Azure cloud-based machine learning platform is used for analyzing data and building the predictive model.

The model evaluations and results indicated that the sequential approach was the best methodology, and the weakest one was the model used by the company. A machine learning model with a sequential structure of BDT and NNR algorithms can be considered the most suitable structure, as it shows the best results for prediction. This model resulted in the improvement of the distributor's KPIs which are "available to promise" and the "operating cash flow" up to 83% and 66% respectively compared to the baseline (company's results).

Key words: Machine learning, distribution, EOQ, demand forecasting, supervised regression

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Acronyms

AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
ATP	Available To Promise
BDT	Boosted Decision Tree
BPNN	Back Propagation Neural Network
CPG	Consumer Packaged Goods
CSV	Comma Separator Values
DF	Decision Forest
EOQ	Economic Order Quantity
FMCG	Fast Moving Consumer Good
GWC	Gross Working Capital
ITR	Inventory Turnover Ratio
KPI	Key Performance Indicators
LR	Linear Regression
MAE	Mean Absolute Error
MARS	Multivariate Adaptive Regression Splines
ML	Machine Learning
MLP	Multi-Layer Perceptron
NNR	Neural Network Regression
NWC	Networking Working Capital
OCF	Operating Cash Flow
OFR	Order Fulfilment Rate
OOS	Out Of Stock
PDM	Physical Distribution Management
PPM	Parallel Predictive Model
PPR	Projection Pursuit Regression
RF	Random Forest
RMSE	Root Mean Squared Error
RSE	Relative Squared Error
SARIMA	Seasonal Auto Regressive Integrated Moving Average
SPM	Sequential Predictive Model
SVM	Support Vector Machine
SVR	Support Vector Regressor
WCM	Working Capital Management

Chapter One

Introduction

1.1 Chapter overview

This research is concerned with developing a supervised regression model to predict the economic order quantity (EOQ) of an Egyptian fast moving consumer goods (FMCGs) distributor through a sequential predictive process. The first chapter is an introductory one that gives an overview of the research in terms of a brief background of the subject in Section One, followed by the main research aims, objectives and research questions in Section Two. Then the methodology applied in the study is reviewed in Section Three and finally the structure of the research is outlined in the last section of the Chapter.

1.2 Research background

Supply chain management (SCM) is a complicated process that is frequently fraught with unpredictability. Many values are stochastic and cannot be determined or described with precision using traditional mathematical approaches. As a result, individual artificial intelligence (AI) technologies, or their combination in the form of hybrid methods, are increasingly used to solve actual and complicated problems (Sremac et al., 2019). The goal of inventory control in supply chain management using machine learning (ML) modelling is to ensure that all actions in the supply chain are completed efficiently, effectively, and inexpensively (Gupta et al., 2022). Companies must now be able to respond quickly to changes in customer demand and implement changes as quickly as possible in order to satisfy their customers. Improving product demand forecast accuracy can result in increased operational efficiency, customer satisfaction, and cost savings across the whole supply chain (Kremer, Siemsen and Thomas, 2015; Trapero, Kourentzes and Fildes, 2015). This is why managers frequently allow forecasting future demands yields information that can help leaders make better decisions on a daily basis and getting crucial knowledge into their operations, such as inventory management, replenishment, safety stock levels, and the appropriate reorder quantity (Meyerhoefer, Panovska and Manski, 2016; Raza and Kilbourn, 2015).

An appropriate EOQ determination promotes safety stock management, productivity, inventory cost reduction, and revenue generation. Traditional mathematical function-based methods have had some success in the past. Calculating reordering points for all products and updating the value on a regular basis takes time for inventory officers (Inprasit and Tanachutiwat, 2019). Manufacturers are unable to keep significant quantities of raw materials on hand or load all their supplies onto workstations. This antiquated technique of stocking inventory results in unpredictable and extended lead times, as well as costly maintenance and waste expenses. Applying a new strategy to assist businesses in reducing inventory expenses might be beneficial to inventory control strategies.

Businesses nowadays use EOQ calculations to determine how much material can be added to inventory, however the methods are not always helpful or practical. EOQ is an inventory management system that shows the quantity of an item in order to lower the total cost of ordering for a company, carrying, shortage and holding (Senthilnathan, 2019). The basic EOQ model is appropriate for usage when demand is known with confidence and is constant over time, no shortages are permitted, order quantities are received all at once, and order lead time is constant (Mubiry, 2015; Mangan et al., 2016). There are some mathematical ways for calculating EOQ, but applying the formulas has significant drawbacks. For starters, formulas are incapable of dealing with ambiguous and unpredictable facts. Second, due to various constraints, in some circumstances, EOQ cannot be calculated by the formulas (Moradizadeh, 2019). The failure of EOQ models to determine the optimal quantity of completed goods inventory and, as a result, lower supply chain performance, was identified by Paul and Azeem (2011). This research will analyse and focus on more variables, which are fluctuating in nature and that will affect the optimum quantity to be ordered by distributors to minimize its inventory costs.

To improve efficiency of the forecasting process and deal with uncertainty, this thesis is using supervised regression models for EOQ prediction. The EOQ can be predicted using this method in scenarios with ambiguous data, uncertainty, no formulas, many inputs, and fusion procedures. The goal behind conducting this research is to select an optimum combination of supervised regression models which will produce the least error measures along with presenting the weekly EOQ to be ordered by the distributor based on newly added EOQ variables that were not covered in the previous EOQ models, which should reduce the inventory levels and eventually decrease inventory costs. This study seeks to address the main gaps observed which are mainly a lack of research to address the importance of the working capital as an EOQ input variable in the EOQ prediction process; a lack of research which reports the ability of ML models to predict EOQ without having all the EOQ essential variables available in the dataset. This would enable the model to work in a deterministic and stochastic environment as well and finally a lack of research that has been undertaken into the Egyptian FMCGs distributors.

1.3 Research aim and objectives

This research aims to develop a sequential supervised regression model that forecasts the weekly EOQ of the FMCGs distributor with a view to improve and optimize the overall accuracy of the entire forecasting process through better inventory performance. A case study for an Egyptian FMCGs distributor will be used to evaluate and validate the model. In this context, the main research objectives are to:

1. Review the literature relevant to the ML (supervised regression) techniques in the supply chain demand forecasting and EOQ determination domain.
2. Analyse the existing developed ML (supervised regression) predictive models to identify the key input variables that affect the distributors' EOQ.
3. Propose a supervised regression predictive model to predict the distributor's weekly EOQ.
4. Evaluate and validate the proposed model and measure the accuracy of the results on the business.

In the light of this framework, the main research questions that motivate the research can be summarized as follows:

1. What are the suitable ML regression algorithms for improving the FMCGs distributor EOQ prediction accuracy?
2. How can the developed ML predictive model fulfil some of the ML success criteria?
3. How can the developed supervised regression predictive model improve some of the key performance indicators (KPIs) by predictions?

1.4 Significance of the study

The FMCGs industry trades in commodities that are classified as essential products. The FMCGs industry comprises a big part of the budget of consumers in all countries (Colicchia et al., 2017). The FMCGs industry primarily focuses on manufacturing, packaging goods, distributing, and some of fundamental activities including sales and marketing, financing, and purchasing and it is found that the share of the FMCGs industries in gross domestic product (GDP) is significant (Malhotra, 2014). In the last few decades, the FMCGs supply chain has faced more challenges due to an increasing tendency towards more demanding service level leading to higher delivery frequencies with smaller shipments sizes and consequent fragmentation of flows (Fernie and Sparks, 2014). In addition, the FMCGs environment is unpredictable and known as the most difficult part of the boom because commodities look similar without real competitive advantage and consumers tend to place a lot of values on different brands. In this industry, competition between competitors is always fierce, and the battle for market share continues (Anselmsson et al., 2014).

The FMCGs distribution companies in Egypt are active and fast organizations in the distribution of a range of products. These organizations are mostly concerned with fast moving products like home care products, refreshments, personal care, and foods. Most of these products are supposed to be consumed within a short duration of time and some have a short-shelf life. Aljunaidi and Ankrah (2014) highlighted the major issues that exist in the FMCGs industry are forecast accuracy, seasonal shifts in demand and supplier reliability. Forecast difficulties are a problem throughout the whole industry. These issues, even if they may vary from company to company, make it difficult to achieve levelled demand. Therefore, the need for effective supply chains and effective production is crucial to compensate for uneven demand. Effective supply chains are mainly needed in order to deliver what is demanded by customers when it is demanded.

Because of the importance of the subject as well as raising the general awareness of technologies applied in the distribution and ordering the economic quantities of products in addition to the importance of goods produced in the FMCGs, it seems a fundamental need to use machine learning techniques in the supply chain. It is widely recognized that the FMCGs represents a key industry to provide an enormous volume of human daily demand in which all individuals not considering the age, gender and boundaries are involved (Nozari et al., 2019). For this reason, supply chain managers at leading companies in the FMCGs industry strive to utilize machine learning techniques and improve their environmental performance throughout the supply chain as a strategic weapon to gain competitive advantage. Therefore, understanding machine learning models to improve the performance of the FMCGs supply chain can be extremely important research on this area. It may be noted that there is little research that focuses on the machine learning models for EOQ prediction, and no work has been done in the inventory management of FMCGs industries as the main sectors of these industries. Moreover, the concept of predictive machine learning models in the FMCG industries in Egypt has not been academically investigated yet and as one the most important supply chains, it should be considered to be a major concern.

This study will shed light on the challenges in the distribution channel, specifically the inventory management activity, of the Egyptian FMCGs distribution companies. This study will offer guidelines to FMCGs distribution companies as well as other sectors in the FMCGs industries to use the created predictive model as a tool to make strategic and operational purchasing decisions. Different businesses in different nations could further validate and verify the model’s usefulness, given its potential for generalizability. Finally, the study will serve as a reference point for students, researchers, teachers, consultants, and academicians who intend to conduct future studies in this area.

1.5 Research methodology

The study employs the deductive approach. It uses a mixed approach for qualitative and quantitative data. It also implements the case study strategy. Data will be collected in both primary and secondary forms (archival data from the case company). An appropriate initial data gathering strategy for problem framing is interviewing, which entails conducting multiple interviews with different individuals from the case company.

This research followed the CRISP-ML(Q) methodology in order to develop the ML predictive model and increase the efficiency and success rate of the developed model. The first phase involves getting a better understanding of the targeted research area and that will be explained through the literature in Chapter two and where the research gaps are identified. The second phase will focus on developing a better understanding of the situation of the case company and how they are conducting their demand forecasting and EOQ determination process. This is done by analysing data that will be collected from the company and through interviewing the managers. This information will be later used in the empirical part of the research. The third phase of the research is the modelling phase, and it starts with pre-processing the data gathered from the empirical part and from the literature review to be able to select the suitable algorithms to build and train the supervised regression predictive model and finetuning it to achieve the expected level of accuracy. The model development phase will cover the conventional methods and the supervised regression algorithms for forecasting. The ML regression algorithms are studied to select the most suitable method for forecasting when conventional methods fail to produce acceptable results due to poor data quality or low quantity of data. The reason for using the company's existing forecasting method is to have it as baseline so that it will be used in a comparative analysis with the ML algorithms that will be trained in the supervised regression model and analyse its performance and prediction results to the traditional methods. Different regression models will be compared against each other and the models with effective and more computational accurate results based on regression measurement criteria will be chosen to develop the model.

The following fourth phase, the analysis phase, will carry out the evaluation and the validation processes of the developed model and then the model will be tested to make sure it is ready to be deployed to predict the targeted output. The dataset that will be gathered from the case company has a time horizon of five years from 2014 to 2018. Splitting the data into training and testing data will be discussed in detail in Chapter 4. Four main measurement criteria for calculating accuracy, RMSE, MAE, RSE and R^2, will be applied. Data preparation is mostly conducted by using data preparation modules provided by the used software in this study, Microsoft Azure Machine Learning Studio. The data set over the first four years is used for training the model, whilst the fifth year (2018) is for testing the developed model. The "Permutation Feature Importance" module will be applied to select the variables that will be used as input data to the model. Two scenarios will be proposed, the parallel predictive model scenario and the sequential predictive model scenario. These two scenarios are going to be evaluated, and their results will be compared to each other to check which one results in more accurate predictions of the targeted output. The model will be then validated and prepared to be deployed.

The final phase of the research is to monitor the performance of the developed model to make sure the model always achieves the most accurate results and then check whether the model needs updating if it receives new data or not.

1.6 Structure of the thesis

This Chapter introduced the overall framework of the research along with the research aim, objectives, and research questions. The next Chapter, Chapter Two, reviews the literature, which will address the importance of ML techniques in the demand forecasting and the EOQ determination process as well as reviewing the research done regarding the inventory management of the FMCGs distributors. It then ends with specifying the research gaps.

Chapter 3 presents the methodology employed in the study, including the research framework, case study technique, data gathering, and data analysis methodologies. The Chapter also shows the main phases that the research will follow to develop the ML predictive model.

Chapter 4 details the data preparation phase and modelling phase of the proposed model along with displaying its results.

Chapter 5 addresses the validation and deployment phases of the developed model with a detailed analysis of its results. This is followed by a sensitivity analysis applied to the model.

Chapter 6 is the discussion Chapter where the research contributions to theory and industrial practice are discussed, and the research main objectives are linked with its findings.

The research ends by outlining the main general conclusions of the research in Chapter 7 along with identifying the limitations of the existing work. It also includes the recommendations of the research for both academic work or for the industry.

1.7 Chapter summary

This Chapter has introduced the research context and overall framework in terms of the research aim, objectives, and the research questions as well as the methodology adopted throughout the research. The Chapter ends with a structure of the whole thesis. Chapter Two will review relevant literature as regards the ML techniques in the supply chain context focusing on the applications applied in the FMCGs distribution area and following this the research gap will be identified.

Chapter Two

Literature Review

2.1 Chapter overview

This chapter describes the ML applications applied for demand forecasting and the EOQ determination of the FMCGs supply chain for better inventory management and overall supply chain performance. The literature review is organized as follows: firstly, an overview of the distribution process is provided, which includes the main activities of distribution and an overview of the FMCGs industry and its effect on the economy. Secondly, the literature explaining the significance of demand forecasting, forecasting tools and their applications in the recent past is reviewed. Then an overview of the EOQ models implemented in the literature showing the effect they have on inventory management is clearly reviewed. Thirdly, an overview of the ML techniques in supply chains is provided focusing on the supervised ML techniques in detail and its applications in the demand forecasting and EOQ determination. The chapter ends by identifying the research gap, followed by a summary.

2.2 Distribution in supply chain management

A supply chain is a network made up of suppliers, manufacturers, warehouses, distributors, and retailers who work together to transform raw materials into finished items (Chandra and Grabis, 2007). The essential supplies and products must be delivered in the proper amounts and quality to manufacturing facilities or customers, at the right time and at the lowest cost. Product creation, procurement, manufacturing, physical distribution, customer relationship management, and performance measurement are the most significant supply chain processes (Olson, 2012). Domschke and Schield (1994) emphasize that the term "distribution" refers to a system of operations involving the transfer of economic products between manufacturers and consumers. It entails coordinating the preparation of produced goods according to their kind, volume, space, and time, in order to meet supply deadlines (order fulfilment) or meet predicted demand efficiently.

The importance of the distribution process and the integration that should be present in distribution systems was underlined by ensuring that clients receive their items at the appropriate time and location. If the product does not arrive at its intended location on time, the competitive advantage and client retention will suffer. Every firm must develop an efficient distribution process to convey finished products from the producer to the ultimate consumer in order to be effective (Karaxha and Kristo, 2016). The term "physical distribution management" (PDM) refers to the management of all aspects of the distribution process. PDM is best created as a specialist function within the organisation or contracted out to a professional (Little and Marandi, 2003). The key objective of PDM is to find the most cost-effective way of meeting customer needs in relation to purchasing their product, whoever and wherever they are. Yeboah et al. (2013) highlighted the main functions included in the PDM which are: customer services, order processing, materials handling, warehousing, inventory management and transportation.

This research has mainly focused on the inventory management function being a critical area of the PDM because stock levels have a direct effect on levels of service and customer satisfaction. Few businesses could never run out of inventory, but if this happens frequently, market share will be lost to more efficient competitors. Carrying stock below the re-order mark may result in a stock-out, whilst maintaining excessive stock levels is unneeded and costly (Geraldine, 2013). If the company's marketing strategy requires that high stock levels be maintained, this should be justified by a profit contribution that will exceed the extra stock carrying costs.

A wholesaler's function in consumer goods wholesale distribution is to supply a diverse range of products from various suppliers to its consumers. In this arrangement, the wholesaler adds value to the consumer by making requested products available for purchase at a specific time (Ehrenthal et al., 2014). The primary purpose of the wholesaler is to maximise the difference between what retailers are prepared to pay and what vendors will accept as payment for the goods they sell. Distributors frequently have a lot of negotiating leverage, which allows them to get favourable contract conditions from businesses, including profit margins of up to 6%. (Holweg and colleagues, 2016).

Growing expenses, diminishing margins, new competition, and demanding customers confront wholesale distributors. Successful wholesale distributors generally distinguish themselves from those that are continuously struggling through effective supply chain management. Canitz (2017) outlined the key supply chain management actions that every wholesale distributor should consider, beginning with adopting a demand-driven business model, inventory optimization, buying inventory only when needed, improving inbound transportation capabilities, and finally improving long-range planning capabilities.

These steps assist distributors in moving beyond their conventional focus on low prices, resulting in major competitive advantages, rewarding operational efficiency, extra working capital, and greater levels of customer care. This research has focused on the inventory optimization of the distributors and how this could be achieved through buying inventory when its only needed and through incorporating a predictive EOQ model that goes beyond the spreadsheets and embrace ML techniques that would be able to model complex distributor constraints and uncertain demand patterns.

2.3 Characteristics of the FMCGs supply chain

Majumdar (2007) has defined the FMCGs term representing goods that are sold at lower price but moves quickly to consumers. These goods have high demand, and they donot stay longer in the retailers' shelves. This has led to many manufacturers both local and international entering that industrial sector to have their market share (Wasamba,2008). Cohen et al. (2017) cite that FMCGs (fast moving consumer goods) include processed foods, beverages, canned goods, soft drinks, snacks, sweets, and chocolates, as well as personal care and cleaning products. Many FMCGs have a short shelf life due to quick deterioration, as is the case with perishable commodities such meats, fruits, vegetables, and dairy products. Electronics and fashion clothes, for example, have short lifecycles, quick obsolescence, are often updated, and offer a plethora of competitive alternatives.

FMCGs are products that have a high turnover rate and are inexpensive (KPMG International, 2016). In emerging countries, FMCGs are the driving force behind economic growth and development. Increased employment, capital savings, and poverty alleviation are all advantages of the FMCG sector (Friday et al, 2011). Both policymakers and consumers are interested in FMCGs in order to ensure that high-quality consumables are offered at a reasonable price. Bala et al., (2010) highlight the issues faced by the FMCGs supply chains which started with the fact that supply chains own various production plants, which increase complexities in the supply chain. Another issue was that distribution is handled by specialized firms, which increases the pressure on relationships. Aljunaidi and Ankrah (2014) discussed other major issues within the FMCGs industry which are forecast accuracy and seasonal shifts in demand. Forecast difficulties are a problem throughout the whole industry and they are due to the consumer's decision to purchase. Therefore, effective supply chains and effective production are mainly needed to deliver what is demanded by customers when it is demanded. The main area that this research focus on is how important is to have accurate demand and EOQ forecasting to have better inventory management and more optimized inventory levels for the FMCGs distributors. This will be illustrated in detail in the following sections.

2.3.1The Egyptian FMCGs industry analysis

In comparison to other sectors such as automobiles, electronics, and aeroplanes, the FMCGs sector's growth rate is consistent and is unaffected by recessions or economic disturbances (World Bank, 2011). Furthermore, because FMCGs are small things that are traded in big quantities, the profit in this sector can be substantial (IGD, 2004). Nonetheless, competitors can easily duplicate these products. In other words, the rivalry is fierce, making it difficult for businesses in this market to gain a competitive advantage through low-cost or differentiation techniques. As a result, businesses must constantly remain ahead of the competition by ensuring that their inventions are distinct and original (Kunc, 2005).

The Egyptian FMCGs industry is important to many investors because Egypt's economy is the third largest in the Arab world behind Saudi Arabia and the United Arab Emirates (BMI research, 2015). The economy slipped into recession in 2011 as a result of the Egyptian revolution (British Broadcasting Corporation, 2011), but economic and political situations have significantly improved since then. The Egyptian economy's fifth largest industry segment is fast moving consumer goods (CAPMAS, 2014). As a result, this industry has grown into a significant economic segment that attracts significant investments and is marked by constant growth (GAFI, 2014). The Egyptian FMCG industry has exploded in recent years, thanks to the expansion of major international chains into the Egyptian market. Furthermore, consumers had access to a wider range of products, their income increased, and brand promotion expanded (Mansour, 2009; Negm et al., 2011).

Accordingly, the following reasons summaries and justify the selection of the Egyptian FMCGs industry in this study:

- After Saudi Arabia and the United Arab Emirates, Egypt has the third largest economy in the Arab world (BMI research, 2015a).
- The Egyptian FMCG market is vast and is regarded as one of the largest in Africa and the Middle East (BMI research, 2015b).
- The FMCG industry is Egypt's fifth largest industry sector, drawing significant investment (CAPMAS, 2014; GAFI, 2014).
- The ever-increasing demand for low-cost FMCGs among Egyptian low-income customers (CAPMAS, 2014).
- The Egyptian FMCG business is mature, with a strong presence of multinationals, a well-established distribution network, low operating costs, and fierce competition between planned/controlled and unplanned segments (Negm et al., 2012).

Table 2. 1. Egyptian FMCGs SWOT analysis

STRENGTH	WEAKNESSES
• The Arab world's third largest economy • One of Africa's and the Middle East's largest FMCG marketplaces • Mature sector • Strong multinational presence • Well-established distribution networks • Low operational costs	• Exchange rate fluctuations • High unemployment rate • Low purchasing power • Low GDP per capita
OPPORTUNITIES	THREATS
• Attractive investment prospects • Growing population • Growing industry • Increasing demand for FMCGs • Food and beverage spending accounts for 40% of household spending	• Instability in politics • Economic uncertainty

Source: (Haddad, 2016, p.117)

Given the strengths points listed in the SWOT analysis in Table 2.1 Egypt's FMCGs market is one of the largest in the Arab world, Africa, and the Middle East. It qualifies for this study because it has a mature industry, strong multinational presence, a well-established distribution network, and low operational costs. Furthermore, this market offers various investment and business growth opportunities, including a growing population, an expanding industry, rising demand, and household spending on consumer goods. These opportunities create a favourable business climate, and case studies demonstrating effective and efficient techniques can be found in such a market (Negm et al., 2012; CAPMAS, 2014; GAFI, 2014; BMI research, 2015b). The Egyptian FMCGs market also has several weaknesses and risks, such as shifting exchange rates, a high unemployment rate, and limited purchasing power. Multinational and local companies see the potential of the Egyptian FMCGs market and invest, operate, and develop long-term strategies to stay competitive (BMI research, 2015b; Euromonitor International, 2015h).

The following section will discuss inventory management in detail along with implemented models, its challenges, and its important relationship with the demand and EOQ forecasting process and how this affects the overall performance of the FMCGs supply chain.

2.4 Inventory management and its challenges in supply chain management

Inventory, according to Udeh (2016), is the stock of things a company produces for sale, as well as the components that make up those goods. Inventory is defined by Mbula et al. (2016) as an itemised list of items or assets with their estimated value, specifically the annual accounting stock taken in any business. Inventories are kept because of the benefits they provide to the company, but there are certain costs connected with keeping them. As a result, they should be maintained at optimal levels. Inventory management is the process of managing resources, ensuring their availability, controlling, utilising, and acquiring items, which might include raw materials, work-in-progress, finished goods, and supplies stored by a company to help with operations in the manufacturing process. Amahalu and Ezechukwu (2017) define inventory management as the use of a variety of methodologies to optimise stock, raw materials, work-in-progress, and finished goods levels. Inventory management is necessary at multiple locations inside an organisation or across multiple sites in a supply chain to prevent the company from running out of resources or commodities, or from keeping large inventories, which would result in additional costs. The firm's performance can easily be improved with an effective inventory management system in place (Ajayi et al., 2021).

Inventory management is a key aspect of the SCM process, where the producer evaluates and determines inventory procurement, inventory level, and production costs, as well as ordering and holding costs (Pan et al., 2004). Gupta et al. (2022) summarised the inventory management objectives as minimising transportation costs and time, calculating quantity and frequency of purchases for selected raw materials items, and calculating EOQ, Re-Order point (ROP), Safety Stock (SS), and Total Inventory Cost (TIC) for selected raw materials items. Inventory management also involves a trade-off between the advantages of keeping items on hand to meet customer demand and the expense of carrying inventory. Inventory control strategies are critical components, and most businesses may significantly cut expenses related with material flow (Simic et al., 2019). Maintaining optimal inventory levels is a critical duty for a company because high inventory levels boost responsiveness to consumers while increasing costs, whereas low inventory levels may result in shortages, damaging the company's reputation (Glock et al., 2014).

Pinto (2011) pointed out that the primary purpose of inventory management is to match supply and demand of the items. However, the difficulty of measuring uncertainty can drive companies in general to overstocking and understocking problems. Hamisi (2011) highlighted the inventory management’s primary aim is to excel in customer satisfaction and offer the vital customer service in control of the lowest everyday inventory costs. According to Relph (2015), it's crucial to figure out how much has to be ordered to match supply with demand, as well as how much more is needed to account for unanticipated demand, late delivery from suppliers, and other unforeseen events. The causes of the mismatch between sales and purchase data must be identified in order to be effective in inventory management. To accomplish so, the inventory's performance should be evaluated in light of the aspects that influence inventory levels, such as forecast accuracy, delivery time, delivery precision, and inventory balance accuracy. Due to a lack of planning and inventory control, the service level, logistics expenses, and tied-up capital will be higher than required if performance is not maximised.

Inventory is stock purchased with the intention of reselling for a profit, and it is the most expensive cost for businesses, particularly manufacturing businesses (Panigrahi, 2013). According to Salla (2013), inventory management success is strongly dependent on technological and managerial resources. According to Pandey, a company needs a control system to successfully manage inventory, and the system it uses must be the most efficient and effective (2008). Grablowsky (2005) found that only large companies used sound inventory control systems to determine inventory reorder and stock levels, using EOQ and linear programming to provide additional information for decision making, whereas small companies relied on management judgement and experience without quantitative support. Computerized accounting systems are critical in planning stocks based on forecasts, contracts, and supply based on existing stock, according to (Capkun, 2009). Inventory holding should be well managed to help a company's operations while taking into account reordering, hauling, and stock out costs. According to Nyabwanga's (2013) research, good performance is linked to inventory management efficiency, which includes inventory level tracking. Both too many and too few inventory are undesirable.

Many inventory management models have been developed and implemented. In their paper (De kok et al., 2018), the authors evaluate literature sources on stochastic models of inventory management and present a general overview. The writers of a research paper (Fattah et al., 2016) looked at the performance of inventory management systems from both a stochastic and a deterministic model standpoint. Publications (Mawandiya et al., (2016); Mishra (2016); Vandana and Sharma (2016); Serrano et al., (2017)) discuss deterministic models, or inventory-oriented models with deterministic demand. Authors have written about the impact of inventory management on total supply chain performance (Srivathsan and Kamath (2017); Pamulety et al., (2017); Jain et al., (2017); Cholodowicz and Oelowski (2018)). Researchers are currently interested in determining the optimal level of inventory in any practical supply chain situation while taking into account some of these concerns. Many other characteristics, such as reordering point, EOQ, economic production quantity (EPQ), backorder, shortage level, and so on, must be considered simultaneously while creating an inventory system model. To obtain an optimal level of inventory, these mathematical models are solved utilising various predictive and metaheuristic methods. In such circumstances, nature-based optimization algorithms are used, and their performance for diverse supply chain networks is assessed. To predict these events in advance, machine learning algorithms based on past data from a corporation can produce some fascinating outcomes (Sarwar et al., 2020).

Mitra and Chatterjee (2004) explored the primary challenges surrounding inventory in a distribution system, stating that placing the majority of inventory at the lowest stage enhances customer service while also increasing inventory carrying costs. If, on the other hand, the majority of the inventory is moved away from the lowest stage, the inventory carrying cost falls, but the delivery lead time rises, resulting in a decline in customer service. As a result, while deciding on the quantity of inventory in a distribution system, a trade-off between these two issues should be established. This is research addresses that trade-off by focusing on different variables that could be considered while forecasting the optimal order quantity that should be purchased by the distributors.

Kegley (2018) reviewed some of the biggest challenges' distribution centers face when it comes to inventory management that are summarized in lack of visibility, inefficient processes, and meeting customer demand. That is why distributors should take a holistic view into knowing both their inventory core vs. non-core items and understanding what is in stock, what is going to be ordered, the size of that order, and what needs to be replenished. Nemtajela and Mbohwa (2017) add to the current literature on FMCG companies by discovering that demand uncertainty has an impact on inventory management. They agree that the more the demand uncertainty, the more difficult and challenging it is to keep stock in a company. Inventory management in any organisation avoids the company from producing low-quality items, disappointing customers, and losing money. Even if the inventory problem is a traditional issue that always exists, Benmamoun et al. (2018) pointed out that the application for slow moving and fast-moving raw materials is an advantage, especially if the implementation was done with real data for industrial enterprises affected by this issue.

The coming section will highlight the relationship between demand forecasting and inventory management and the effect of applying intelligent forecasting techniques on improving the inventory management.

2.4.1 Demand forecasting and inventory management

Mathematical models for retail store management were created, with a particular focus on inventory management, considering aspects like delivery lead times, perishability, and stock-outs. Demand seasonality analysis at the retail level (Ehrenthal et al., 2014), seasonal and trend time-series forecasts for the retail stage (Zhang and Qi, 2005), multi-criteria inventory management for perishables with product substitution (Duong et al., 2015), forecasts for retailers (Wang and Xu, 2014), and forecasts for retailers (Mou et al., 2018a) are all examples of research in the direction of demand forecasting (van Donselaar et al., 2016; Ali et al., 2009).

Demand planning should be a dependable procedure that helps inventory planners enhance revenue forecast accuracy and link inventory levels with actual customer demand. Demand forecasting is a fundamental component of production planning and supply chain management, affecting competitiveness and profitability by providing critical information for purchasing decisions, production, stock levels, logistics, finance, and marketing (Yue et al., 2016, Bertaglia, 2017, Martnez et al., 2018, Arvan et al., 2019).

The challenge in effectively estimating demand stems from two inventory issues: overstock and stock-outs, which are at opposite ends of the spectrum. Companies have a tendency to overstock in order to avoid missed sales due to inventory shortages. Companies aim to lower inventory levels since keeping inventory is costly and reduces profit margins; thus, the inclination to stock-out of inventory develops (Bai and Zhong, 2008). Leaders use good forecasting to reduce demand uncertainty and assist organisations in adapting to economic and regulatory changes (Chang et al., 2016). The leader's utilisation of an adequate forecasting framework or model, as well as the presence of capable in-house expert opinion and judgement, are both required for a successful demand plan and strategy (Sindelár, 2016). An expert's capacity to translate, categorise, and organise data into information crucial to the forecasting framework or model input is also critical (Cassettari et al., 2017).

The most crucial aspect to consider when incorporating uncertainties into planning decisions is determining the most appropriate representation of these uncertainty characteristics. Because market dynamics and prediction errors are unexpected, Ashayeri and Lemmes (2006) discovered that a demand forecast would never be flawless, which is why the forecast should not simply include historical data. Forecasts cannot be made at every level due to the lack of precise data, but collaborative forecasts must be conducted at the processing, distribution, and retail stages (Kaipia et al., 2013). Forecasting for various supply chain goods and conditions has been studied at every level (Zhang and Qi, 2005; Ali et al., 2009; Guanghui, 2012; Eksoz et al., 2014; Ruiz- Aguilar et al., 2014; Wang and Xu, 2014; da Veiga et al., 2016).

As seen in Table 2.2, according to Lehman et al. (2012), there are four different kinds of methods of forecasting the future demand: Judgmental, Consumer/Market Research, Cause-effect and Artificial Intelligence (AI). Yet, the selection of the most suitable forecast model does not need to be based solely on either quantitative or qualitative ones; but rather a combination of models from both approaches is often the most effective one.

Table 2. 2. Common strategies of demand forecasting models

Qualitative method **(judgmental)**	**Combined method** **(Judgmental and statistical)**	**Quantitative method** **(Numerical and statistical)**
-Survey -Executive jury method -Sale force composite -Delphi technique	-Artificial intelligence methods • Artificial neural networks • Expert/group method of data handling • Support/believe vector machines -System dynamic (casual loop system)	-Casual forecasting • Regression analysis • Econometric models • Input-output models -Time series • Trend/pattern analysis • Regression analysis • Exploratory analysis

Source: Lehmann *et al.* (2013), p.5297

Demand forecasting tools are often based on qualitative (judgmental) or quantitative (numerical and statistical) methods, or a combination of the two. The most frequent forms of demand forecasting strategies used in most decision-making are listed in Table 2.2. Quantitative demand analysis is critical for accuracy, which has led to the development of mathematical models and computer-based demand estimation methods (Berkes et al. 2003). Input-output modelling with time series projection is a common demand forecasting method; other methods integrate qualitative data with quantitative analysis (e.g., from data mining, statistics, rule-based forecasting, or discrete event simulation). While no demand forecasting strategy is perfect, combining estimates can increase accuracy and lessen the risk of large errors.

Armstrong and Green (2017) stated in their research that forecasters should use more than one method for forecasting and combine the forecasts so that the resulting forecast will not be the worst forecast, and that it will perform at least as well as the typical component forecast. For various products and domains at various stages of the supply chain, a plethora of research studies are initiated using traditional and time-series forecasting techniques such as moving average, exponential smoothing, linear regression, hybrid regression models, state space and auto-regressive integrated moving average (ARIMA) (Gilbert and Chatpattananan, 2006; Ramos et al., 2015), seasonal ARIMA (SARIMA), and quantile regression (QR) hybrid model (Arunraj and Ahrens, 2015) for various products and domains at various stages of the supply chain following different linear and non-linear trends, namely seasonality, promotions, stock-outs, product substitution, perishability and non-perishability.

Istiningrum et al. (2021) employed the Croston method's demand forecasting as an input in determining the optimal ordered quantity with Probabilistic EOQ. Total inventory cost was compared to ML predicted EOQ and total inventory cost to the company's existing technique to assess the inventory cost reduction. Dania et al. (2019) used demand forecasting as a first step in inventory control to determine the demand for each type of flour. An accurate demand forecasting is a vital stage in the inventory control to allow the flexibility in the operation process and assist the company in providing the raw material as needed in the right time (Ren et al., 2019). The demand forecasting is generated from the historical data of demand that is available in the company. Based on the demand forecasting result, the optimal order quantity, reorder point, and the safety stock are usually calculated based on specific formulas.

Linear, non-linear, and non-stationary data patterns are all handled by machine learning. The hybrid model is a forecasting model that is created by combining two or more methodologies. By combining the benefits of each distinct technique, the hybrid model outperforms a single model for many forecasting situations (Das et al., 2018). Da Silva et al. (2017) make a point about the use of forecasting tools, stating that while time-series methods can usually be applied to historical sales data with a high level of precision, traditional statistical techniques are not the best option because they assume a linear relationship between input and output variables, which is rarely the case.

2.5 The economic order quantity (EOQ) model

The EOQ method is used to determine the volume or quantity of orders that are most suited to the requirements in place at the time of purchase. Costs can be cut as much as feasible by lowering the expense of ordering items during the purchasing period (Yahya, 2018). If the order timing and quantity are known, the utilisation of EOQ can be maximised (Rezaei, 2016). Every time an order is placed, the lead time is known and is consistent (Holmbom & Segerstedt, 2013). Whereas the number of economic orders that might be suited to this method can be calculated by the formula (Sarjono & Kuncoro, 2014):

$$\text{EOQ Method} = \sqrt{\frac{2DS}{H}}$$

EOQ: number of items in each order

D: annual demand for raw material inventory

S: costs required per order

H: the fee required for storage per unit annually

The classical EOQ's key premise is the perfect order quantity. However, most proposed inventory models are built and adjusted in the deterministic area due to the presence of many elements that cannot be ignored (Khan et al., 2011; Pentico and Drake, 2011; Yousefli and Ghazanfari, 2012). The EOQ's main point is that stock outs are not permitted. Furthermore, the demand assumption and lead-time are set and known. The EOQ model, according to Tungalag et al. (2017), posits that demand is constant and that inventory depletes at a fixed rate until it reaches zero. At that point, a specific number of items arrive, restoring the inventory to its previous state. Because the model assumes rapid replenishment, there are no inventory shortages or associated costs. As a result, the inventory cost of the EOQ model is a compromise between inventory holding costs and order costs. In inventory management, the EOQ formula is very essential. Researchers and practitioners in the disciplines of operations management and operations research have employed EOQ models. In Harris (1913), a very simple deterministic inventory planning model with a trade-off between fixed ordering cost and inventory carrying cost was described. The deterministic and stochastic EOQ models were created in parallel (Drake and Marley, 2014; Pentico and Drake, 2011; Rao and Bahari-Kashani,1990; Zhang et al., 2011; Brill and Chaouch,1995). The EOQ is the quantity of units a company should add to inventory with each order in order to reduce inventory total costs, such as holding charges and shortage costs. The EOQ is utilised as part of a continuous inventory system review in which inventory levels are constantly checked and a predetermined quantity is ordered each time inventory levels reach a defined reorder point. The EOQ is a methodology for determining the proper reorder point and optimal reorder quantity to ensure that inventory is replenished instantly and without shortages.

To estimate the maximum level of inventory or ordering lot size, most businesses use the EOQ model. The basic EOQ model is appropriate for usage when demand is known with confidence and is constant over time, no shortages are permitted, order quantities are received all at once, and order lead time is constant (Mubiry, 2015; Mangan et al.,2016). With a given order amount and interval, demand must be entirely even and predictable, which is extremely rare. An order point system is one in which the order quantity is fixed but the interval varies. In this system the EOQ is calculated, and a new order is placed when the inventory level reaches a decided order point.

The EOQ model is simple and makes a number of unrealistic assumptions, including continuous demand and purchasing price, deterministic setup, no lack of finished goods, and immediate delivery of finished goods. There are various variables that are not fixed in nature, such as demand and price, and these variables change through time and in relation to market and socio-economic factors. Because a simple EOQ model cannot incorporate such factors, the EOQ model's relevance to companies is limited. Paul and Azeem (2011) discovered the EOQ model's failure to predict the optimal number of finished goods inventory and, as a result, the supply chain's performance.

Models for inventory management with uncertain demand, such as variations of Harris formulation (Cárdenas-Barrón et al., 2014; Nobil and Taleizadeh 2016; Budd and Taylor 2019), Markov equation-based ones (Boute et al., 2007; Broyles et al., 2010), and Wilson's formulation (Wilson, 1934; Schwartz et al., 2006; Sarkar, 2013). They believe that completely satisfying an unpredictable and difficult-to-predict demand is too costly, if not impossible. All of these models are based on the constant order quantity principle, in which the size of the next order is determined by the goal of lowering the total cost of inventory management. Unpredictable and continuously changing demands, which affect the quantity and frequency of orders, cause traditional inventory management models to fail to solve actual inventory management difficulties, prompting the search for new or modified alternatives. In the last decade, there has been a rise in scientific interest in tackling this challenge. To begin, Sana (2011) proposed an EOQ model for perishable items that respond to changes in retail prices. Later, Dobson et al. (2017) argued that perishable commodities with a linearly falling demand rate as a function of product age behave similarly to non-perishable goods with a unit holding cost equal to the contribution margin to lifespan ratio. Zeng et al. (2019) propose an extension to Wilson's model with changing order quantities and ordering times. When a large change in consumer demand is detected and a long period of logistics planning is required, their model delivers a big economic effect. In their study, Benmamoun et al. (2018) examined three traditional inventory models: the EOQ, the Interval order quantity, and the minimum maximum inventory, taking into account a variety of factors such as uncertain demand, costs, and delivery delay. The comparison revealed that the EOQ produces the greatest outcomes for fast-moving products; however, for slow-moving parts, it is preferable to cover the lead time to avoid shortages by using the interval order quantity model.

Most of the developed forecasting models for different industries like retail, transportation, wholesale distribution and manufacturing industries; focused on demand indicators as inputs to their models that included various variables in common like: cycle stock, demand variability, seasonality, safety stock, current inventory level, lead time, price, promotions, shelf life and historic demand data (Bouganim and Olsson, 2019; Priyadarshi et al., 2019; Granda et al., 2019; Kilimci et al., 2019; Pezente, 2018; Jurczyk et al., 2016; Sustrova, 2016; Slimani et al., 2015; Kochak and Sharma, 2015). This research would analyze and focus on more variables, which are fluctuating in nature and that would affect the optimum quantity to be ordered by distributors. That is why the EOQ model would be incorporated to determine the exact needed quantity by distributors due to the dynamic nature of all the factors that affect their inventory levels. The next section will highlight how the working capital could be considered as one of the demand indicators and the important link between the working capital and the inventory management.

2.5.1 Working capital and the EOQ

Working capital is a term that refers to all short-term balance-sheet elements (Meyer, 2007). Working capital is divided into two categories: Net Working Capital (NWC) and Gross Working Capital (GWC) (GWC). Schulte (2011) defines working capital as GWC that only includes a company's current asset investments. As a result, increasing overall investments increases working capital (Chadamiya and Menapara, 2013). Working capital management (WCM) is the guiding, planning, and control of a company's operative investments, including cash, receivables, inventories, and payables, as well as their interrelationships (Hofmann et al., 2011). WCM also includes inventory management, cash in hand and at the bank, receivables management, and creditor management, according to Egide et al. (2016). A significant amount of cash is required to respond to unanticipated expenses as well as to stock raw materials and finished goods. Additionally, businesses must deal with customers who do not pay immediately after receiving items (Berk and DeMarzo, 2013). Last but not least, Egide et al. (2016) emphasised the necessity of effective asset and liability management in achieving a balance between profitability and risk that adds value to the company. To examine working capital, proper management of accounts receivable, payable, and inventory is required.

Inventory management, which is an element of working capital management, is seen as a critical factor in guaranteeing business profitability (Aminu, 2012). Because the optimal inventory level is determined by sales, sales forecasting is required before target inventories can be created. Furthermore, because mistakes in setting inventory levels result in lost sales or excessive carrying costs, firms use sophisticated computer systems to monitor their inventory holdings (Brigham and Houston, 2021). As a result, inventory size has a direct impact on working capital and its management, and it must be carefully managed. Inventory management, as part of working capital management, is a critical area with a lot of room for improvement in terms of operational efficiency (Alsulayhim, 2019; Khalid et al., 2018; Deloof, 2003; Nihiu and Dermaku, 2017). Though inventory management as a branch of working capital management is a prominent topic for academic research, most studies focus on its impact on a company's financial performance and profitability by looking backwards and extrapolating data from the past (Priniotakis and Argyropoulos, 2018; Dooley, 2005; Ivanov et al., 2017). To succeed in stock optimization and better performance, companies must revalue stock control difficulties and practise and shift to a more predictive strategy (Barrat, 2004; Subramanian et al., 2014; Tonetti, 2019).

According to Kabuye et al. (2019) and Pais and Gama (2015), a reduction in inventories maintained by enterprises, as well as the number of days it takes to settle liabilities and collect payments from consumers, is linked to improved corporate profitability. Reduced cash conversion cycle boosts business profitability, according to Lyngstadaas and Berg (2016). To summarise, WCM is critical for a company's profitability (Baker et al., 2017; Singh and Kumar, 2014), which means that efficient and effective WCM ensures that a company may continue operations while also having enough cash flow to pay down short-term debt and cover upcoming operating needs (Altaf and Shah, 2018). According to Agha (2014), a sustainable business requires effective inventory management, and the more the profit a company reports, the better the company is perceived to be generating more money on capital spent. According to Ashok (2013), inventory can be utilised to assess a company's liquidity and operational efficiency. Inventory applications could be evaluated using inventory turnover, which is defined as the number of times stock or inventory is replaced per year. The study by Lazaridis and Dimitrios (2006), which looked at the relationship between working capital management and corporate profitability, found a strong negative relationship between inventory turnover in days and a firm's profitability.

The following section will highlight the role of ML in the supply chain management and why this research has chosen the supervised regression algorithms to be used as a forecasting tool to forecast the EOQ of the FMCGs distributors for better inventory management.

2.6 Machine learning techniques in a supply chain context

Scientific and technical growth has an impact on every sector of the economy, and its capabilities are being leveraged to find solutions for better supply chain organisation and efficiency. SCM interruptions have harmed company performance in recent years (Ho et al., 2015). Previously, even with inefficient SCM, the most productive and commercial organisation could generate a profit (Tempelmeier, 2011). That is not the case today, because most businesses make a tiny profit (Bokor, 2012). Cost reduction entails rationalisation across the board (Stevic et al., 2017), with research in the field of SCM indicating that savings of up to 30% are achievable (Chen et al.,2013). For logistics and supply chain management, AI and machine learning have been seen as next-generation technologies. Learning by example, learning by analogy, and learning through experience are all ways for computers to expand their capabilities. ANN and genetic algorithms are two prevalent methods (Negnevitsky, 2005). An ANN is based on the idea that the human brain is a highly complex, nonlinear, and parallel computer. ANN can be used in a variety of disciplines, including prediction, clustering, pattern categorization, and pattern alerting (Haykin, 1999). The prediction component of regression algorithms is highlighted in this study for the aim of estimating the EOQ for FMCGs within supply chain distributors.

Taking into account the current knowledge in the field of SCM (Azadeh et al., 2015; Bhatnagar and Chee-Chong, 2009; Fallahpour et al., 2017), researches in the literature focus on whether the dynamic model on the principle of the hybrid method of AI (Abdollahzade et al., 2015; Fallahpour et al., 2016; Ghorabaee et al., 2017; Tamosaitiene et al., 2017; Tavana, Fallahpour, Di Caprio and Santos- Arteaga, 2016) can be used for planning, organising and implementation of order quantity. All the differences of SCM processes, as well as the nature and degree of the influence of important factors in establishing EOQ for the observed company and the type of commodities, were considered throughout the decision support system design (Zavadskas et al., 2017). To assess EOQ and its realisation by a retailer, Sremac et al. (2019) suggested a decision support system based on a hybrid neuro-fuzzy AI technique. This method performed well in determining the quantity of EOQ, and it is described as a useful tool for SCM planning.

According to Herbert et al. (2017), machine learning is a subfield of AI that is used to detect and identify correlations in data. Both linear and nonlinear issues are handled by ML. With today's technology and the growing amount of data in enterprises, there is an opportunity to improve business processes. As demonstrated in Figure 2.1, ML and technology areas overlapping this concept are many and the lines between the different concepts can sometimes be hard to distinguish.

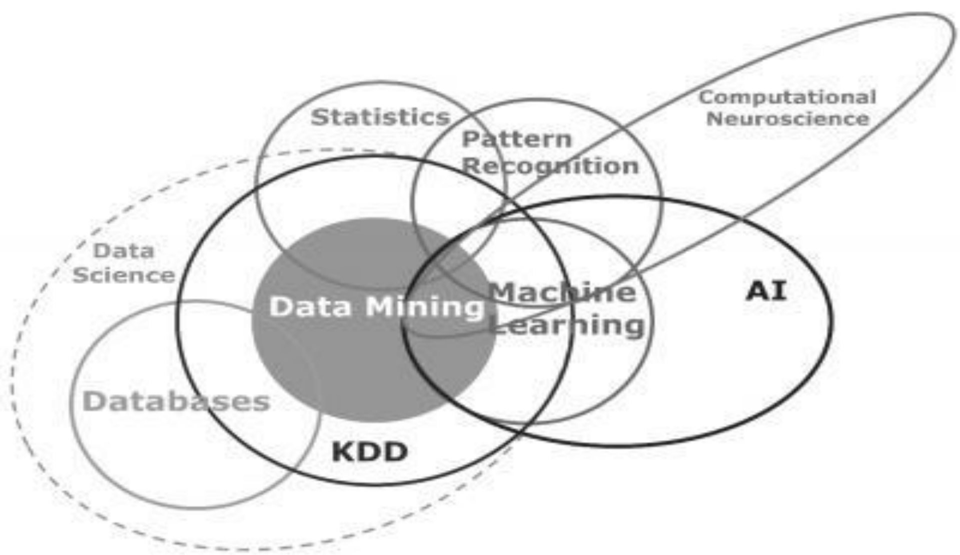


Figure 2. 1. Multidisciplinary nature of ML. Source: Hall et al., 2014, p.3)

According to Schapire (2018), the ideal strategy to identifying an appropriate algorithm for the problem is to choose a few algorithms that fit the problem well in terms of their application domain. As illustrated in Figure 2.2, ML models are divided into supervised and unsupervised learning techniques. In the face of uncertainty, the goal of supervised machine learning is to create a model that makes predictions based on evidence. A supervised learning technique trains a model to create plausible predictions for the response to incoming data using a known set of input data and known responses to the data (output). To construct prediction models, supervised learning employs classification and regression algorithms. The unsupervised learning method, on the other hand, looks for hidden patterns or intrinsic structures in data (MathWorks, 2019).

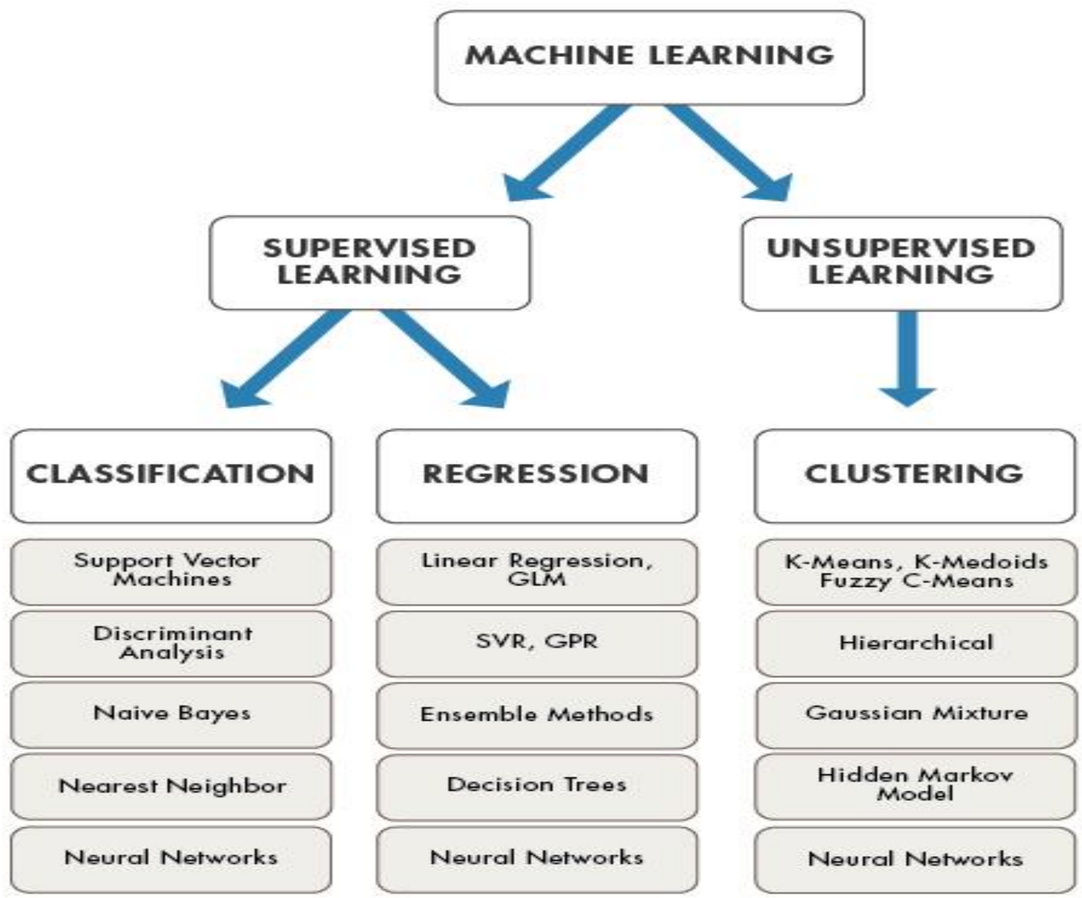


Figure 2. 2. Machine Learning algorithms classification. (Source: MathWorks, 2019)

There are different sorts of machine learning models, and they can be classified in a variety of ways. The process- and function-based segmentation models are explained in the next two sections.

2.6.1 Process-based segmentation

To characterise ML algorithms, there are three commonly used process-based models (Abu-Mostafa, 2012). Supervised learning, unsupervised learning, and reinforcement learning are the three models (Jones, 2017). This split is based on how the ML learning process is carried out (Suthaharan, 2015). This section will describe the supervised and unsupervised learning algorithms.

2.6.1.1 Supervised learning

Jones (2017) claims that all supervised learning algorithms have one thing in common: they are all trained with labelled data. The model receives feedback during training by processing labelled output data, which is an important aspect of the learning process. Depending on the type of prediction needed, supervised learning algorithms can be used for a variety of techniques. Classification and regression models are the most employed estimator types in supervised learning (Microsoft, 2017).

2.6.1.2 Unsupervised learning

Unsupervised learning differs from supervised learning in that the training technique is carried out on unlabelled data (IBM, 2018b). There is no feedback loop that gauges the algorithm's performance when processing unlabeled input (McKinsey, 2018a). An unsupervised algorithm identifies a structure in an unlabeled dataset and then divides the dataset members into segments with comparable characteristics (McKinsey, 2018b). Clustering is the most prevalent unsupervised learning paradigm (Anon, 2017a).

2.6.2 Function-based segmentation

Regression, classification, and clustering models are some of the most commonly used machine learning models. This segmentation is based on how machine learning could be modelled (Suthaharan, 2015).

2.6.2.1 Regression modelling

A regression model is a type of supervised learning model that is used to create quantitative predictions. The model provides predictions by determining the link between a dataset's input and output variables (see Figure 2.3). (Suthaharan, 2015; Bousqaoui and Achchab, 2017).

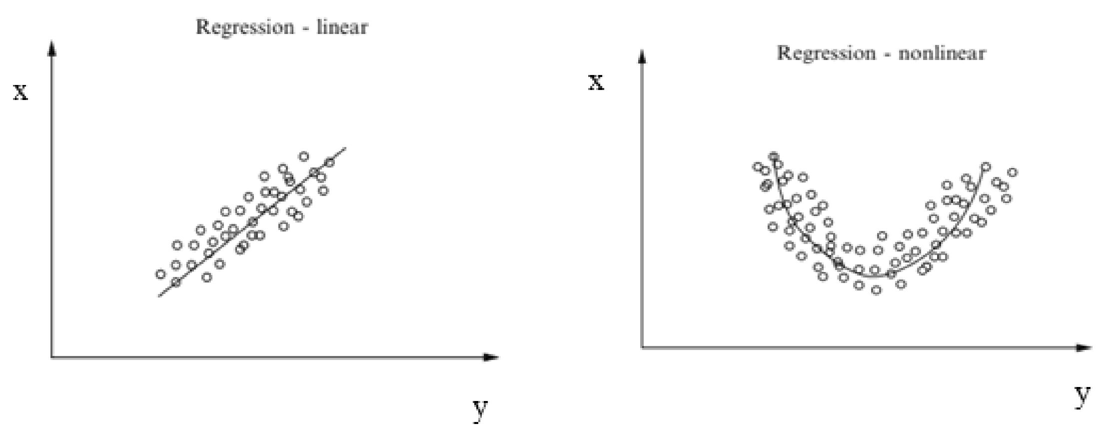


Figure 2. 3. An example of linear and nonlinear regression models (Source: Sutharaharan, 2015)

There are both linear and nonlinear regression models, as shown in Figure 2.3. (Suthaharan, 2015). The variables in a dataset fit a linear equation in linear regression. When the variables in a nonlinear regression model fit a nonlinear equation, the same principle applies. When the data fits the equation, a prediction of the y value for a given x value can be made (Suthaharan, 2015). Predicting stock prices and demand is a practical example of a typical use for a regression model (Anon, 2018b).

2.6.2.2 Classification modelling

A classification model is a supervised learning model that predicts the category of members in a dataset. The algorithm can be trained to identify rules that can be used to classify other datasets that aren't tagged because the data is labelled. A dataset containing two classes, represented by black and white dots, is shown in Figure 2.4. The straight line in the right graph represents the identified rule, which is utilised to classify new data (Suthaharan, 2015). Common uses include medical imaging, image and speech recognition, and credit scoring.

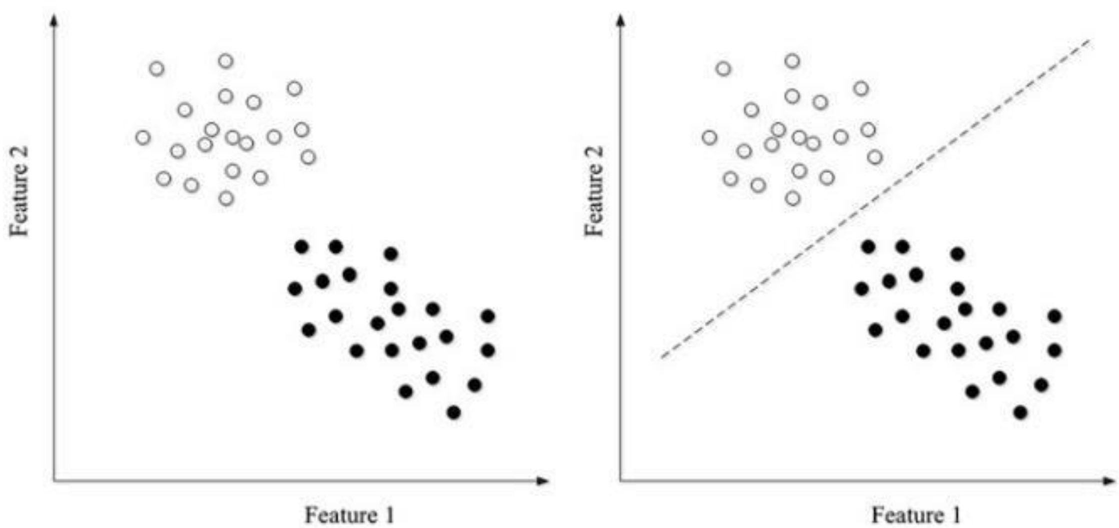


Figure 2. 4. Class formation in a classification model (Source: Suthaharan, 2015)

2.6.2.3 Clustering modelling

Clustering is a type of unsupervised learning in which the algorithm divides a dataset into groups. Clustering is done differently than in a classification model because there are no labels from which a rule can be derived. The geometrical pattern of the dataset members, which are plotted in their graphs from their variables, as illustrated in Figure 2.5, provides the foundation for cluster construction. For a single or few variables, the members of the dataset are assigned to the cluster with the shortest distance between them and the cluster's members (IBM, 2018a; Suthaharan, 2015). Gene sequence analysis, market research, and object recognition are all examples of clustering applications.

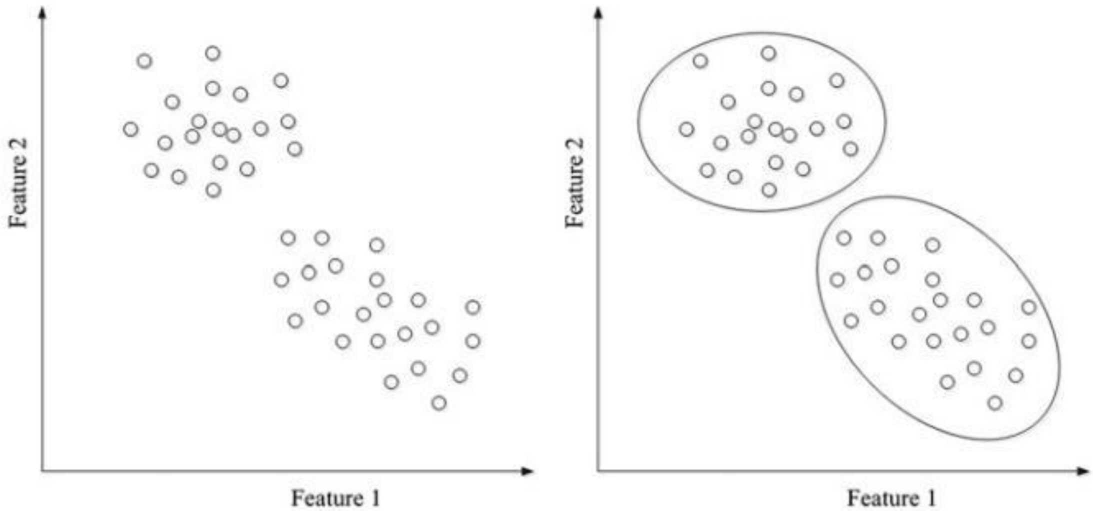


Figure 2. 5. An example of a cluster formation (Source: Suthaharan, 2015)

The accuracy of demand projections is critical to the success of a supply chain. However, supply chains are subject to the impacts of uncertainty, which result in the bullwhip effect, therefore improving prediction accuracy requires lowering this effect as well as the supply chain's total costs (Bousqaoui et al.2017). As a result, machine learning techniques are a valuable asset for supply chains, as they provide better projections than traditional methods. Min (2010) emphasised AI's value as a decision-aid tool that helps a company engage with its supply chain partners by facilitating information flow among multiple business organisations. Learning algorithms are used in ML-based forecasting to detect underlying demand drivers and find insights (Chase, 2017). Table 2.3 summarizes the comparison between traditional and ML forecasting approaches.

Table 2. 3. Comparison between traditional and ML forecasting approaches

	Traditional Forecasting	Machine Learning Forecasting
Predictor variables count	Single or few	Unlimited
Data Source	Mainly demand history	Multiple
Algorithms	A number of single-dimension algorithms	An array of integrated algorithms
Manual Data Manipulation and cleansing need	High	Low
Data requirements	Low	High
Technology requirements	Low	High

Source: Kharfan and Chan (2018)

This table shows that machine learning and predictive analytics outperform traditional forecasting methods that rely on a small number of demand parameters to generate more accurate demand projections. Many parts of the supply chain, both downstream and upstream, involve machine learning algorithms, including planning, procurement, and supply management, production, inventory, and storage, and lastly transportation and distribution. Figure 2.6 represents which machine learning algorithm are used in each of those different areas.

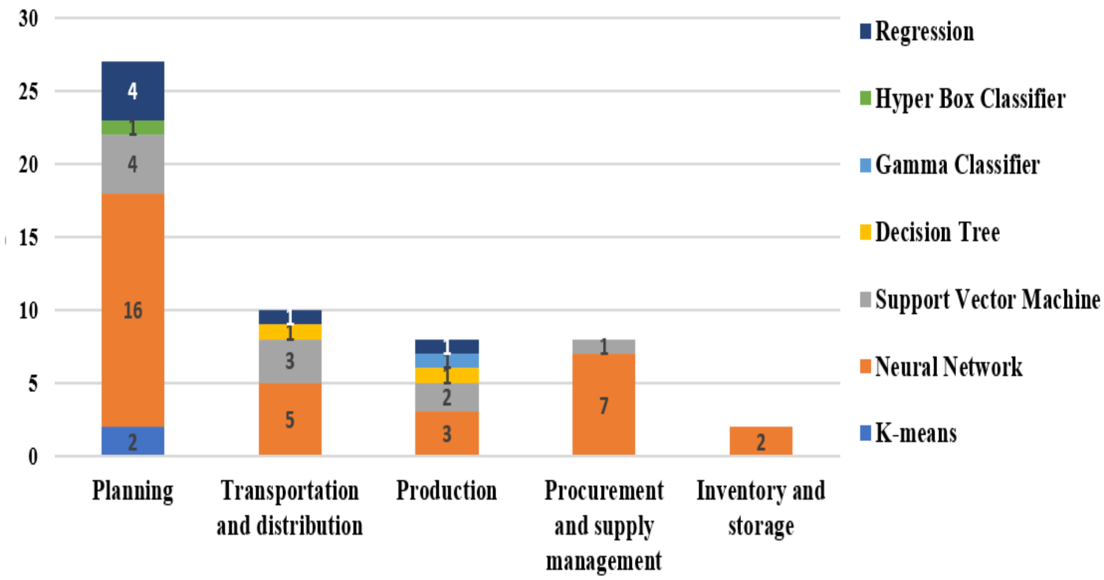


Figure 2. 6. The ML algorithms applied in each area of the supply chain (Source: Bousqaoui et al., 2017, p.4)

According to Rooij (2017), regression and classification are similar in that both require a training set of inputs and outputs, and the researcher must learn a function that connects the two in order to predict outputs given new data. The only distinction is that the outputs in classification are discrete, but the outputs in regression are not. In real-world issues, if the variable is discrete/categorial, it is a classification problem, but if the variable is a real number/continuous, it is a regression problem, according to Jain (2014).

The existence of dozens of supervised and unsupervised machine learning algorithms, each taking a distinct approach to learning, can make choosing the proper algorithm appear daunting. Overfitting data occurs when highly flexible models slight alterations that could be noise. Simple models are easy to understand, but they may be less accurate. As a result, selecting the best algorithm necessitates weighing one benefit against another, such as model speed, accuracy, and complexity (MathWorks, 2019).

Thus, ML techniques constitute a real asset for supply chains, since they give better forecasts than the traditional approaches. This research aim is to predict the EOQ (value), and that is why a supervised learning regression algorithm has been chosen to fulfil this aim as it was suitable for solving these kinds of problems. The next section will review the supervised ML algorithms to choose the most suitable algorithm during the development phase of the ML predictive model.

2.6.3 Supervised machine learning algorithms

Random forests, artificial neural networks, support vector machines, gradient boosting, and k-nearest neighbours have a high potential in decreasing demand forecasting error, according to some literature in applying different traditional forecasting techniques and machine learning algorithms in supply chain contexts. The generic and trending strategies used in various studies in the literature to deal with excessive noise present in data, time steps, and forecasting periods include ANNs, bagging, boosting, various types of AdaBoost, gradient boosting, classification and regression trees, and random forests (Sutton, 2005; Araujo and New, 2006; Voyant et al., 2017). The following sections will review four supervised ML algorithms that were most suitable for demand forecasting based on the literature. The prediction performance of these algorithms will be analysed and the ones with the accurate prediction results will be chosen for developing the ML predictive model.

2.6.3.1 Linear regression (LR)

One of the most basic and often used classical predictive models is linear regression. This method is most commonly used to predict the value of an output variable from a set of explanatory variables. By fitting a regression line to the output variable and explanatory factors, the LR model establishes a link between them (Oance, 2014).

2.6.3.2 Random Forest (RF)

Random forest (RF) regression is an ensemble machine learning (ML) model made up of numerous decision tree regression models powerful enough to represent complex nonlinear relationships; each decision tree regression model has a prediction result (Naghibi et al., 2016). Many decision trees are built in RF models, and then these trees are used to forecast fresh data by aggregating the trees' predictions (i.e., the proportion of votes for classification, or the average for regression) (Liaw and Wienner,2002).

2.6.3.3 Boosting decision tree (BDT)

The gradient boosting algorithm is an error-based optimization algorithm. Gradient boosting is a machine learning technique for solving classification and regression issues. It creates a powerful prediction model by combining weak prediction models like the decision tree (Wei et al., 2020). With a modest risk of less coverage, this method tends to improve accuracy (Microsoft Azure Machine Learning Studio, 2019).

2.6.3.4 Artificial neural networks (ANN)

ANNs offer a way to define neurons in the same way as the human brain does to solve complicated issues (Huang, 2009). The black box with unknown inner structure and known outputs is how ANNs are described. Neural networks relate to a single hidden layer back-propagation network or single layer perceptron, which has grown into a wide range of models and learning methodologies (Hastie et al., 2009). The neural network's primary idea is to extract linear combinations of inputs as derived features, then model the observations of interest as a nonlinear function of the fitted features. Organizations use a variety of elements to forecast product demand, including prior demand, lead time, pricing, product quality, economic situation, and competitors' price and supply. As long as fresh training data sets are available, a neural network can use past demand data as input and update knowledge over time. The neural system can also learn new demand patterns that weren't present in the training data set, where demand can be flat, trend, seasonal, cycle, or random (Lee et al. 2012).

The following section will focus mainly on reviewing the machine learning algorithms applied in demand forecasting, highlighting the results produced from these algorithms and comparing their accuracy and precision to those produced by other traditional forecasting techniques.

2.7 Machine learning applications for inventory management

Because of its smarter ways to boost income and save time in tackling complicated challenges, machine learning techniques are becoming increasingly important in the industry. One of the most important applications of machine learning in supply chain is anticipating client demand in the future (Makkar et al., 2019). ML-based demand and sales forecasting is one of the areas of supply chain and applications where ML algorithms are now in use. The coming section reviews the ML techniques applied in the demand forecasting and the EOQ determination areas.

2.7.1 ML techniques in demand forecasting

According to (Tugay and Oguducu, 2020), the research studies on demand forecasting can be grouped into three main categories:

1. Statistical Methods.

   Some statistical methods for demand forecasting include linear regression, regression tree, moving average, weighted average, and Bayesian analysis (Liu et al., 2013).

2. Artificial Intelligence Methods.

   Because AI approaches are efficient and accurate, they are frequently utilised in literature for demand forecasting (Chang and Wang, 2006; Gutierrez et al., 2008; Zhang et al., 1998; Yoo and Pimmel, 1999).

3. Hybrid Methods.

   Hybrid approaches combine several methods and make use of their strengths.

AI in general and machine learning specifically are highlighted as having significant potential to improve costs over traditional analytical techniques (Chui et al., 2018). The field of supply chain management and the consumer-packaged goods industry are identified as among the best candidates for adoption of these techniques. The cases reviewed for demand forecasting that implemented AI to identify underlying causal drivers show a 10-20 percent improvement over existing methodologies for the value of augmenting existing analytical capabilities with ML and AI.

Many authors have applied ML to demand forecasting and compared forecast accuracy against the accuracy of traditional forecasting methods. Potočnik et al. (2019) show that recurrent neural networks are more accurate than empirical models in forecasting natural gas demand, and they suggest implementing a LR model instead when computational resources are limited. ML based demand forecasting using recurrent neural networks and SVM can show better performance than traditional techniques (naïve forecasting, trend, moving average, and linear regression), but it should be noted that improvement in forecast accuracy with those more complex models is not always more statistically significant than using linear regression (Carbonneau, Laframboise, and Vahidov, 2008). Saloux and Candanedo (2018) also argue that advanced ML approaches, decision trees, SVM, ANN, improve demand forecasts compared to traditional LR models. ML based demand forecasting can also be used to improve forecasts when demand is intermittent. Neural networks can perform better than Croston, moving average and single exponential smoothing when demand is irregular, as in spare parts supply chains (Amirkolaii et al., 2017). Vargas and Cortes (2017) claim that ANN perform well in the sample period, but they are less steady than ARIMA in post-sample period forecasting of irregular spare parts demand.

Weber and Aburto (2007) used a hybrid demand forecasting model that included auto regressive integrated moving average (ARIMA) models with neural networks to examine demand forecasting in supply chains. In terms of percentage error, neural networks surpass ARIMA models in forecasting. Lu et al., (2012) used monthly sales records from a computer wholesaler in Taiwan to explore sales forecasting for computer wholesalers. Across a variety of performance metrics, MARS surpasses BPNN, SVR, extreme learning machine, ARIMA model, multivariate linear regression model, and four two-stage forecasting methods.

For a demand forecaster who agrees that ML based demand forecasting can perform better than traditional approaches, the next challenge is to pick the right machine learning technique. Therefore, part of the literature surveyed focuses on comparing machine learning methods with each other. Gaur et al. (2015) used a simulation using a confusion matrix as a performance indicator to compare nearest neighbours and Bayesian networks for demand forecasting in supply chain management, concluding that the latter outperforms the former. Guanghui (2012) implements SVR and radial basis function neural networks to forecast demand of weekly sales for a large paper enterprise and shows that SVR performs better. In a study comparing three ML approaches to forecast demand of bike-sharing service, LR performs better than neural networks and RF. Combining multiple techniques to build ensemble or hybrid models is also common when implementing ML in general. Efendigil et al. (2009) use an adaptive neuro fuzzy inference system to utilize both neural networks and fuzzy modelling to get more accurate demand forecasts. Johansson et al. (2018) use ensembles of machine learning algorithms for operational demand forecasting and argue that extreme learning machines provide the best accuracy.

Forecasting demand for FMCGs is challenging due to reasons like shelf-life and seasonality. For the same reasons, this is an area where applying ML techniques can result in better forecasts. as ML models can capture complex relationships. The studies that have been analyzed regarding applying ML to demand forecasting of FMCGs products show promising results. While a large selection of ML algorithms has been implemented, neural networks, SVM and RF are among the common ones. Table 2.4 summarizes papers that generally focus on demand forecasting of different FMCGs products and summarizes the methods and features used along with the conclusions. Research into the application of machine learning in the field of demand forecasting is still in its early stages and has shown mixed results. There is no one-size-fits-all approach when it comes to replacing traditional demand forecasting methods. The selection of the ML model plays a significant role in the final forecast accuracy.

Table 2. 4. Review and summary of similar demand forecasting studies

Authors	Forecasted FMCG product	Methods Used	Conclusion
Ghanbari (2019)	Construction equipment	Simple linear regression, Polynomial regression, Simple moving average, SVM linear, SVM radial, RF	SVM Linear method outperformed the other algorithms based on business and statistical accuracy measures.
Priyadarshi *et al.* (2019)	Fresh Vegetables	Box–Jenkins-based ARIMA model, long short-term memory (LSTM) networks, SVR, RF regression, GBR, Extreme GBR (XGBoost/XGBR)	Other demand forecasting models performed worse than the LSTM and SVR.
Granda *et al.* (2019)	Water Bottles	MLP Neural Networks	Neural networks offer more robust results than the "Exponential smoothing" technique.
Goli *et al.* (2019)	Dairy Products	Statistical tests, Time series neural network, Improved MLP neural network, Novel meta-heuristic algorithms	In the hybrid technique, the forecast error was reduced by 1.8 times by combining the GWO and CA with MLP.
Liu and Fricke (2018)	Footwear	Regression trees, RF, K-nearest neighbors, Linear regression, Neural networks	Ensemble methods and RF gave the best predictive performance.
Mupparaju *et al.* (2018)	Grocery store items	Moving average, Gradient boosting, Factorization machines, Deep neural networks	Neural network model with a sequence to-sequence approach performs best.
Pezente (2018)	Sugar commodity demand	Linear regression, ARIMA, ANNs	Neural network models were significantly more accurate.
Taghizadeh (2017)	Weather-sensitive retail products	The MLP Neural network, Time delay neural networks, Recurrent neural networks, Bagging, Linear regression	The BP MLP learning algorithm performs best.
Yu *et al.* (2013)	Newspaper/magazines	Traditional regression, SVR	SVR performs better than traditional regression algorithms.
Mahbub *et al.* *(*2013)	Furniture product	Feed-forward back-propagation ANN model	FF BP ANN performs much better than the linear model.

Kandananond (2012)	Detergents	MLP neural network, Radial basis function (RBF), SVM, ARIMA	SVM perform better than ARIMA and ANNs.
Paul and Azeem (2011)	Finished goods inventory	Feed-forward Back Propagation Neural Network	The multilayer feed forward performs accurately to determine the optimal amount of finished goods inventory.

To study the multitude of approaches adapted for forecasting, the plenty of literature consists of many classical, statistical, and ML based forecast methodologies for supply chain, as shown in Table 2.4 which elicits the utility of ML algorithms in demand forecasting with special focus on the demand forecast of the FMCGs. As shown in the previous applications, companies have major challenges in using suitable methods to improve their forecasting ability. The general academic approach in the studies examined was comparing a few selected ML techniques to traditional approaches. The consensus is that ML based methods are promising in improving demand forecasts even if they do not necessarily perform better than traditional methods under every scenario. And also, ML integrated approaches applied in some of the mentioned studies in the table indicated their ability to achieve better results compared to traditional approaches, due to the strong relationship these integrated approaches establish between the input and the output values of the training data (Goli et al., 2019).

Combining forecasting approaches can combine the benefits of several methods and give useful tools, particularly when dealing with non-linear data patterns or intermittent and lumpy demands (Sharif Azadeh et al., 2013). Although many advancements have been made in forecasting demand of the FMCGs, still many possible methodologies remain untested in this area. Integration of machine learning algorithms for demand forecasting in the distribution sector could be a promising study subject in this regard. Furthermore, incorporating dynamic data into distributor forecasting methods can improve forecast accuracy, according to Ghalehkhondabi et al. (2020). This research aims to develop dynamic demand forecasting methods that can make decisions based on real-time data, which will save companies a lot of money.

2.7.2 Developed EOQ models in the deterministic and uncertain environment

Many scholars have looked into the EOQ problem in recent decades. Most of the inventory models offered were created in a deterministic context. Deterministic EOQ models were reviewed by Pentico and Drake (2011) and Khan et al. (2011). However, some of the researchers took into account real-world scenarios and provided inventory models in uncertain conditions. Fuzzy EOQ models, stochastic EOQ models, and hybrid EOQ models are the three types of uncertain EOQ models. The traditional technique (Axsater, 1996; Harris, 1913) is one of the earliest EOQ models in the disciplines of operations and inventory management, however it has limited assumptions and cannot be altered or operate efficiently in today's environment. Individual artificial intelligence methods (Celebi, 2015; Kazemi et al.,2016; Mondal and Maiti, 2003; Roy and Maiti, 1997) resulted in more flexible models than the classic ones, which were characterised by simplicity and robustness. Individual AI methods offer numerous benefits, but they are unable to cover all of the nuances of the order process in SCM, and so produced models lack sensitivity and adaptability. Under the complicated conditions of real-world commercial operations, the best outcomes are obtained by employing some of the hybrid artificial intelligence technologies listed below: Teksan and Geunes, 2016; Liou et al., 2016; Zavadskas et al., 2016; Yazdani et al., 2017.

The availability of suitable raw materials in the proper quality and quantity influences the availability, quality, and quantity of desired output to some extent. In raw material management, determining the EOQ and optimal stock levels is critical (Akindipe, 2014). Rossi et al. (2017) conducted a case study utilising mixed integer linear programming to construct an EOQ model for a multi-item framework. Huang and Wu (2016) created various cost functions based on structural attributes that can be solved using an efficient method for minimising average inventory cost in a B2B context to handle a periodic inventory model problem with backordering. Dhull et al. (2018) investigated the optimization of supply chain management inventory control in a company using novel regression techniques. Furthermore, Sarwar et al. (2020) suggested a multi-item multi-constraints inventory control model that uses a MOPSO algorithm to determine the optimal purchase and production quantity to minimise overall inventory cost and space required. Gupta et al. (2022) employed the EOQ to estimate inventory management parameters and found that the various regression approaches predicted the same values. Different simple regression algorithms are used to compare the typical EOQ model with predicted values. Furthermore, Bikulov et al. (2020) pointed out that while the optimization approaches examined in previous studies can effectively solve inventory management problems, they are frequently incomprehensible to real managers due to their great complexity.

Inventory control in supply chain management focuses on ensuring that all operations involved in the supply chain process are carried out efficiently, effectively, and economically through the use of modelling techniques. Inventory control using the EOQ model reduces total holding costs and reordering costs while also determining the appropriate inventory level, which is advantageous from both a managerial and practical standpoint. In general, most published studies dealing with built models predicting EOQ by ML have either ignored or treated working capital as a constant component of the EOQ. This research is focused on an in-depth analysis of the developed model structure to be able to function effectively in the deterministic and stochastic environments. The goal of this research is to develop an EOQ prediction model that, when used in practise, will allow a corporation to optimise inventory levels as well as the entire supply chain while taking into account a wide range of parameters that have yet to be included by existing models.

2.8 Research gap

Companies seek possibilities in the global market by cutting production costs while boosting investment without compromising product quality. Data accuracy becomes a critical source for a business to determine sales forecasts based on market demand. Managing all the company's assets is one of the company's tactics for increasing benefits. Inventory management in a business should give precise information about the inventory of goods and services, especially in large businesses that handle high-value items (Wanti et al., 2020). The correctness of information about ordering and releasing items has an impact on the company's performance. Supply chain managers benefit greatly from demand sharing and forecasting since they provide a valuable source of information for planning and decision making (Abolghasemi et al., 2019). Improving product demand forecast accuracy can result in increased operational efficiency, customer satisfaction, and cost savings across the whole supply chain (Kremer et al., 2015; Trapero et al., 2015). That is why managers use forecasts to predict future needs, resulting in the generation of information useful for guiding leaders in day-to-day decision-making and gaining critical insight into their operations, such as inventory management, replenishment, safety stock levels, and proper reorder quantity (Meyerhoefer et al., 2016). (Raza and Kilbourn, 2015). In this regard, this research aims to analyze and develop a model that can be used by companies to provide decisions related to the prediction of the EOQ.

According to literature and research, there are numerous methodologies and approaches in supply chain management for estimating quantity, total inventory prices, reorder point, and safety stock under various scenarios (Gupta et al., 2022). Most businesses use the EOQ model to establish their maximum inventory level or order lot size (Ali et al., 2011). Classic EOQ approaches are based on assumptions that do not account for the characteristics of modern complex logistical systems, such as demand being constant in unit time, lead time being deterministic and stationary, and price being constant (Maddah and Noueihed, 2017). However, in SCM, decisions are made in an environment where objectives and limitations are rarely, if ever, properly specified (Latif et al., 2014; Seker et al., 2013; Taleizadeh et al., 2016). As a result, a degree of approximation is essential to obtain a high-quality model of a real system in which AI plays a significant role (Sremac et al., 2013). Consequently, individual methods of AI (Ghorabaee et al., 2017) or their combination in the form of a hybrid method are increasingly used in solving real and complex problems (Liou et al. (2016); Radeerom and Kulthon (2013); Teksan and Geunes (2016); Zavadskas et al. (2016)).

This research targets the distribution sector of the FMCGs supply chain, and it focuses mainly on determining the stock to be ordered as this leads to appropriate inventory management and wise purchasing decisions, which, if not managed properly, can involve dramatic consequences (Fisher, 2009). Trying to avoid out-of-stock and surplus situations these two cases should be addressed through applying advanced hybrid ML techniques that have proved its better forecasting performance and accurate results than the standalone techniques

(Das et al., 2018). Applying ML in the field of demand forecasting is still showing mixed results. ML is a very dynamic area of research where new techniques are continuously being developed, as there is no single model that performs well for all different types of demand series when it comes to replacing traditional demand forecasting methods (Abolghasemi et al., 2019). Throughout the literature, it was proved that hybrid models can integrate the advantages of various forecasting methods. These models have been used for several forecasting applications used for forecasting of power generation (Das et al.,2018), tourism and passenger demand forecasting (Ghalehkhondabi et al., 2020), retailer's demand forecast (Bottani et al., 2019), vegetables' retailer demand forecast (Priyadarshi et al., 2019); achieving better and more accurate results than the stand-alone techniques. Furthermore, hybrid machine learning techniques can provide a greater level of precision in demand forecasting than standard statistical techniques, which improves inventory balancing, reduces stockout rates, enhances customer availability, and increases profitability in the FMCG market (Taralleo et al., 2019).

Three aspects of research gaps can be observed. First, the proposed approach addresses the "working capital" variable that has not been included as one of the inputs to the previous EOQ prediction models. Most of the previously developed EOQ models for distributors focused on the current demand, current inventory, purchase cost, demand patterns and promotions as input variables to their demand forecasting models ((Sustrova, 2016; Gdowska and Mikulik, 2016; Merkuryeva, 2019). Second, from a more technical perspective, there are very few examples of applying hybrid ML predictive models using regression algorithms in the demand forecasting domain of the FMCGs distributors. Botchkarev (2018) highlighted that current research focused on developing a tool that would embrace multiple types of regression models in the same experiment, use diverse performance metrics that are the same for all the algorithms, and that would allow for easy change in input datasets. To the best of my knowledge, this is the first attempt to consolidate three predictive models in a sequential implementation, each one of them is predicting a variable that would be used as an input to forecast the optimal quantity to be ordered by the FMCGs distributors, as the studies carried before (Ghanbari et al.,2019; Priyadarshi et al., 2019; Goli et al., 2019; Liu and Fricke, 2018; Pezente, 2018) were just comparing the results of different algorithms implemented as single methods but not incorporated in one framework. The developed model will not only forecast the general demand that the distributor needs but it should forecast the optimum quantity of goods to be ordered on a weekly basis based on the available cash the distributor has now, to maintain the distributor inventory levels and to optimize the overall performance of the inventory. From a scientific point of view, the proposed cascade approach addresses the prediction of demand, inventory, and sales before forecasting the optimal quantity to be ordered by the distributor. This is an important point because in the wholesale distribution, the selling price is expected to have to have an impact on the demand of the product (Bottani et al., 2019). Thirdly, there is also growing need for research in the areas of demand forecasting using advanced ML techniques with specific applications in the Egyptian distribution and retailing sectors, as they depended on traditional forecasting techniques in their operations and they needed to raise the performance level of their demand forecasts to enhance the overall supply chain performance, to cope with the worldwide changes in this field. To address this gap, this study considers a case study application to an Egyptian FMCGs distributor (QEBAA).

The goal behind conducting this research was to select an optimum combination of supervised regression models which will produce least error measures along with presenting the optimal weekly quantity to be ordered by the distributor based on newly added demand predictors that were not covered in the previous demand forecasting models. The purpose of this study is to select the appropriate forecasting model to be implemented at the distribution stage for FMCGs supply chain to reduce the inventory levels and will decrease inventory costs.

2.9 Chapter summary

This chapter has reviewed the literature available on the inventory management process in the distribution along with the main inventory management challenges. It also reviewed the research undertaken on the ML applications in the supply chain context generally focusing on the supervised ML regression algorithms that this research would be focusing on during the model development. Then a detailed review of the developed ML models in the demand forecasting and EOQ determination domain has been presented. The detailed literature evaluation resulted in the unambiguous identification of research gaps in the chapter's last portion. The methodology for the entire thesis will be discussed in the following chapter. It will describe the many methodological techniques that could be used in a research project, followed by a detailed explanation of the methodology used in this study.

Chapter Three

Research Methodology

3.1 Chapter overview

This chapter deals with the methodology of the research. It starts with introducing the scope of the research and presents its framework process. The next part of the chapter discusses the research philosophy followed by the research approaches that are used in this research. Then a review of the research strategy used is carried out along with justifying the reasons behind this selection. Then an overview on the methodology that is used in the research is explained. The chapter finally concludes by presenting the initial framework of the ML predictive model with the variables used in building it.

3.2 Scope of the research

The scope of this research was essentially defined by the relationship between the research problem and its aims. This refers to a set of activities and tasks that must be completed to achieve the research's principal goal. The following figure, Figure 3.1, shows the overall framework of the research process that relates the undertaken activities and tasks to the desired research objectives. As Figure 3.1 indicates, the study starts with reviewing literature related to inventory management operations, demand forecasting, EOQ models and ML forecasting models performed within FMCGs companies focusing more on distributors. This step was carried out and well acknowledged through reviewing relevant literature in Chapter Two. The following step was dedicated to the empirical data collection from the selected Egyptian FMCGs distributor as the case company of the research, to describe in detail the forecasting techniques implemented in the company and then investigate how does the company performs the demand forecasting process for ordering their goods from their suppliers. This step also involves the preparation and the processing phase of the dataset gathered from the case company to be in the appropriate form ready for the model input. The third step is developing the ML predictive model, selecting among different supervised ML algorithms that would train the developed model using the input dataset. After training the developed model, the analysis phase starts by evaluating the model, testing it, and preparing the deployment strategy of the model so it would predict the targeted output (EOQ). The last step of the research process concludes with the main findings from analysing and testing the ML predictive model ending up with the main contributions of the research and pointing out the major areas of future work.

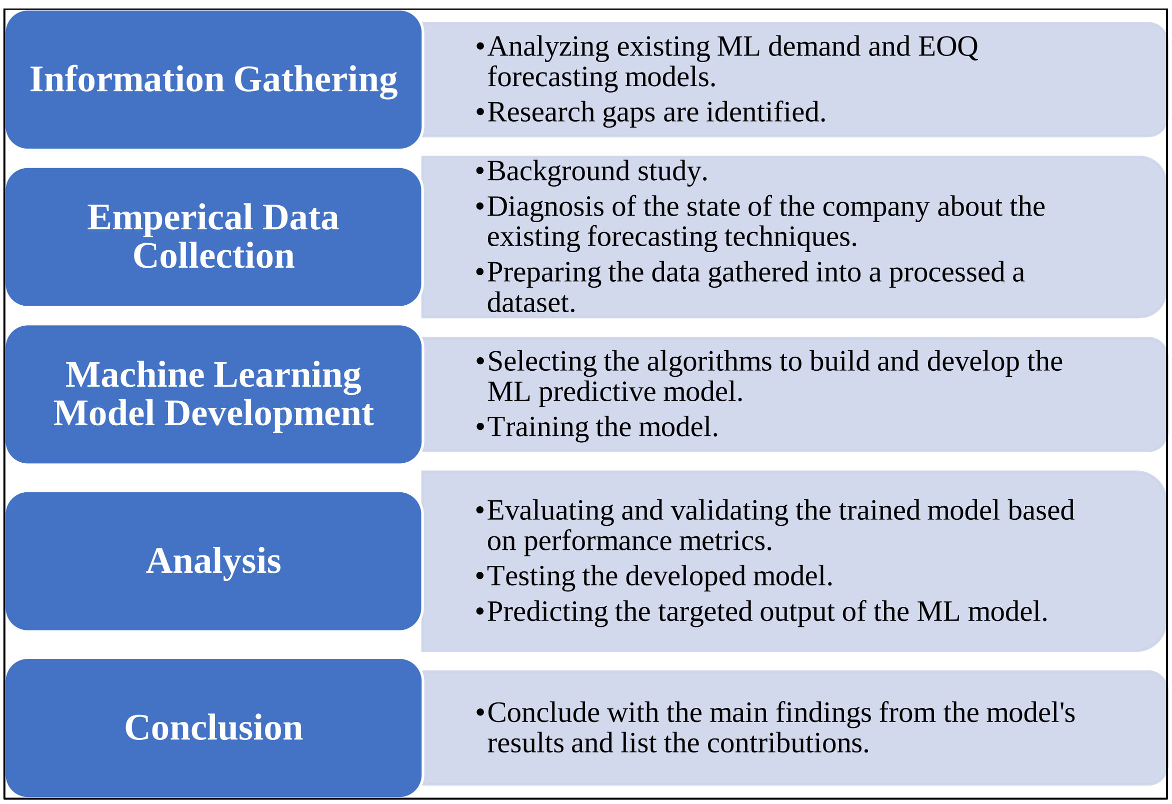


Figure 3. 1. Framework of the research process

The study of the case company (QEBAA) has been carried out in different phases. The phases were conducted in parallel throughout the research. The first phase objective was to get a better understanding of the targeted research area, which would be later examined. This was mainly done in Chapter Two where literature about demand forecasting and EOQ determination, inventory management and how ML techniques are applied in supply chains to improve the overall performance. The following phase focused on developing a better understanding of the situation of the case company and which problems they were facing. This was done by analysing data that was provided by the company and elicited through interviews with employees. This information was later used in the empirical part of the research. The final phase of the research was the modelling phase and it started with pre-processing the information gathered from the empirical part and from the literature review to be able to build the supervised regression predictive model to draw conclusions, compare the results and the forecast accuracy, and present the most appropriate mix of regression algorithms with the most accurate results predicting the EOQ of the FMCGs distributor for optimizing its inventory levels.

3.3 Research philosophy

For every research, the interaction between research philosophy, approach, and strategy is critical. Saunders et al. (2009) describe four business research ideologies. Positivism, realism, pragmatism, and interpretivism are among them. Positivism holds that study phenomena can be objectively determined when the researcher is self-contained and has little connection with the research subjects. It employs empirical research in accordance with a set of stringent rules, resulting in measurable observation analysis. Realism is a philosophy that takes a scientific approach to knowledge acquisition. The essence of realism is that what our senses reveal is reality, implying that objects exist independently of our minds. According to pragmatism, the research question is the most important factor in determining one's philosophical perspective. Interpretivism is concerned with subjective, qualitative phenomena involving high levels of interaction and/or engagement by the researcher.

Purchasing, logistics, operations, transportation, and marketing are all fields that have contributed to the development of supply chain theory and have a history of predominantly adopting the positivist paradigm (Burgess et al., 2006; Davis et al., 2011). Quantitative methods are often employed to research supply chain issues, with bigger samples gathered to test theories and create generalisations. Because of the overwhelming dependence on quantitative methods, there are an increasing number of studies that look into research methods in various fields to support requests for a more balanced approach to research that includes qualitative approaches (Ellram, 1996; Mentzer and Kahn, 1995) and/or numerous methodologies (Boyer and Swink, 2008; Spens and Kovacs, 2005; Taylor and Taylor, 2009).

This research is directed by the positivistic philosophy because the researcher will establish the findings on observable phenomenon. A positivism aspect can assist the researcher to generalize phenomena into simplest fundamentals. An interpretivism aspect is not suitable for this study since it is subjective. Interpretivism perspective is usually based on qualitative data, thus making it difficult for the researcher to be fully objective in the way that the data is interpreted.

3.4 Research approaches

There are two research methodologies, according to Saunders et al. (2009): deduction and induction. Understanding an issue, gathering, and analysing facts, and formulating a theory are all part of induction. The strength of this technique is that it allows researchers to better understand how humans interpret their social environment (Easterby-Smith et al., 2008). The most common method in natural sciences is deduction, which starts with identifying the theory, deducing a hypothesis from that theory, expressing a hypothesis in operational terms, seeking evidence to prove or disprove the hypothesis through testing, analysing the results, and, if necessary, modifying the theory based on the findings (Saunders et al., 2009, Greener, 2008). Table 3.1 summarises the major differences between deductive and inductive research approaches.

Table 3. 1. Major differences between deductive and inductive research approaches

Deduction emphasizes	Induction emphasizes
• Scientific foundations • Transitioning from theory to data • The requirement for causal links between variables to be explained. • The gathering of quantitative information. • The use of controls to guarantee that data is accurate. • The operationalization of concepts in order to achieve definition clarity. • A well-organized strategy. • The researcher's independence from the subject of the search. • The need to choose samples that are large enough to generalise conclusions.	• Gaining a better grasp of how others interpret situations. • A thorough awareness of the study's setting. • The gathering of qualitative information. • A more adaptable structure to allow for shifts in research focus as the study advances. • A realisation that the researcher is a participant in the investigation. • There is less of a need to generalise.

Source: Saunders et al., (2009)

According to Dawson (2009), qualitative research investigates attitudes, behaviour, and experiences by investigating various social situations and the groups or individuals who inhabit them. Non-numerical data is used in qualitative research (Saunders et al., 2009). Quantitative research, on the other hand, generates statistics that are expressed in numeric data to establish specific facts or connections between facts to construct population generalisations. Qualitative research explores narrative data, making it useful when the purpose of the study is to investigate a wide range of dimensions related to a specific issue. It delves deeper and more thoroughly into themes than quantitative research, although it may have less generalizability when compared to quantitative methods (Young, 2007; Wilson, 2014). Inductive studies are usually connected with a qualitative strategy, while deductive studies are usually associated with a quantitative method. However, because each research strategy has benefits and drawbacks, there is no universally superior research methodology.

According to Creswell (2017), most tactics are not wholly quantitative or qualitative, but rather a hybrid of the two methodologies known as mixed method research. A mixed method approach mixes a theoretical framework with assumptions that can help researchers better understand their research. This study's findings were analysed quantitatively and qualitatively. The goal of this strategy was to forecast the best quantity to order in order to maximise the distributor's inventory levels. As a result, both interviews and numerical data interpretation were used to determine where in the supply chain the company's employees believed they had the most problems. The phenomena of employing machine learning predictive models as a demand forecasting tool for distributors would be a good place to start the quantitative investigation. The variables would have to be identified and understood before this phenomenon could be effectively measured. The quantitative research methodology would next be used to describe the correlations between the variables (Creswell, 1998).

The quantitative research approach was chosen for this investigation. Because the study is exploratory in nature, this decision was made. A qualitative approach allows for a better understanding of the phenomenon and its application to the QEBAA forecasting process. The research will follow a deductive research approach whereby a mixed method research design is incorporated. The research framework will be created using a quantitative research methodology, while empirical validation of the research framework will require both quantitative and qualitative research approaches. The research framework will be implemented using a single quantitative case study, but the explanation of quantitative findings and empirical validation of research propositions based on those findings will require qualitative understanding.

3.5 Research strategies

The researcher's research approach allows them to answer the research questions or basic questions that form the study's flow and structure. According to Saunders et al. (2009), research questions and objectives determine the choice of research strategy. Similarly, the level of prior information and the amount of time available are critical.

3.5.1 Case study research method

According to Yin (1994, p.13) "*A case study is an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident.*" Easton (2010, p.119) defined a case study as "*a research method that involves investigating one or a small number of social entities or situations about which data are collected using multiple sources of data and developing a holistic description through an iterative research process.*"

For many years, case studies have been widely employed by academics from several disciplines to gain a thorough understanding of a certain topic or scenario and to identify situations that are particularly informative (Dinwoodie and Xu, 2008). This strategy is likely to employ a combination of data collection techniques known as triangulation. Interviews, observation, documentary analysis, and surveys may all be used in this combination (Saunders et al., 2009). In carefully planned and prepared analyses of real-life circumstances, concerns, and difficulties, researchers continue to apply the case study research approach with effectiveness (Elmesmary, 2015). Table 3.2 lists some of the advantages and disadvantages of the case study research method.

Table 3. 2. Advantages and disadvantages of the case study research method

Advantages of the Case Study	Disadvantages of the Case Study
• Case study research is a well-established research approach that may be used in both qualitative and quantitative studies (Cronin, 2014). • Case studies can "close in" on real-life circumstances and put theories to the test as events unfold (Flyvbjerg, 2006). • A case study gives a detailed analysis of a specific situation (Lindvall, 2007). • Case studies are best used to supplement current knowledge and improve humanistic understanding (Stake,1978). • Case studies have a larger web of material to catch (Merriam, 1994). • Case studies are capable of handling and combining a variety of data collection methods (documents, interviews, questionnaires, objects, and observations) (Eisenhardt,1989 and Merriam,1994).	• In terms of utility and veracity, case study findings and suggestions cannot be confirmed or refuted (Murphy ,2014). • There is no way to establish the reliability or generality of conclusions based on a small number of cases (Soy, 1997). • Case studies are frequently insufficiently limited to make causal findings (Solberg Silen and Huber, 2006). • External validity is stated to be low in case studies (Jacobsen, 2002). • Case studies are only used as a preliminary research tool and cannot be utilised to describe or test hypotheses (Yin, 2009). • Potential biases in data collection and interpretation (because the data is gathered and analysed by a single individual) (Noor, 2008, Crowe et al, 2011, and Easton, 2010)

Source: Adapted from Krusenvik (2016)

3.5.2 QEBAA (the case company)

Case study methodology is often used in multidisciplinary sciences to bring multiple different methods together. In the field of ML, case studies are often used to teach concepts using an application (Segaran, 2007; Kelleher et al., 2020). This research adopted a single case study performed from a FMCGs distributor's perspective, QEBAA Headquarters, which represents many other units that are similar in characteristics to it before generalization. The data collected for studies like these must be measurable. The goal of this method is to gain a better grasp of the subject at hand. It's also used to keep track of alternate approaches and hazards, as well as to gain a wide picture of the results (Bryman and Bell, 2011). The qualitative type of research proves suitable for use in a case study research design as the researcher can do an in-depth examination of a particular case before generalization to others (Cresswell, 2013).

QEBAA (the case company) was established in 1979 in Alexandria, Egypt. The restless efforts and the dedication of an energetic professional team have placed QEBAA as one of the most successful and fast growing FMCGs companies in the Egyptian market. Today, QEBAA is considered as one of the biggest agents and importers of famous FMCGs. Moreover, it is the main distributor of food and nonfood products in the Egyptian market as it distributes an extensive range of a variety of food commodities and household products. QEBAA serves different classes of customers including wholesalers, hypermarkets, supermarkets and convenient stores. QEBAA's strength and profound understanding of the Egyptian consumer and famous trademarks as well as its wide distribution skills have contributed effectively in its rapid growth in the FMCGs field. QEBAA has rapidly scaled up presence in FMCGs distribution comprising branded foods and commodities, at an impressive pace over the last several years. the company's unwavering focus on quality, innovation and differentiation backed by deep consumer insights further strengthen its leadership position in the Egyptian FMCGs industry. The competitiveness of QEBAA's diverse businesses rest on the strong foundations of institutional strengths derived from its deep consumer insights, cutting-edge research & development, distinguished product distribution, efficient trade marketing and dedicated human resources.

QEBAA aims to market and distribute FMCGs while offering innovative value-added services. The main mission is to serve the Egyptian market at all scales; starting from the biggest supplier to the smallest consumer through using all our capacities and resources to maximize the benefit for all the stakeholders and for the company as well. QEBAA's management has built a company culture revolving around the concept that every day is a new beginning with new possibilities and opportunities, such culture has always kept QEBAA's team morale where they always aspired it to be.

QEBAA is an agent and an authorized distributor for a big range of famous brand names that are recognized from trips to the supermarkets or from ads on television: the ones everybody knows and trusts. QEBAA is an authorized agent of some of the leading FMCGs companies:

- Nestlé (Alexandria &Matrouh)
- Henkel
- Al Rashidi Al Mizan (Alexandria &Beheira)
- Johnson Johnson Wax (Alexandria & Al Beheira)
- Dream (Alexandria and Al Beheira)
- Govertina (Al Beheira And Kafr El Sheikh)
- Afia Egypt
- Hero
- Iffco Egypt
- Pepsi
- Americana
- Juhayna
- Belle Egypt
- President
- Heinz
- Al Jawhara

- Imperil Corned Beef
- Arosa Tea
- Regina
- Papyrus for Paper Industry
- Coca Cola
- Saqr (Rotana)
- Macaroni Queen
- Mansour (Sunshine)
- Kraft Egypt
- Fine

In 2018, QEBAA expanded in Cairo and Beheira. QEBAA further expanded its portfolio by adding warehousing solutions through our partnership with Unilever. In 2019, current QEBAA was transformed from a limited partnership company to an Egyptian joint stock company. QEBAA has offices across Alexandria, Cairo, Beheira and Kafr el Sheikh. QEBAA now has 1500 employees among them workers, drivers, accountants, sales and distribution representatives, supervisors and sales managers. QEBAA has a storage space of 18 warehouses and a fleet of 400 light, medium and heavy load vans.

QEBAA is one of the most successful and rapidly developing FMCG firms in Egypt, serving as one of the largest agents and importers of well-known brands. Furthermore, it is the largest distributor of food and non-food products in Egypt, distributing a wide range of food commodities and household products to a variety of customers including wholesalers, hypermarkets, supermarkets, and convenience stores. QEBAA's strength and in-depth knowledge of the Egyptian consumer and well-known brands, as well as its extensive distribution capabilities, have all contributed to the company's rapid success in the FMCG sector. Over the last several years, QEBAA has significantly expanded its footprint in FMCG distribution, including branded foods and commodities. QEBAA was still following the method of taking orders manually on paper forms and then the specialized personnel input the data from these forms into the system. QEBAA prefer to operate semi manually because they like to be hands-on with their business. They do have an ERP system where all the historical records of the products are kept but they do not depend on technology for forecasting their demand. Currently, the company does not record the inventory level status periodically. The absence of a periodic written record of inventory level becomes the system's weakness, which leads to a shortage of research data. Furthermore, even though they have implemented their own system, the management still thinks they have high inventory cost. The company also did not have the exact number that indicates the excess inventory because they have no criteria to determine whether an inventory level is too high or too low. Furthermore, the company does not have a method to determine the appropriate amount of order since currently, the company does not have any inventory model. Having the appropriate order amount will help the company obtain the right inventory level and reduce its inventory cost. As a start, the company can implement a ML model to predict the EOQ to manage its inventory level since the model is robust and the total inventory cost is effectively proven to be insensitive to order quantities. This research aimed to reduce FMCGs inventory costs by implementing a ML predictive model to predict the EOQ. This study was expected to contribute to QEBAA in determining the optimal number of orders.

3.6 Cross industry standard process for ML applications (CRISP-ML(Q)) methodology

Many project organisations rely on alternative models that are closely connected to ML, such as the Cross-Industry Standard Process for Data Mining (CRISP-DM), due to the lack of a process model for ML applications (Chapman et al., 2000; Wirth and Hipp, 2000; Shearer, 2000). It is based on industrial data mining experience and is the most suitable among similar process models for industrial applications (Kurgan and Musilek, 2006). CRISP-DM, on the other hand, has two fundamental flaws, according to Studer et al. (2021). First, CRISP-DM does not address the application scenario in which a machine learning model is maintained as a programme. Second, CRISP-DM lacks quality assurance process guidelines. Quality is characterised not only by the product's suitability for its intended use (Mariscal et al., 2010), but also by the quality of task executions at any point during the creation of a machine learning application.

Amershi et al. (2019) and Breck et al. (2017) presented process models for ML applications as a complement to CRISP-DM (see Table 3.3). Amershi et al. (2019) did an internal Microsoft study on the obstacles of ML projects and developed a nine-phase process model. Their process approach, on the other hand, lacks quality assurance technique and does not address business needs. Breck et al. (2017) developed 28 tests to quantify flaws in the machine learning pipeline and reduce the technical debt of machine learning systems. Their exams, however, do not fully cover all project phases, such as the business knowledge activity. Quality was initially considered in the context of data mining process models by Marban et al. (2009). Studer et al. (2021) developed a process model for machine learning applications that includes a quality assurance technique (CRISP-ML(Q)), which can assist enterprises improve the efficiency and success rate of their ML projects. It walks ML practitioners through the whole ML development life cycle, including maintenance and monitoring, and provides quality-oriented methodologies for each phase and activity. The approaches presented have been demonstrated to be best practises in automotive industry and academic projects, and they are mature enough to be used in current projects.

Table 3. 3. Mapping of the different ML phases into process phases

<table>
<tr><th></th><th>CRISP-DM</th><th>CRISP-ML</th><th>Amershi et al.</th><th colspan="2">Breck et al.</th></tr>
<tr><td rowspan="9">Phases</td><td>Business Understanding</td><td rowspan="2">Business and Data Understanding</td><td>Model Requirements</td><td></td><td></td></tr>
<tr><td>Data Understanding</td><td>Data Collection</td><td rowspan="4">Data</td><td></td></tr>
<tr><td rowspan="3">Data Preparation</td><td rowspan="3">Data Preparation</td><td>Data Cleaning</td><td rowspan="6">Infrastructure</td></tr>
<tr><td>Data Labeling</td></tr>
<tr><td>Feature Engineering</td></tr>
<tr><td>Modeling</td><td>Modeling</td><td>Model Training</td><td>Model</td></tr>
<tr><td>Evaluation</td><td>Evaluation</td><td>Model Evaluation</td><td></td></tr>
<tr><td>Deployment</td><td>Deployment</td><td>Model Deployment</td><td></td></tr>
<tr><td></td><td>Monitoring and Maintenance</td><td>Model Monitoring</td><td>Monitor</td><td></td></tr>
</table>

Source: Studer et al. (2021), p. 4

CRISP-ML(Q) is divided into six phases and adds a maintenance phase to CRISP-DM, as illustrated in Table 3.4. Furthermore, business and data understanding are combined into one phase since these two tasks, which are separate in CRISP-DM, are highly connected and are best addressed concurrently, because business objectives can be established or revised based on accessible data. This research will follow the CRISP-ML(Q) methodology for building up the ML predictive model as shown in Figure 3.2.

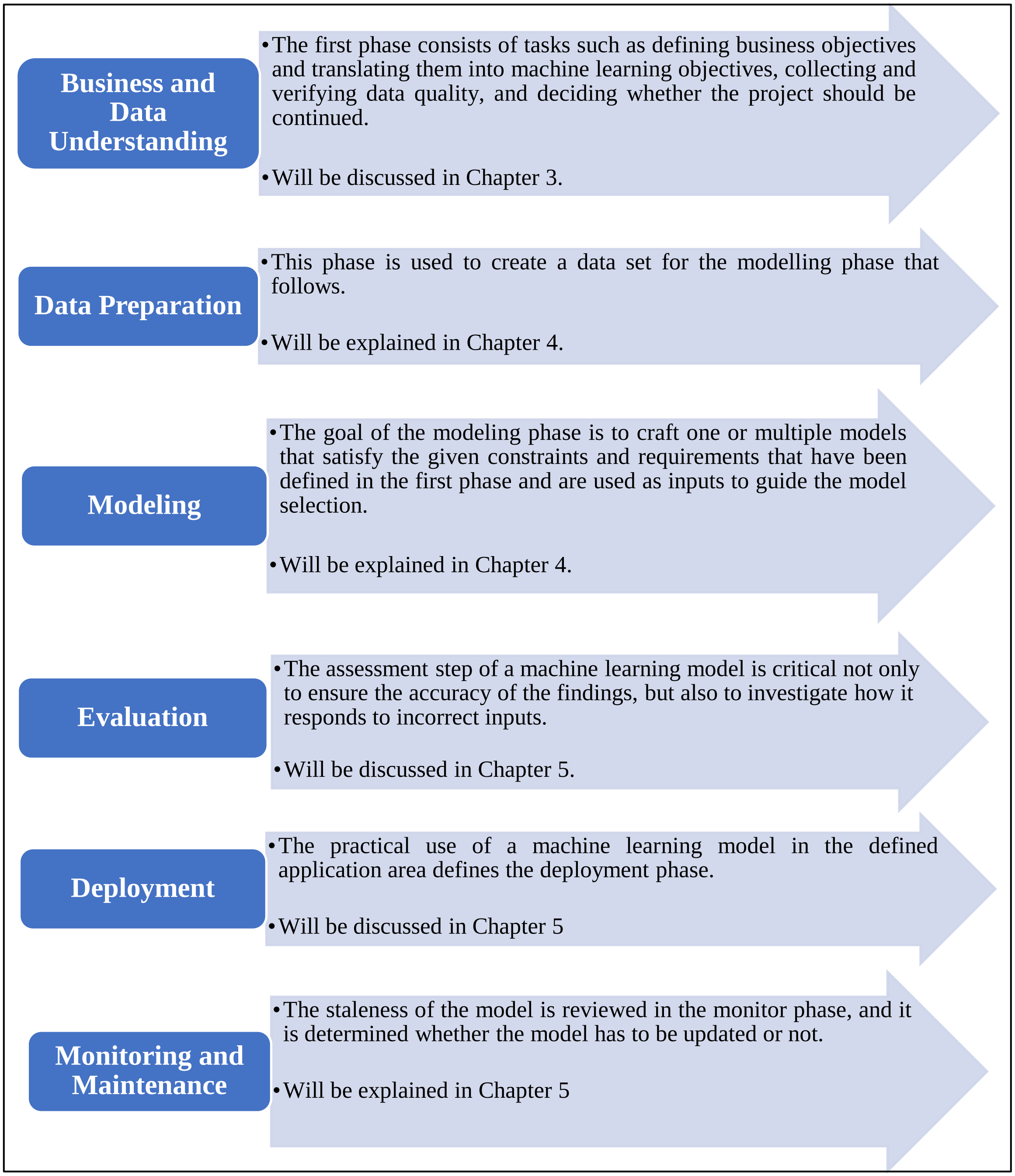


Figure 3. 2. CRISP-ML(Q) phases interpretation in the research (Adapted from Studer et al., 2021)

3.6.1 Business and data understanding

The business understanding phase is the first and most significant part of the study. This phase tries to understand the project objectives from a business viewpoint, turn this business perspective into a research problem statement, and then design a plan to attain these objectives (Vasudev, 2019). The aim of this research is to forecast the weekly EOQ to aid the distributor's purchasing decisions. To forecast the EOQ, the historical data is used to analyse the demand, the cost, and the inventory levels. The purpose of this research is to propose a ML predictive model based on a combination of supervised regression algorithms aligned in a sequential way to be able to predict the EOQ in a sequential way. This model should produce the least error measures along with presenting the EOQ to be ordered by the FMCGs distributors, which will reduce and optimize the inventory levels and eventually will decrease the carrying and ordering cost.

3.6.1.1 Defining the scope of the ML application

The characterization of the investigated business was the first step in solving the case company problem. As a result, historical data on demand for cleaning supplies and hygiene products can be collected. It was discovered at first that the corporation had a policy of documenting customer orders, which had a stronger validity in forecasting matters than the data from final product bills. It may also be discovered that the corporation under investigation does not analyse the product's long-term market behaviour. Work is defined at daily time intervals during a short-term planning period in the present, medium-term comprises quarterly or semi-annual time intervals, and long-term is defined as annual time periods. It was possible to characterise the company's current forecasting system, which relies on spreadsheets and forecasts are made judgmentally based on the experience of the company's managers, without the use of advanced forecasting methods, which makes it difficult to measure the accuracy of the initial forecast methodology, through semi-structured interviews with the managers.

Before developing the model, the researcher had to choose among the ML software available in the market. There has been an increase availability of free and open-source software, which enable ML to be implemented easily. Mallouli et al. (2018) brought up a wide range of open-source ML frameworks available in the market, which enable ML engineers to build, implement and maintain ML systems, generate new projects, and create new impactful ML systems. These frameworks included Apache Singa, Amazon Machine Learning, Azure ML Studio, Apache Mahout, Caffe, H2O, Massive Online Analysis, ML lib (Spark), Mlpack, Pattern, Scikit-Learn, Shogun, TensorFlow, Theano, Torch, Veles, Oryx 2 and Weka.

Several large data driven companies developed cloud-based platforms offering ML as a Service (ML aaS): e.g., Amazon Web Services (AWS), Microsoft Azure, Google Cloud. Microsoft has rolled out an Azure ML Studio which has a potential of expediting ML experiments from weeks and months to hours and days (Botchkarev,2018). But these ML platforms all come with their own limitations. Users are usually required to upload their data to the larger cloud platform. It's tough for a company to use another vendor's services or open-source tools for other tasks if all of its data is in one vendor's cloud. Table 3.4 compares the cloud machine learning vendor solutions (Burns, 2017).

Table 3. 4. Cloud ML vendor comparison

	Amazon ML	**Google Cloud Machine Learning**	**IBM Watson Machine Learning**	**Microsoft Azure Machine Learning**
Overview	A highly automated platform that applies machine learning algorithms to data stored on Amazon Web Services.	Gives consumers access to Google's cutting-edge algorithms for search and other industry-leading applications. Users can also create custom models.	REST API connectors are primarily used to get models into production.	Users can apply a vast list of predefined algorithms to their own data. Other options are less automated.
Algorithms and modelling methods	Users can bring their data to prebuilt algorithms, including: -Regression -Binary Classification -Multiclass classification	Users can create their own models from scratch or use models that have already been trained to support certain applications: -Video analysis -Image analysis -Speech recognition -Text analysis -Translation	REST API connectors allow users to create their own algorithms in any language.	Users can bring their data to prewritten algorithms, including: -Scalable boosted decision tree. -Bayesian recommendation systems. -Deep neural networks. -Decision jungles. -Classification. The service also supports these algorithms: -Multiclass and binary classification. -Regression clustering.

Data location requirements	Before using the ML service, data must be stored in Amazon Web Services.	In Google Cloud Storage, data must be stored, and models must be staged.	In IBM Bluemix, data must be stored, and models must be staged.	Small data sets from third parties, such as AWS, can be imported, however sets bigger than a few gigabytes must be stored in Azure.
Automatic algorithm suggestion?	Yes	Yes	No	No
Other considerations	An automatic data transformation tool is included.	Because there is less abstraction, coders have more control, but less tech-savvy users may encounter a learning curve.	The service focuses on using API connections to create machine learning-based apps.	Users may only have a limited understanding of how models work behind the scenes due to the visual interface.

Source: Burns (2017)

In this research, Azure ML Studio was chosen to build the ML predictive model, as it offers a convenient integrated development environment with specific benefits, including cloud-based ML offered as a service; web-based solution; Drag and drop canvas interface that is simple to use; various built-in regression modules that are ready to use; the ability to code experiments using R and Python languages; integration of functions from R packages; capability to re-use published experiments or their components. The research depended on this software for the advantages listed below:

- Microsoft Azure ML is a set of cloud services that allow developers to create, deploy, and manage applications over a global network of Microsoft data centres. The flexibility, agility, and scalability of the cloud platform are highlighted in this cloud computing paradigm (Harfoushi et al., 2018).

- Multiple machine learning algorithms for regression, classification, and clustering are also supported by Azure ML. It enables for model customisation with Python and R. (Qasem et al., 2015).
- Modules and datasets can be dragged and dropped into Azure ML Studio, which then ties them together. This experiment can be taught to become a predictive experiment. Users can utilise this predictive experiment to create their own models (Ericson et al., 2016; Rajpurohit, 2014).
- For beginners/developers/data scientists who need a rapid hands-on feel, Azure ML studio is simple to use; standard experiments can be done with quick results generated in less time. It's a completely managed service with little control and no on-premises alternatives (Narayanan, 2019).

The following capabilities provided by (Botchkarev, 2018) directly contributed to the study's aims, hence the Azure ML Studio was chosen:

- Machine learning as a service on the cloud.
- An intuitive drag-and-drop canvas interface for assembling computing parts into an experiment.
- The ability to publish results of studies on the web and reuse previously published experiments.
- Low or no cost (pay as you go) service.

Dille (2019) was discussing that models' accuracy will not differentiate one software from another as each software would let users import any algorithms. There is no consistent difference between the two softwares in terms of producing more accurate modelling results. The majority of the other tools mentioned was intended for data scientists and developers, whereas Azure ML Studio was created specifically for data scientists. However, Azure ML Studio includes a Jupyter Notebook interface, allowing data scientists to leverage Studio and Azure ML Services' cloud architecture to accomplish what the other tools can do on top of Amazon cloud infrastructure. That is why Azure ML Studio is regarded by the researcher as a more versatile choice right now for developing the predictive model.

The CRISP-ML(Q) suggests measuring an ML project's success criteria on three levels: business success criteria, ML success criteria, and economic success criteria. One of the basic concepts of a quality assurance methodology, according to IEEE (1997), is the requirement quantifiable. This research defined the three success criteria, shown in Table 3.5, that were categorized into business success criteria, ML success criteria and economic success criteria. Each category of these success criteria has been defined solely to prevent contradictory objectives.

Table 3. *5*. Success criteria levels defined in this research

Business Success Criteria	ML Success Criteria	Economic Success Criteria (KPIs)
1. Limiting Manual Processes 2. Keeping the inventory intelligent and organized 3. Automating Order Fulfilment process	1.Performance 2.Robustness 3.Scalability 4.Model Complexity	1.Available to promise (ATP) 2.Operating Cash Flow (OCF) 3.Order fulfilment rate (OFR) 4. Inventory turnover ratio (ITR)

-Business success criteria: From a business standpoint, the initial step is to define the ML application's purpose and success criteria. Business success can be measured objectively and characterised in a variety of ways. The criteria that would be covered in this research will include:

1. Limit Manual Processes (Anindita, 2018)

As customer demand rises and retailers seek faster delivery, the simplest solution is to accelerate the entire distribution process. Manual labour cannot be eliminated by distributors, but it can be decreased. Managing inventory, buy orders, sales orders, and finances, for example, should no longer be done manually. Distributors should use their time and effort to improve other elements of their businesses instead of doing these activities.

2. Keeping the inventory intelligent and organized (Fox, 2017)

Distributors do not need to hold more stock than they require, which is why they must monitor lead times, reorder levels, and stock security to ensure that they do not keep excess inventory. As a result, they should have effective inventory management systems in place so that they can check inventory levels, preserve an accurate stock level, reorder supplies, and assist you regulate stock purchases. New AI-enabled software is enhancing this process by forecasting how stock levels will fluctuate over the following 2-3 months based on consumer purchasing patterns and history. When this software detects that a product is about to run out of stock, it places a replacement order ahead of time.

3. Automating Order Fulfillment Process (Heinz, 2018)

Retailers seek speedier shipment to suit the demands of their customers. If distributors are unable to supply merchants with speedier shipment, their role as a middleman may become obsolete, and shops may opt to buy directly from manufacturers. This problem can be prevented by automating order fulfilment so that distributors do not have to manually process each order. Even if the warehouses are distributed over several locations, warehouse staff may promptly receive orders and process them.

Machine learning success criteria: The next step is to 'translate' the business goal into success criteria for machine learning. (Studer et al.2021) recommends defining a minimum acceptable level of performance for the generated predictive ML model that is good enough to satisfy the business goals.

- Performance: The trained model predictions are compared against the actual (observed) data from the testing data set using performance indicators e.g., MAE, RMSE, RAE, etc.
- Robustness: The property that characterizes how effective the algorithms used are while being tested on the new dataset. The robust algorithm is the one, the testing error of which is close to the training error.

- Scalability: The model's ability to scale to large amounts of data during training and retraining in the production system.
- Model Complexity: The capacity of the ML model should suit the complexity of the data and use proper regularization.

Economic success criteria: KPIs are used by businesses to track their economic success. Including a KPI in a project is regarded best practise and contributes to its success. A KPI tells decision-makers how the project contributes to their company's success and contains data that isn't normally articulated in common machine learning goals. In this research, some measurable KPIs are defined as follows so they can be measured by the predictive ML model. There are many other KPIs related to the distributor's operational and financial process but the listed KPIs were the ones that could be calculated by the input parameters available in the dataset. The calculated KPIs were:

- **Available to promise (ATP)**

ATP is a model that allows firms to keep only the bare minimum of products on hand in order to better manage inventory levels (Vaiana, 2021).

- **Operating cash flow (OCF)**

This liquidity KPI assesses the ability of a corporation to meet short-term obligations using cash generated from its day-to-day operations. The cash created by a company's operating activities is referred to as OCF (Beaver, 2021).

- **Inventory turnover ratio (ITR)**

This KPI determines how many times inventory is efficiently sold and subsequently replenished in a given period (Lopienski, 2020), making it simple for managers to keep track of their inventory and ensuring that there is always a suitable quantity of inventory (Insight software, 2021).

- **Order Fulfilment rate (OFR)**

This KPI measures how often client orders are filled with available stock without requiring a backorder or missing a sale, allowing managers to fill orders swiftly and consistently (Jenkins, 2021).

3.6.1.2 Data collection

The data understanding phase represents the second part of the initial phase of the CRISP-ML(Q) methodology, and it starts with the data collection. Following the acquisition of the relevant data, the data is examined to discover any data quality issues and to gain insights into the data. Data-gathering strategies allow for the methodical collection of information about the study's items and their environments. Using accessible information, observing, interviewing, questionnaires, and focus group discussions are some of the data collection approaches that can be used (Chaleunvong, 2009 and Dawson, 2009). Interviews and numerical data from QEBAA's ERP system were used to compile the data. Interview information has shown to be quite useful, not just in terms of acquiring knowledge about where problems exist in their supply chain, but also in terms of integrating with employees to determine the root causes of difficulties. Secondary and main data were segregated from the empirical data. Interviews with employees provided the primary (qualitative) data, while internal records provided supplementary (quantitative) data.

Interviewing is the primary data gathering strategy employed in this study. An interview is a data collection method that involves asking respondents questions orally, either individually or in groups. An interview, according to Lune and Berg (2017), is just a dialogue with the goal of gathering information. Interviews, according to Oso and Onen (2009), allow the researcher to collect information that cannot be obtained directly, obtain historical knowledge, and gain control over the path of questions. Bryman (2015) and Yii et al. (2014) described the semi-structured interview as an effective qualitative research data collection technique. Yin (2018) and Sparker (2014) suggested that semi-structured interviews are appropriate when seeking out a stronger insight into a phenomenon. Roberts et al. (2014) and Keränen and Jalkala (2014) suggested the use of open-ended questions in a case study to gather direct views. Alexanders et al.(2015) asserted that researchers could obtain a rich understanding of participants' experiences through open-ended questions. Table 3.6 displays a summary of the advantages and the disadvantages of semi-structured interviews.

Table 3. *6*. The advantages and disadvantages of semi-structured interviews

Advantages of semi-structured interviews	Disadvantages of semi-structured interviews
• Can answer questions and dispel doubts. • Make new inquiries. • The interviewer is able to detect nonverbal cues. • Can clarify points with graphic assistance. • It is possible to acquire extensive data. • Responses can be recorded on tape or digitally and then input into a portable computer.	• Respondents may be concerned about information confidentiality. • Interviewers must be skilled and well-trained. • Can lead to interviewer bias. • Respondents have the option of ending the interview at any point.

Source: Saunders *et al.* (2009)

3.6.1.3 Semi-structured interviews

Interviews allow the researcher to obtain information that cannot be directly observed, obtain historical information and to gain control over the line of questioning. According to Kombo and Tromp (2006), the advantages of this form of semi-structured interviews are flexibility because they consist of both open ended and closed-ended questions, in-depth information can be gathered using close-ended questions, and by using both open ended and closed-ended approach the researcher gets a complete and detailed understanding of the issues under research. The use of interview was suitable for this study because it enabled the researcher to ask questions personally, probe further and was able to seek clarifications about the inventory management systems involved in the case company.

Augustsson (2014) and Kihl et al. (2014) recommended researchers conduct face-to-face interviews lasting 30-60 minutes. Face-to-face interviews are common in qualitative studies (Bowden and Galindo-Gonzalez, 2015; Schaupp and Bélanger, 2014; Sorina-Diana, Dorel, and Nicoleta-Dorina, 2013). Face-to-face interviews are flexible for the researcher to clarify responses and expand findings (Pacho, 2015). Face-to-face, semi-structured interviews were conducted in this research to obtain deeper insights into demand forecasting strategies aligned with a primary research question: What are the suitable ML regression algorithms for improving the FMCGs distributor EOQ prediction accuracy?

Researchers realize the advantages of semi-structured interviews as traditionally reflecting rich and extensive results (Frels and Onwuegbuzie, 2013). According to Kihl et al. (2014), researchers can obtain fully understandable perspectives through semi-structured interviews, thus, making the interview format advantageous. Campbell (2015) also highlighted that semi-structured interview questions with probes and follow up questions were designed to allow the participants to tell their story such that the role of the researcher was as a listener. One important aim of using semi-structured interviews was the ability of the interviewee's answers to guide the future research questions and help develop a more robust knowledge base for future research (George,2022). The use of semi-structured interview was suitable for this research because it enabled the researcher to ask questions personally and seek clarifications about the systems involved and the user needs. The interview questions were formulated relating to the specific area of the interviewee. All questions in the different interview guides used in this research have been open, which means that the respondents have been asked questions that they can elaborate on in their own terms.

In this research, it was more beneficial to use semi-structured interviews to learn about new areas and get a deeper understanding of the subject and fulfilling our purpose. The interviews conducted in this research consisted of open questions allowing the interviewee to answer broadly and opened up new areas for us to explore. The interviewee was also encouraged to freely present their area and any other information they might see as relevant to the study. To understand the corporate culture and deepen our knowledge about the area, we conducted semi-structured interviews where we prepared questions based on our literature study. The interviews were conducted to understand QEBAA's corporate culture, existing demand and EOQ forecasting techniques and what prerequisites QEBAA demands from a predictive model. With the combination of the knowledge gained from the literature study and the semi-structured interviews, a framework for the predictive ML model with its input variables was developed.

The interviews took place in a conversational manner about the topic of demand and EOQ prediction and related processes relevant to the departments of the interviewee. Four focused interviews were conducted with four top management staff members of the FMCGs distribution company (QEBAA): the sales manager, purchasing manager, operations manager, and ultimately the CEO of the FMCGs distributor case company. The interviewees all worked within decision making in demand forecasting. The interviews were conducted through personal meetings, in individual sessions of 30 to 60 minutes. The interviews were performed to evaluate the company's inventory management systems. During the interviews, categorical and open-ended questions were asked. The list of the pre-formulated questions asked elicited information about the following:

- A brief history of the sales profile of the case company.
- The likely challenges affecting the distribution strategy of the company.
- The improvement that should be made in the company’s inventory management system.
- The key performance indicators that the company use to measure their performance.
- The forecasting techniques they use to forecast their demand.
- The way they handle stock-outs and over-stocking situations in their inventory.

Employees from these several departments were selected to gain a wide grasp of the problem and to facilitate in-depth conversations. The researcher performed initial interviews with all three departments to have a better grasp of the current situation, and as a consequence, the first problem was recognised. All the interviews were open-ended, semi-structured, and face-to-face, with the goal of learning more about the factors that influence the FMCGs distributor's expected EOQ. After several interviews with the CEO and managers in the case company, it was realized that there was not a formalized inventory control system. Normally, the manager placed new orders, using traditional spreadsheet equations, when inventory happened to be found few left in the information system or as the result of visual check by the staff working in the warehouse. Such practice has two opposite results. The first one is stock-out, where the customers have to wait for a period of time, shorter or longer, if they do not cancel the order. The second one is overstock, where unnecessary inventory accumulates and sits in the warehouse, costly but useless. Therefore, a formalized and standardized inventory control system should be established to solve the problems.

3.6.1.4 Inputs to the dataset

The methodology for qualitative study data analysis often includes case study research designs and analysis of data, systematic and specific (Yin, 2018). Methodological triangulation was used because interviews were conducted, and company documents were reviewed as multiple methods of data collection. Methodological triangulation involves the use of multiple methods of data collection including interviews and company documents (Balzacq, 2014; Durif-Bruckket et al., 2014). Additionally, using methodological triangulation may control bias in the study (Perkmann and Schildt, 2015) and increase the reliability of themes (Joslin and Müller, 2016).

Conversations with specialists helped the researcher understand the parts of the problem that needed to be modelled and how a machine learning prediction model may aid in that situation. The literature assessment revealed how other authors have approached comparable challenges in the scientific literature, allowing the study to compare the results achieved with the constructed model to those obtained by other researchers. Documentation, primarily from internal documents, was the primary source of empirical data in this study. Yin (2009) discusses many types of internal documentation, including written event reports, internal records, personal documents, and mass media. Internal documentations used in this study to convey secondary data came primarily from the case company's ERP system and excel spreadsheets. Information from these sources was gathered over the course of five years of operations (2014-2018) in order to have a thorough grasp of and recognise FMCG distributor demand patterns.

An information requirement exercise was conducted at QEBAA to determine the modelling requirements for this research study. The first thing needed to be done in building a ML predictive model is getting the data. There are several sample datasets included with the Azure ML Studio. Alternatively, one could import data from many sources. In this research, the “Weeks DS” dataset was imported to be used in the experiment. To forecast the “optimum quantity of products to be ordered” for a future year, a dataset made available at QEBAA company was used. The “Weeks DS” dataset was used as the input raw data for this experiment in Azure ML Studio.

Once the required data was acquired, the data was explored to identify data quality problems, if any, and insights on the data gathered. The input parameters in the dataset were selected by the experts based on their previous experience and knowledge and were selected from the existing demand forecasting models in the literature. A prominent challenge in this research was dealing with the low to medium volume of data that was available. More data as input can create better trained modes that would result in better performance and accuracy.

The data set contained over 2,340 weekly records of units sold over five years from 2014 to 2018 and the following 9 columns are the columns present in the dataset:

- **Week:** it referred to the week on which the products were sold.
- **Year:** it referred to the year in which the products were sold.
- **Historical Demand:** it referred to the number of products that have been ordered during a specific period in the past.

- **Historical Sales:** it referred to the number of units sold for a product.
- **Forecasted Demand:** it referred to the predicted future demand of a product during a specific period.
- **Current Inventory:** it referred to the actual number of products currently existing in the warehouse.
- **Unit Cost:** it referred to the purchase price of the product.
- **Working Capital:** it referred to the difference between the distributor's current assets (cash, inventory of finished goods) and the distributor's current liabilities.
- **EOQ:** it referred to the optimum quantity of units to be ordered by the distributor.

The data used in this research consisted of real sales history, product and inventory information from the case company and the data included was from 1 January 2014 to 31 December 2018. This data was used to estimate actual demand and generate different forecasts to be used to predict the optimum quantity of products to be ordered. Not all the main product groups of the chosen distributor were included in the data to be analysed. The chosen product groups included cleaning supplies and hygiene products from "Henkel" account. Only products with relatively long shelf lives were included. Before training the model, one significant task is to process the experimental data into input-output patterns.

3.7 Model development methodology

Demand forecasting is such an important choice that a calculation error could cost a business a lot of money. Each element has its own complicated impact on product demand, and so cannot be easily mapped (Chawla and Soni,2019). The advantage of using ML algorithms in this research is that it maps the dependence of each variable involved in the model development accurately.

3.7.1 Choosing the ML algorithm

Machine learning is divided into two categories: supervised and unsupervised learning. The use of useful information in labelled data underpins supervised learning. The fundamental impediment to supervised learning is a lack of sufficient labelled data. Unsupervised learning, on the other hand, recovers valuable feature information from unlabeled data, making training material much easier to come by. As it was mentioned in Chapter Two, that supervised learning algorithms has been chosen to build the developed forecasting model, a taxonomy of the supervised ML algorithms is illustrated in Figure 3.3.

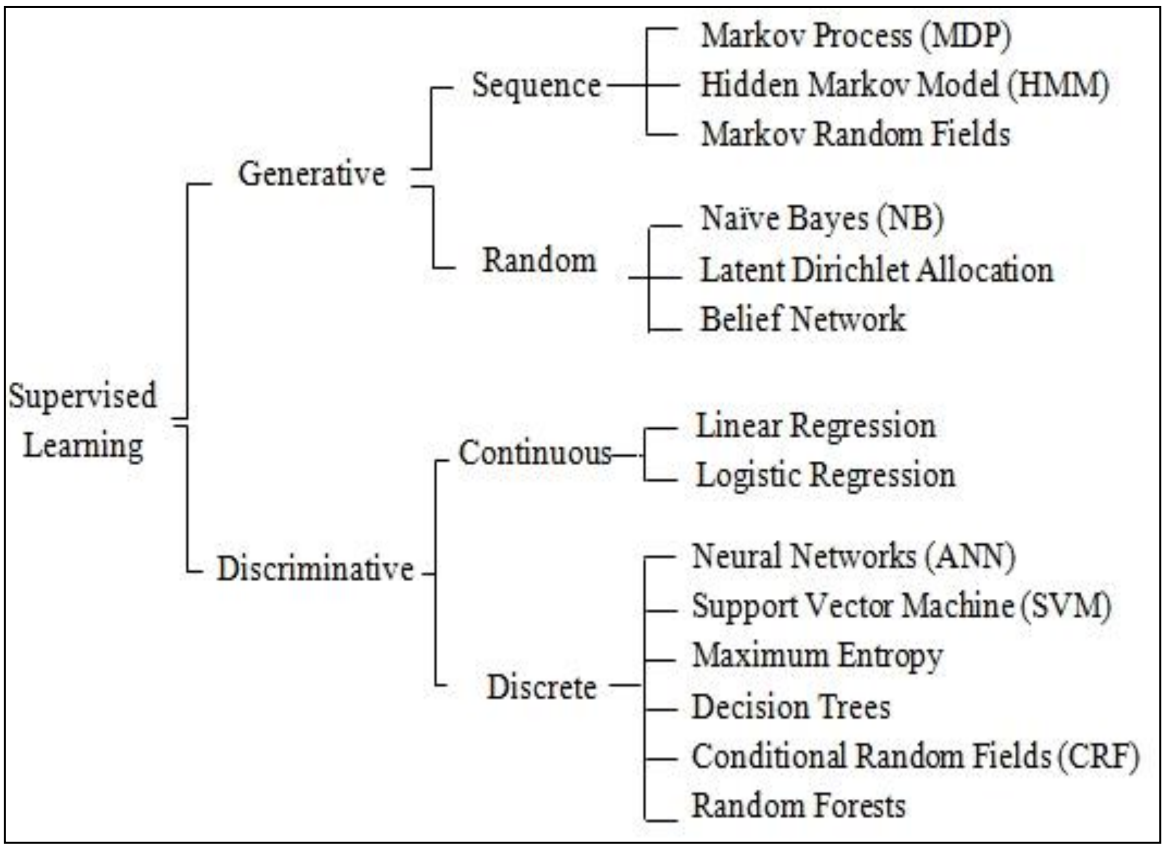


Figure 3. 3. Taxonomy of supervised learning algorithms (Source: Nicolas, 2015)

In supervised learning, models are developed for prediction using two techniques (Agarwal and Jayant,2019). The first technique is the classification technique that predicts categorical data such as whether a cancer is malignant or benign and email is spam or genuine etc. Models developed using this technique work on discrete responses and classify data into categories. The second one is the regression techniques work on data which are continuous such as price rise of houses in a particular area or fluctuation in temperature or changes in power demand.

Previous studies have shown that those three techniques, namely, ANN, SVM, and RF perform better prediction. Also, because the given data in this research is numerical data, then it is necessary to consider strong performing algorithms for regression problems (Ghanbari, 2019). Microsoft Azure Machine Learning Studio provided many algorithms necessary for predictive analytics solutions. Choosing a specific algorithm is driven by both the nature of the data and the question the research is trying to answer. Since the research aim is to predict the EOQ to be ordered by the distributor, then algorithms that predict values only should be chosen for the ML model development. The research would choose the LR, neural network regression (NNR), decision forest (DF) regression and the BDT as they are suitable for regression problems trying to predict values. These algorithms were selected among other regression algorithms provided by Microsoft Azure ML Studio because of their accuracy and training time measure, as shown in Figure 3.4.

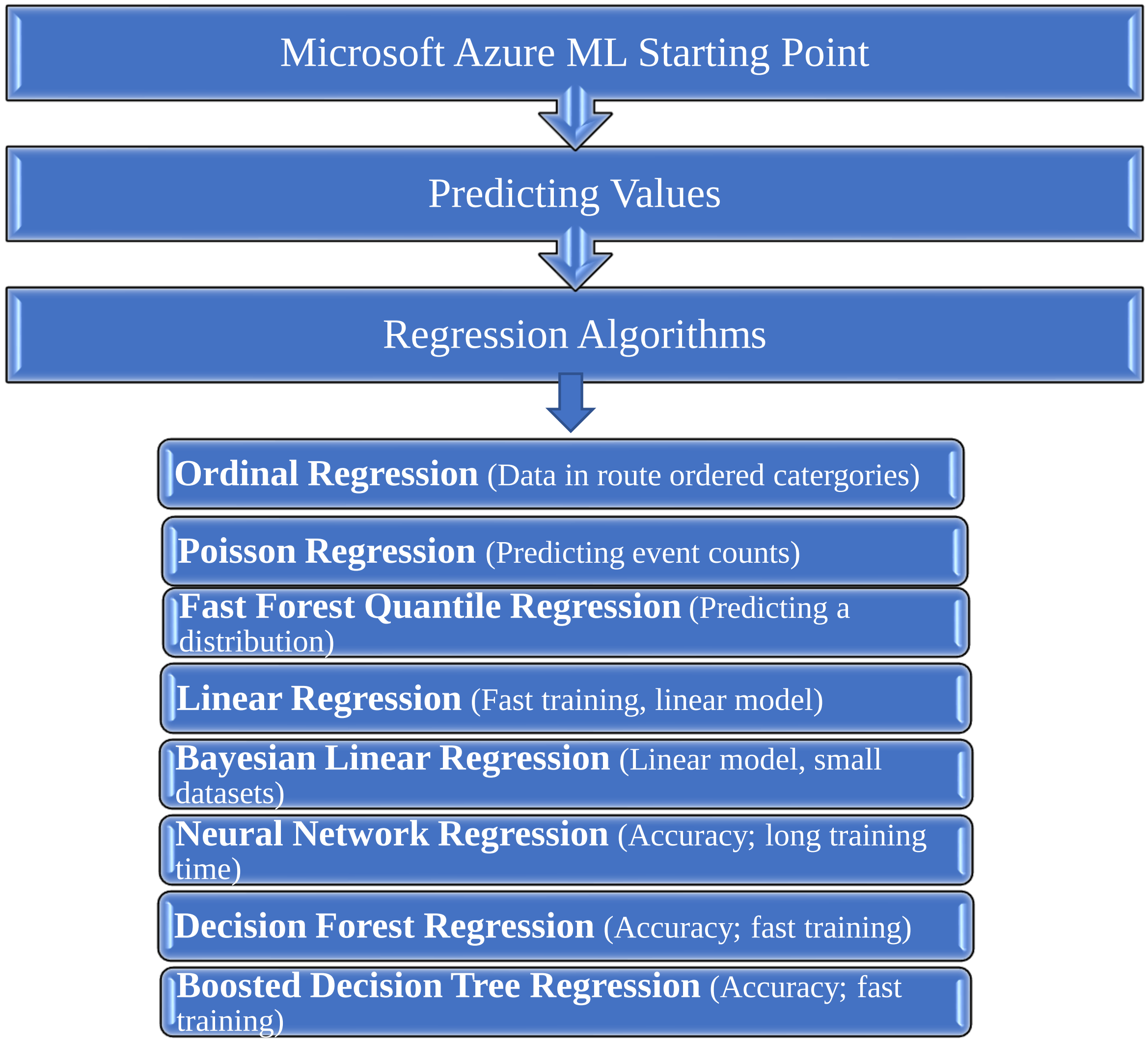


Figure 3. 4. Regression algorithms available in Microsoft Azure ML Studio. Source: Adapted from (Microsoft Azure ML, 2018)

Various ML algorithms are used to optimize different processes of supply chain management. Each algorithm has its own advantage in predicting the outcome of the process or optimizing the process in which that algorithm is applied. Table 3.7 presents a comparative analysis of various supervised ML algorithms used for regression problems. SVR was the only algorithm excluded from the algorithms that were used in this research.

Table 3. *7.* Comparing supervised learning algorithms for regression

	Linear Regression	Support Vector Regression (SVR)	Decision Trees	Neural Networks
Problem Type	Regression	Regression	Either	Either
Average Predictive Accuracy	Lower	Higher	Lower	Higher
Training Speed	Fast	Slow	Fast	Slow
Prediction Speed	Fast	Fast	Fast	Fast
Advantages	• Simple to perform. • Useful and performs well if the simulation model is linear. • Easier to implement, interpret and very efficient to train.	• Has good generalization capabilities • Using the Kernel technique, can efficiently handle non-linear data. • Can make use of the predictive power of linear input combination • Can forecast outcomes in a number of situations. • The outcomes are simple to comprehend.	• Easy to interpret. • Able to deal with missing values. • Works well with huge datasets and can handle both numerical and categorical data.	• Have strong fitting ability. • Able to tolerate noisy input. • Can be employed when input and output have a complicated, non-linear pattern relationship. • Have good prediction generally. • Incorporate the predictive power of different combinations of inputs.
Disadvantages	• Not useful if the model is	• Has very high algorithmic complexity	• Easily over fit. • Computationally intensive.	• Prone to overfitting.

	non-linear. • Prone to noise and overfitting. • Prone to multicollinearity.	and memory requirements • Requires feature scaling before applying it. • Takes a long training time on large datasets. • Difficult to understand and interpret. • Handling mixed data formats and computing scalability are both shortcomings. • Sensitive to tuning parameters and kernel choice.	• Cannot operate with linear feature combinations. • In many instances, it is less predictive. • Practical decision-tree learning algorithms cannot ensure that the best decision tree will be returned.	• Model training is time consuming. • Network structure is difficult to understand. • Finding the correct topology is difficult. • Dealing with massive data and a sophisticated model is difficult.

Source: Adapted from (Liu and Lang, 2019; Naresh Kumar, 2019; Gupta and Kaushik, 2018; Ossianwo et al., 2017; Lidong Wang et al., 2017; Markham, 2015; Tappenden et al., 2004)

There are many different types of supervised machine learning algorithms, as shown in Table 3.8, and supervised regression techniques were chosen for developing the predictive model based on the literature discussed in Chapter two, which showed how ML models provide better and more accurate forecasts. The supervised learning technique uses records with a known output variable to provide an algorithm. The algorithm "learns" how to anticipate this value with fresh records when the output is unknown, which makes it appropriate for this study because the model's goal is to estimate the EOQ to be ordered by the distributor. These methods were designed to solve issues where a typical regression model could not.

3.7.2 Proposed supervised regression predictive model

This section covers the creation of the proposed ML predictive model as well as the selection of the input variables used to assess the model's performance. The processing algorithms for analysing data are devised and implemented at this stage, as are the parameters to measure the performance of the models used as processing algorithms.

The proposed model’s structure below is inspired by the demand forecasting models created by (Paul and Azeem, 2011; Sustrova, 2016; Chai et al.,2018; Bottani, 2019). The previous models focused on most of the variables mentioned in the below model, but they did not include some variables that would have an important effect on the distributor’s EOQ determination process. The managers, in the case company highlighted the importance of the “working capital” and “seasonality” as variables that have a direct effect on the inventory management and the EOQ during the interviews conducted. The proposed model architecture outlined in Figure 3.5, consists of input variables, four supervised regression algorithms and one output (EOQ). The input parameters included in the predictive model, in Figure 3.5, were briefly defined as follows:

- **Historical demand:** it refers to the number of products that have been ordered during a specific period in the past, and this input would be used to forecast the demand. Most companies assume they have a large historical demand database to use for forecasting, according to Caplice (2003), but all of these records are sales histories, not demand histories. Having past demand data is helpful for making accurate projections, but it isn't always enough to forecast to the appropriate level of precision (Hyndman and Athanasopoulos, 2014). Because many historical data-based statistical forecasting models lack the capacity to explicitly collect contextual information or dynamically update as new data becomes available, this is the case (Lawrence et al. 2006).

- **Historical sales:** it refers to the historical amount of product sales during a specific period. Sales records should be supplemented by estimates of "lost demand" in order to forecast future demand, but this is difficult to do (Caplice, 2003). To create a good forecast, most machine learning and statistical approaches require some historical data. Mik (2019) explained that when a product's past sales data has a lot of volatility, even more months of sales history are required to predict what sales would be over a certain period.

- **Forecasted demand:** it refers to the predicted future demand of a product during a specific period. Forecasted demand is a method of anticipating future demand for a company's products and services in order to meet consumer demands over a set time period. It is done utilising previous data, typically demand data (Heizer and Render, 2017). Because practically any producer, distributor, or retailer might expect seasonal demand swings for some of their product lines, Chapman (2019) emphasised the need of forecasting seasonal demand. Seasonal demand components should be kept distinct from base demand estimates, as this maintains the data clean and makes forecasting easier in the future.

- **Current inventory:** it refers to the actual number of products currently existing in the warehouse. Lopienski (2019) advices that its necessary to have access to live inventory management, knowing exactly how many units are available in each distribution centre.

- **Purchase price:** it refers to the purchase price of products that the distribution pays when buying products from the suppliers. Price-dependent demand models are the most often utilised, according to Huang et al. (2013), presumably because pricing strategy is the most effective instrument for influencing a firm's demand. As a result, when projecting the distributor's EOQ, we must definitely include the impact of its price.

- **Working capital:** it refers to the difference between the distributor’s current assets (cash, inventory of finished goods) and the distributor’s current liabilities. Though inventory management as a subset of working capital management is a prominent topic for academic research, most studies focus on its impact on a company's financial performance and profitability by looking backwards and using historical data to forecast future outcomes (Priniotakis and Argyropoulos, 2018; Dooley, 2005; Ivanov et al., 2017).

Supervised learning is the task of machine learning to learn a function that maps an input to an output based on sample input-output pairs. It uses labeled training data and a collection of training examples to infer a function. Supervised learning is carried out when certain goals are identified to be accomplished from a certain set of inputs (Sarker et al.,2020), i.e., a task-driven approach. The goal of supervised learning is to learn a model from labelled training data that allows users to make predictions about future data (Eissa, 2016). For supervised machine learning to work efficiently, the algorithm needs to be fed with two things: the labelled training data and the new input data. The concept of this learning focuses on labelling of training data. Supervising here, as shown in Figure 3.5, means helping the model to predict the right things. The data will contain inputs with corresponding outputs. This has hidden patterns in it. The algorithm will learn these patterns and will try to apply the same knowledge to unseen data. The aim is to predict future values.

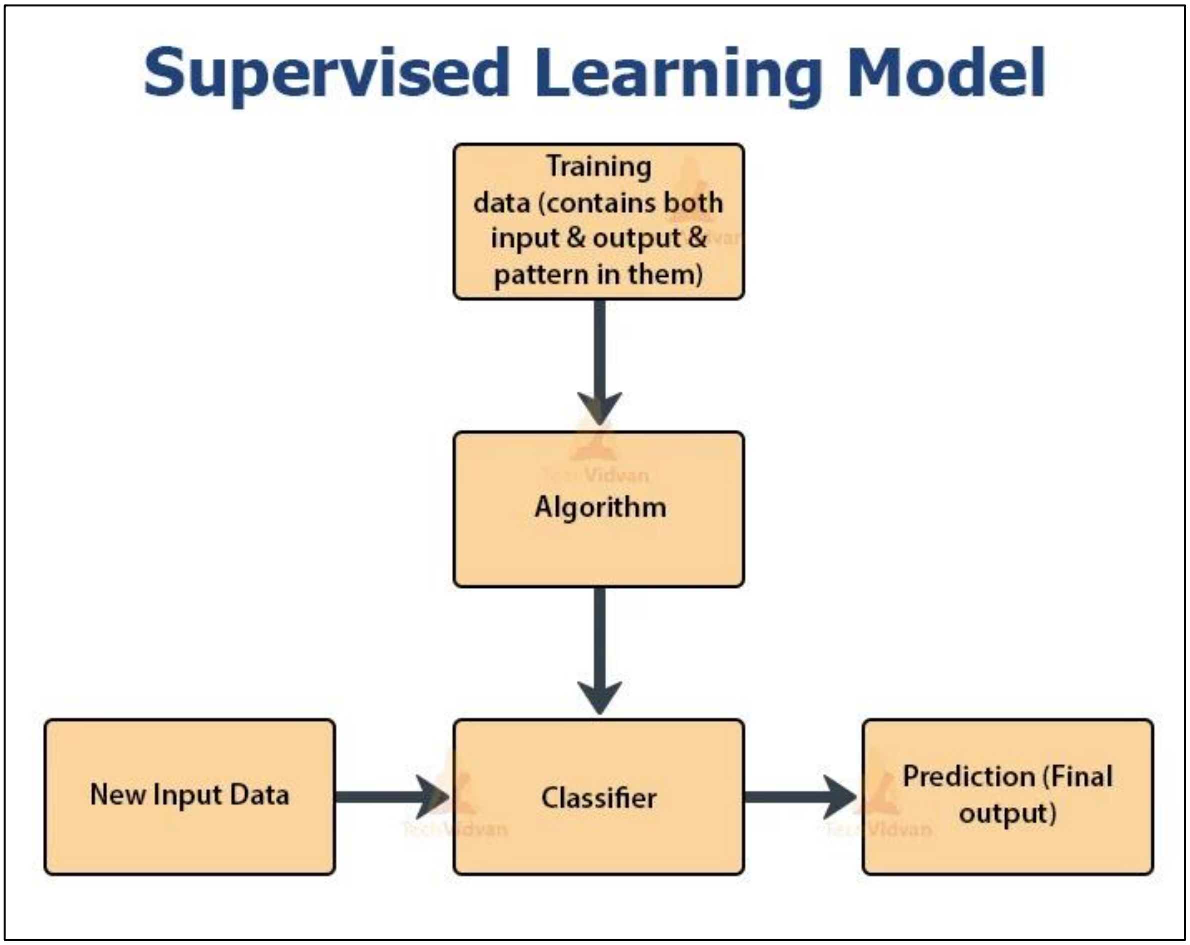


Figure 3. 5. Supervised learning (TechVidvan, 2023)

This research predictive process flow is explained in Figure 3.6. It followed the same way any supervised ML algorithm uses to train the data and predict an output. First a group of supervised ML algorithms that are suitable for solving regression problems are chosen for developing the predictive ML model. These algorithms are trained using labelled training data (dataset gathered from the company). After the training process is completed, the proposed model will be ready to be tested by new input data in order to predict new results and check the accuracy of these results.

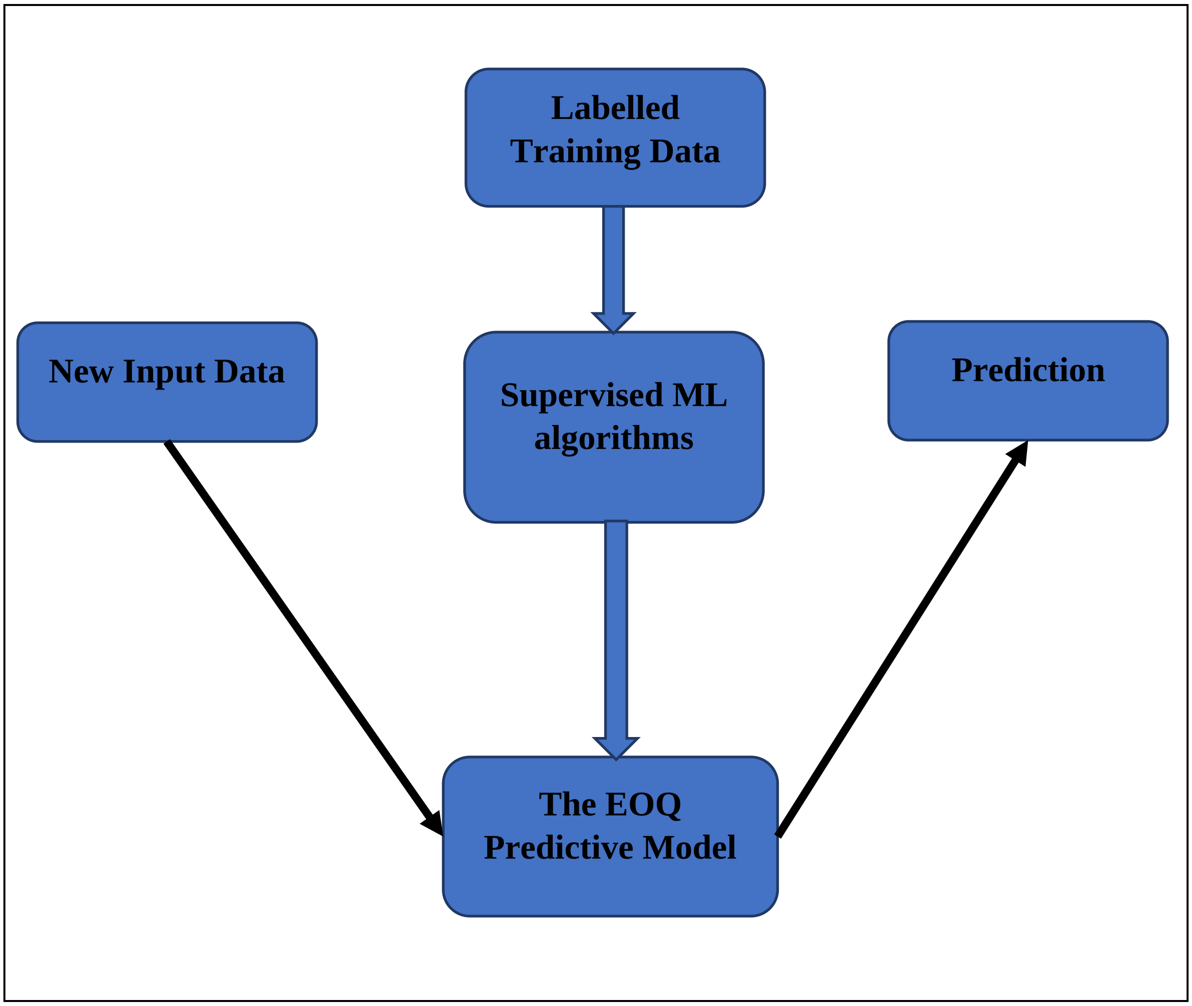


Figure 3. 6. The research predictive process flow

Although the structure of the model is of general validity, it should be mentioned that the factors used as input in the ML predictive model are relevant for the context of wholesale distribution and it could be relevant in a different context and in other sectors in the FMCGs industries. Several variables can influence the dynamics of demand as mentioned by (Abolghasemi et al., 2019), and hence a deterministic model that depends on steady demand is insufficient to produce accurate forecasts. That is why this research cared to include more factors that would affect the demand and the EOQ determination and accordingly would affect the level of performance of the inventory management of the FMCGs distributor. The model is now ready for development after gathering the dataset and selecting supervised regression algorithms that will train the model. The next chapter will cover the ML predictive model development phase along with reviewing the possible scenarios to ensure the development of an accurate model.

3.8 Chapter summary

The approach used throughout the study was detailed in this chapter. It began by outlining the various research philosophies and demonstrating how positivism was applied into this study. The various research strategies are discussed, with the case study strategy serving as the primary strategy used in this study. The chapter then stated that the study uses both qualitative and quantitative data in a mixed methods approach. The main data collection procedures used were interviewing and analysing internal documents, according to the report. The research focused on the supervised regression algorithms that will be used to develop the supervised regression predictive model. The next chapter will present the developed predictive model with a description of the preparation phase of the model development in detail, the dataset gathered from the case company, and its preparation phases before it would be interpreted in the model.

Chapter Four

The Supervised Regression Predictive EOQ Model

4.1 Chapter overview

This chapter provided a detailed explanation of the developed supervised regression predictive model along with its two implementation scenarios that covers the demand forecasting first followed by the EOQ determination of the FMCGs distributor. The chapter reviews the two main phases necessary for building the supervised regression predictive model along with the different supervised regression algorithms used to train the models. A detailed review of the data preparation phase is covered followed by the modelling phase that includes the model selection and training. The chapter finally concludes by presenting the predictive experiments of the model.

4.2 Methodology for developing the ML predictive model and software implementation

This research followed the phases of the CRISP-ML(Q) methodology reviewed by Studer et al. (2021) that was used for developing ML applications. As mentioned earlier in Chapter 3, the CRISP-ML(Q) methodology consists of six steps; one was performed in the previous chapter, two would be outlines in this chapter and the last three phases would be outlined in the coming chapter. There are six major phases for developing the predictive supervised regression model (as explained in the previous Chapter in Section 3.6). The first phase was already explained in Chapter 3, the following two phases would be conducted in this chapter, as shown in Figure 4.1, and the last three phases will be discussed in the next chapter. The (Data Preparation) phase of the CRISP-ML(Q) methodology is responsible for evaluating data for missing values and then conducting various operations to correct the data or insert new values to avoid difficulties caused by missing data that could develop during model training. The third phase is the (Modelling) phase that consists of two main parts; the first was about selecting the model with the algorithms that would be implemented in it, and the second part was about training the model training.

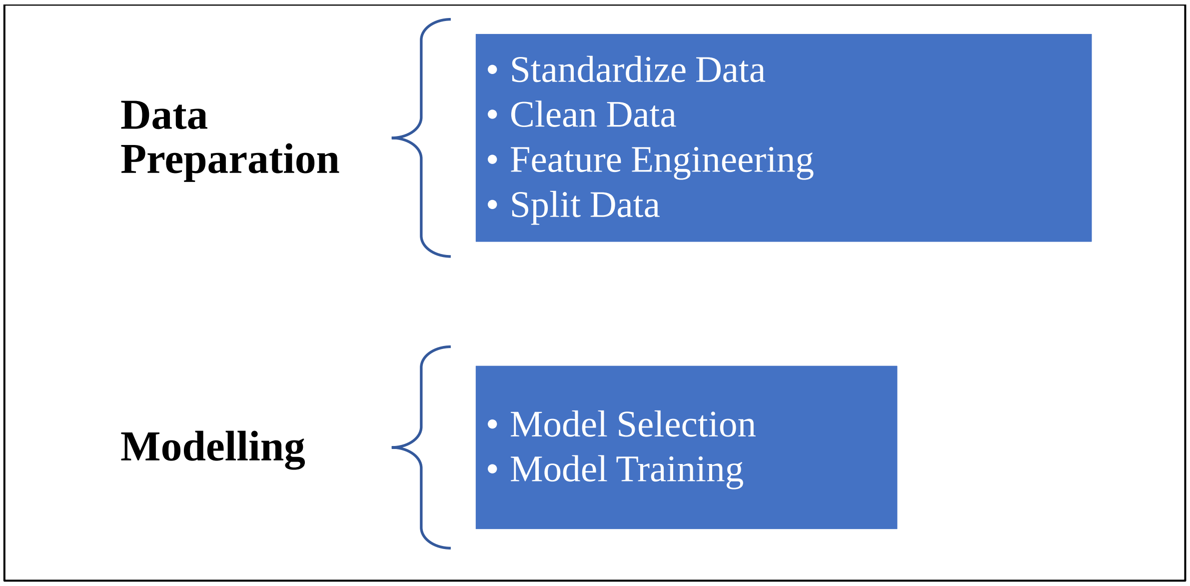


Figure 4. 1.Phases for the ML predictive model development and training

This research followed Bottani et al. (2019)'s idea of the cascade ANNs implementation they followed in their research to improve the effectiveness of the forecasting performance of the wholesalers than the separate implementation of the ANNs. For this reason, this research reviewed two scenarios for the predictive ML model; a sequential predictive model scenario that followed the cascade implementation of Bottani et al. (2019) and a parallel predictive model scenario that would act as a baseline model. These two scenarios used supervised regression algorithms and their results have been evaluated to have a base for the model validation in the next chapter.

The proposed approach makes use of two supervised regression predictive models. Both models take six factors as inputs and returns the EOQ to be ordered by the distributor as output. This output can be used by the distributors to support their purchasing decisions and hence optimizing their inventory levels. The two models have been trained and tested on a real FMCGs distributor dataset, and two scenarios were considered for the implementation. For each scenario, forecasting performance of both predictive models regarding the output (EOQ), in terms of the regression performance metrics, were evaluated.

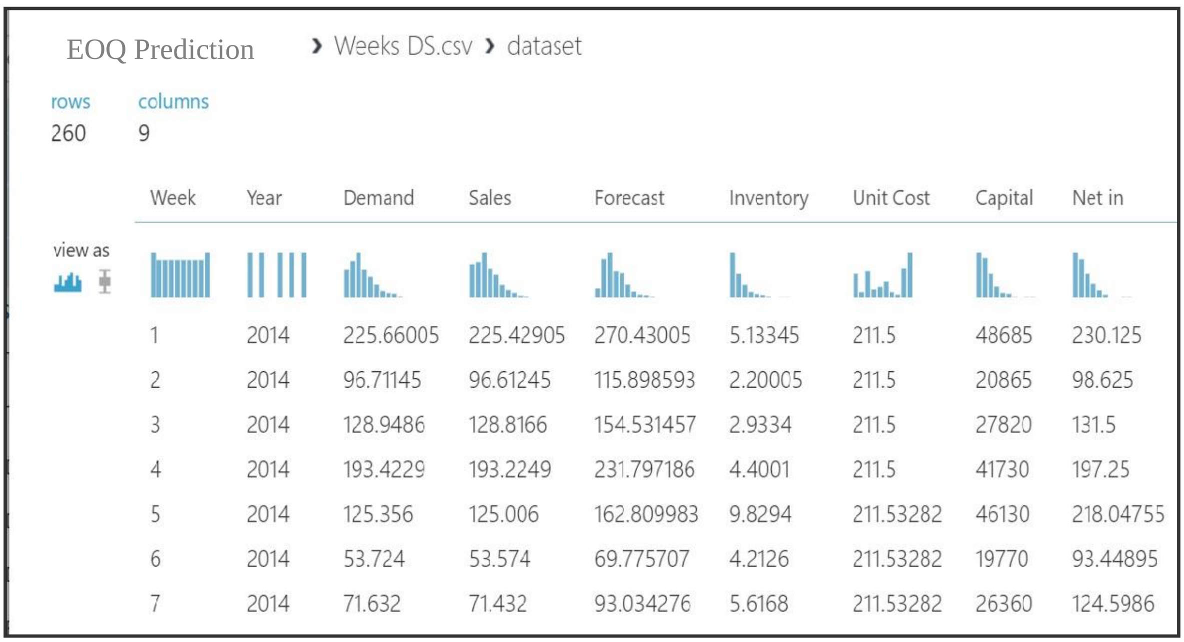
The following sections illustrate the phases mentioned in Figure 4.1, explained in detail to give a full and clear explanation of the data preparation phase, followed by the model selection and training phase.

4.3 Data preparation

This phase, sometimes known as data pre-processing, is responsible for creating a dataset for the modelling phase that follows. According to Jamshed et al. (2019), data pre-processing entails converting a raw dataset into a comprehensible format. Cleaning, integration, transformation, and reduction are all examples of data pre-processing. Pre-processing is important, according to Misra et al. (2020) since it tries to make the training/testing process easier by suitably modifying and scaling the entire dataset.

4.3.1 Standardize data

Data normalisation and standardisation are essential for obtaining good results and greatly speeding up the process. When input data has several properties with distinct units, standardisation is critical. Certain weights may update faster than others in the training process when features are on various scales (Brownlee, 2020). To create a consistent dataset, the data and its format should be standardised by converting it to a common file format and normalising the features and labels. The dataset was acquired and was ready to be imported to Azure ML Studio. The "Weeks DS" dataset included entries for an individual product, including information such as sales, inventory levels, unit cost, demand and working capital. Before uploading the dataset into Azure ML Studio, it has been transformed into the comma separator values (CSV) file format fulfilling the software requirement that the input variables should be in a specific format. After uploading the dataset, a visualization step should be undertaken to give a detailed view of the rows and the columns included in the dataset, as shown in Figure 4.2.


EOQ Prediction › Weeks DS.csv › dataset

rows 260 columns 9

Week	Year	Demand	Sales	Forecast	Inventory	Unit Cost	Capital	Net in
1	2014	225.66005	225.42905	270.43005	5.13345	211.5	48685	230.125
2	2014	96.71145	96.61245	115.898593	2.20005	211.5	20865	98.625
3	2014	128.9486	128.8166	154.531457	2.9334	211.5	27820	131.5
4	2014	193.4229	193.2249	231.797186	4.4001	211.5	41730	197.25
5	2014	125.356	125.006	162.809983	9.8294	211.53282	46130	218.04755
6	2014	53.724	53.574	69.775707	4.2126	211.53282	19770	93.44895
7	2014	71.632	71.432	93.034276	5.6168	211.53282	26360	124.5986

Figure 4. 2. Data visualization

In this dataset, each row represents a product, and the variables associated with each product appear as columns.

4.3.2 Clean data

Before a dataset can be analysed, it usually needs to be pre-processed. These missing values must be cleared before the model can properly analyse the data. Data cleaning identifies elements of datasets that are incomplete, erroneous, imprecise, or inappropriate (Tamraparni and Theodore, 2003). Missing value strategies include deletion methods, replacement methods, model-based methods, and machine learning methods (Xu et al., 2015). Some methods handle missing values by removing the records that contained them. Delete these entries from a tiny dataset, however, limits the sample size and makes it less useful for statistical analysis. Deletion methods were the methods used in this research for cleaning the data as they are considered the simplest procedure to handle incomplete data sets to eliminate any time point that contains missing values. The dataset that was used in this research was relatively small and did not contain many records that had missing values. This module completely removes any row in the dataset that has one or more missing values. In the “Clean Missing Data” module, any rows that have missing values were removed using the “deleting particular row” technique. After adding that module, the experiment was run. Once the experiment finished running, a clear set of data was ready to be used to define the features that would be included in the model development.

4.3.3 Feature engineering

Feature engineering is the process of selecting and producing final characteristics for model fitting and prediction. The process of excluding features that aren't acceptable for the machine learning algorithms employed is known as feature selection. This effort was completed in partnership with the distributor case company to ensure that the features chosen for the machine learning algorithms will be available for future predictions. Experimentation and knowledge of the problem to be solved are required to find a solid set of features for constructing a predictive model. Some traits are better than others at predicting the target. For the model to be able to make future predictions, the features that were selected to be excluded were “unit of measurement”, “warehouse code”, “payment method” and “sales representative”. These features do not have any direct impact on the demand forecasting process; hence they have other uses in the dataset. (QEBAA, data structure meeting (2019).

The other nine features were not further selected because they were all deemed relevant for the ML techniques to be incorporated in the model. Nine continuous features were designed for each product based on the product history. The model in this research was built using a subset of the features in the uploaded dataset “Weeks DS”. The selected features can be changed, and other different features can be later selected, and the experiment could be run again to see if better results could be obtained. To start the experiment, the following features were tried: “Week, Year, Demand, Sales, Forecast, Inventory, Unit Cost, Capital, Net in”, as shown in Figure 4.3.

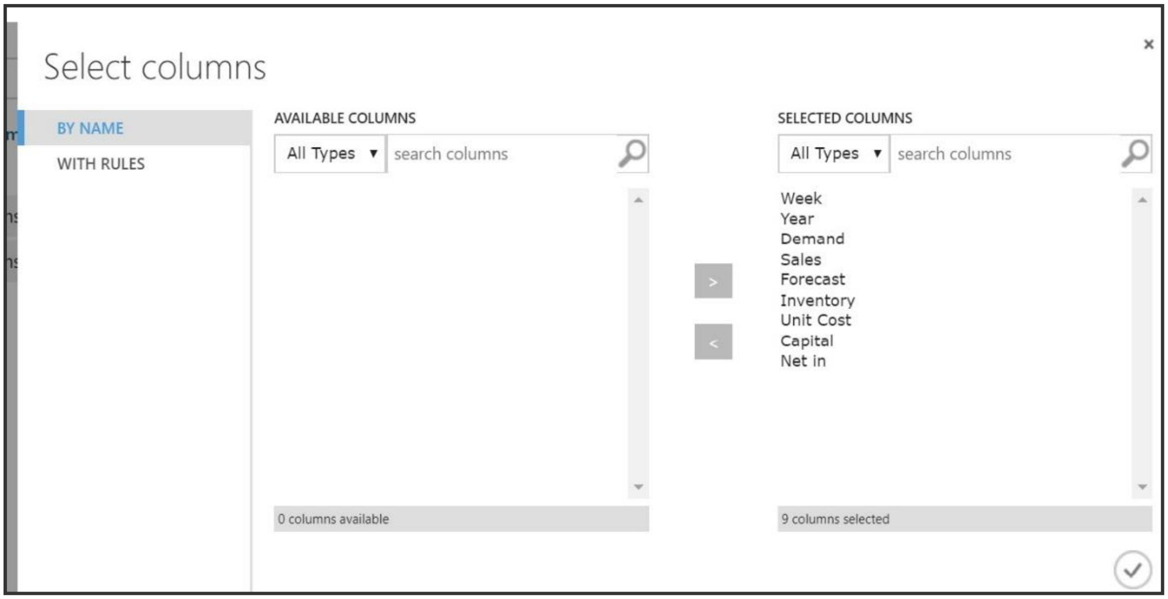


Figure 4. 3. Feature engineering for the dataset

The "Select Columns in Dataset" module produces a filtered dataset containing only the features that will be passed to the learning algorithm to be used in the model as shown in Figure 4.3.

4.3.4 Split data

To prepare the data input into the model, this phase of the data preparation was required. This stage involved dividing the data set into a train and test set. After then, a predictive model was built using the data that had been collected. A strategy for partitioning a data collection into disjoint "splits" or subsamples that may then be used for various statistical tasks is data splitting. Romano and DiCiccio (2019) showed how data splitting could be used in prediction, as in this research, to evaluate the performance of models where a portion of the data was used to pick and/or fit a model and the rest was used to evaluate the performance of the selected model, or in inference to run significance tests after hypotheses or test statistics were chosen.

The data was divided into training and testing sets before being used to develop the general model. The data from January 2014 to December 2017 served as a training set for the model, while the data from January 2018 to December 2018 served as a validation set for assessing the model's prediction ability. The division of the dataset is illustrated in Figure 4.4.

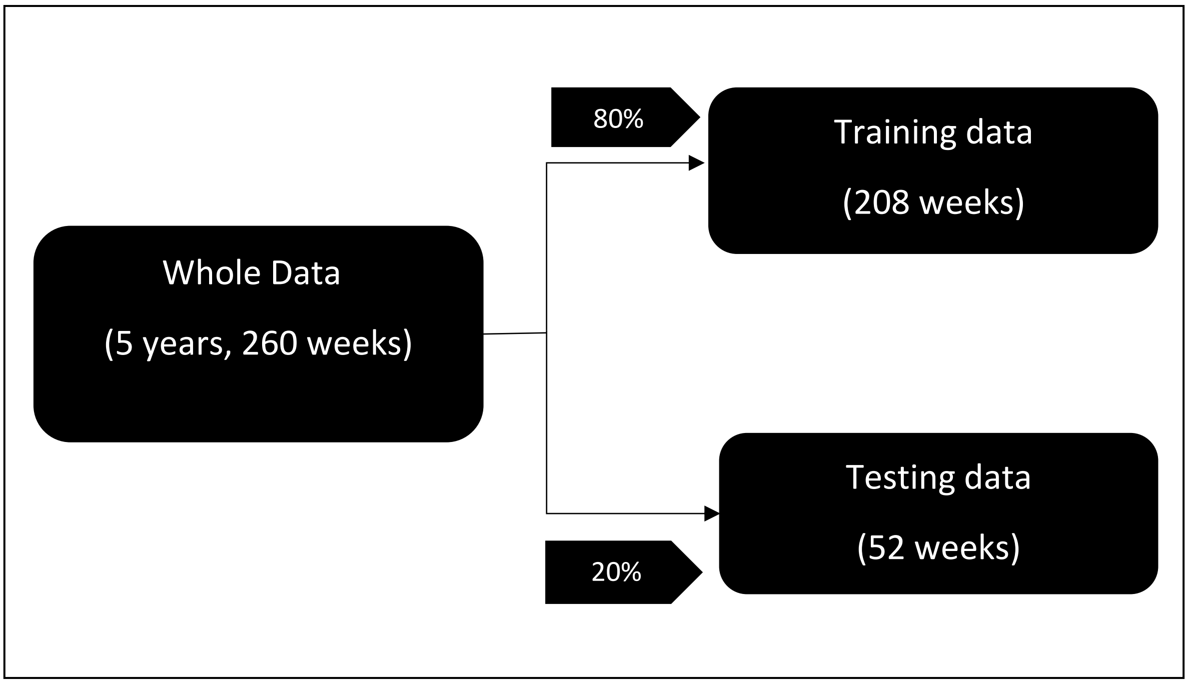


Figure 4. 4. Division of the original dataset into training and testing sets

The entire 60-month (260-week) dataset was separated into two sets using the 80/20 method. The training dataset contains 80% of the data (208 weeks), which was used to fit the model, while the testing dataset contains 20% of the data (52 weeks), which was used to offer an unbiased evaluation of the model on the training dataset. Because the sample size was so tiny, it was critical to choose the right data for training and testing. Three modes were available in Azure ML studio that dealt with data splitting, and they were: Split rows, Regular expression split and Relative expression split. The “Weeks DS” dataset was split by implementing the “Split Rows” mode from the “Split Data” module in Azure ML Studio as shown in Figure 4.5 This mode was chosen because the dataset needed only to be split into two parts; with specifying 80% of the data to be used in the training split and the other 20% of the data to be used in the testing split. This ratio was represented through entering a decimal number between 0 and 1 in the “Fraction of rows in the first output dataset” to determine how many rows would go into the “training dataset” so that the all the other rows would go into the “testing dataset”.

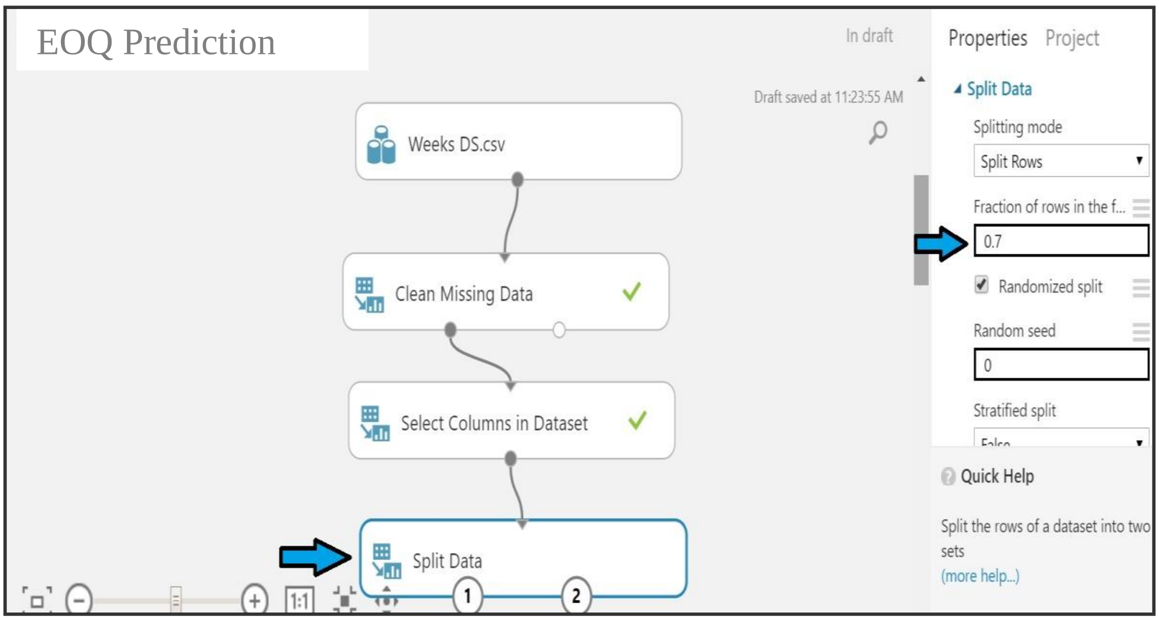


Figure 4. 5. Splitting data into training and test sets

With the training dataset, which is also labelled, the algorithm used in the model would start making it learn to predict. With the first test, the accuracy of the algorithm will be tested, to see if any parameter adjustments must be made or if it needs to be compared it with the other ones. The coming section reviews the modelling part of the experiment, including the algorithms chosen, the training and scoring of the models.

4.4 Modelling

The modelling methodologies used are determined by the ML and business objectives, as well as the data and situations that the predictive ML model contributes to. The business and data understanding requirements specified in Chapter 3 are utilised as inputs to narrow down the model selection to a subset of appropriate models. The modelling phase's purpose is to create one or more models that meet the specified specifications. A methodology of the model development has been thoroughly reviewed in Chapter 3, explaining the structure of the model along with the input variables, the algorithms that would be used for training the model and the targeted output of the predictive model.

An FCMGs distribution company provided historical data and related information for 60 months (from January 2014 to December 2018). After looking over the firm database and speaking with supply chain professionals, it was discovered that they were using excel sheets to forecast demand and that excess stock and stock out issues were present. The statistical linear model fails to determine the EOQ, resulting in lower supply chain efficiency (in the case of surplus stock) and responsiveness (in case of stock out). Demand affecting variables were selected and introduced to the predictive supervised regression model as inputs that would affect the demand for a specific product after analysing the company scenario. Currently, the company does not record the inventory level status periodically. The absence of a periodic written record of inventory level is the system's weakness, which has led to the shortage of research data. Furthermore, even though they have implemented their own system, the management still thinks that they have high inventory costs. The company also did not have the exact number that indicates the excess inventory because they have no criteria to determine whether an inventory level is too high or too low. Furthermore, the company does not have a method to determine the appropriate amount of order since currently, the company does not have any inventory model. Having the appropriate order amount will help the company obtain the right inventory level and reduce its inventory cost. As a start, the company can implement a ML model to predict the EOQ to manage its inventory level since the model is robust and the total inventory cost is effectively proven to be insensitive to order quantities. This research aimed to reduce FMCGs inventory costs by implementing a supervised regression predictive model to predict the EOQ. This study was expected to contribute to QEBAA in determining the optimal number of orders.

This research depended on two scenarios for the ML predictive model developed. The reason for implementing these scenarios was to give the chance for different supervised regression algorithms to train the model in two different structures (parallel and sequential) and compare their prediction results. The model with more accurate results and least errors will be verified as the chosen developed model. The way the two models are developed to forecast the EOQ of a specific product to be ordered was different. In the SPM implementation, the demand, inventory level and the sales were determined by standalone predictive models that were connected to each other through their input parameters. Meanwhile the PPM implementation reflects the real demand, inventory level and the sales applied by the distributor. The PPM was largely used to tweak the parameters of the predictive models and to discover the configuration of the four models that gives the greatest predicting performance because it used real input and output data. In contrast, the SPM was created to see if a precise description of demand, inventory level, and sales, as an anticipated output from each stage of the model, might assist increase the efficiency of projecting the EOQ to be bought and, as a result, lower inventory carrying costs. The SPM was also beneficial in determining whether a hybrid implementation of predictive models is more effective than using separate predictive models in estimating the distributor's EOQ. The models were created in Microsoft Azure Machine Learning Studio, and the results of their predictive trials are detailed in the sections below. The goal of the project was to create an Azure ML studio tool and compare various types of regression ML models for EOQ prediction, with the highest performing models being chosen for future investigation.

The following assumptions have been used in the developed model:

- The EOQ is predicted weekly.
- The unit cost is fixed.
- The lead time is constant.
- Sales, demand and inventory are predictable variables.

In a very dynamic and changing business environment, the generated model can be employed effectively in the observed company. One of the goals is for the suggested model to be flexible and adaptable to other organisations and different types of goods in SCM. The primary motivation for creating such a model is to create an EOQ tool that can fully replicate, control, and replace the job of logistics professionals, or perform sophisticated and real-world SCM operations utilising a hybrid AI technique. The goal of this study is to develop an EOQ model that, when implemented, will allow a corporation to optimise inventory levels and the entire supply chain.

4.4.1 The parallel predictive model (PPM)

The PPM presents separate predictive models' implementation with different regression algorithms. This model has been tested by real data from the distributor to forecast the EOQ. The PPM consists of four separate predictive models with different algorithms, accepting the same input to the four models and then a comparison between the results of the four algorithms was made to explain the differences between the performance metrics generated by each standalone predictive model to measure the forecasting accuracy of each model.

The PPM model depends on the real data coming from the distributor which was used as input into the four separate sub models. Each sub model trains the dataset with a different algorithm then the EOQ is forecasted and compared with other results. The PPM works well with data sets that contain well-structured data that would be trained by different algorithms in a parallel way with the aim of comparing the results of these algorithms and knowing which one produce best forecasting results. The PPM used the features in the dataset and started the training process given that all the features were given. Unlike the SPM model, it depended on the prediction of three features selected from the dataset and performed a sequential prediction process on the three of them before forecasting the final EOQ.

4.4.2 The sequential predictive model (SPM)

The SPM addressed the prediction of the product inventory levels, sales and demand in a sequential order first, before forecasting the final EOQ. The EOQ model determines the amount of quantity to be placed in an order in order to minimise the annual total cost of inventory handling and order processing for an item to be ordered. In its most basic description, these two types of costs are the key categories utilised to determine the EOQ (Senthilnathan, 2019).

In terms of the SPM, inventory managers must decide when to buy, how much to buy, and from whom to buy each item in order to meet future client demand (Bala, 2012). The wholesaler's decision on the purchased product amount may be influenced by factors such as the purchase price, lead time, and existing inventory level. First, the suggested SPM helps the process of estimating sales, inventory, and demand before projecting the EOQ. This was an important consideration for predicting the ultimate EOQ in a distribution context. Second, in order to represent three sequential processes, the suggested approach used three ML predictive models that were connected in series. It was created to see if anticipating revenues, inventory, and demand before the EOQ may assist the distributor improve forecast quality. The SPM model could be used to improve inventory management and the company's ordering system by optimising inventory levels. This explains why the sequential prediction process is vital because inventory levels, sales history, and product demand are predicted to have a significant impact on the EOQ for a specific FMCG product in wholesale distribution.

The SPM consists of four consecutive predictive models linked together, as the output of each model is added as one of the inputs to the following model. The prediction of the first model is the “weekly product sales” and this output is fed in as one of the inputs to the second model. The prediction of the second model is the “weekly product inventory levels” and this output is fed in as one of the inputs to the third model. The prediction of the third model is the product “weekly demand”, and this output is fed in as one of the inputs to the fourth and last model that forecasts the main output which is the “weekly EOQ”. The forecast precision achievable using the SPM was evaluated and compared with those generated by the PPM.

The SPM would work well with datasets that might contain missing data concerning some of the input variables. This model works on predicting the sales first followed by the inventory then the demand and ends with forecasting the optimum quantity to be ordered. This model does not totally depend on the real data from the distributor, but it takes a part of the sales data from the available dataset then produces a dataset with a newly predicted “sales” variable, which goes as an input in the next predictive model that predicts the “inventory” variable. Then another new dataset with predicted sales and predicted inventory is produced and used as input in the next predictive model that predicts the “demand” variable. The last dataset with the predicted sales, inventory and demand is produced that is used as input to the last predictive model that forecasts the EOQ.

4.4.3 Quality measures of the ML predictive model

According to Baylor et al. (2017), a model should be evaluated based on two properties: it must be safe to serve and have the appropriate prediction quality. ML models, according to Studer et al. (2021), should be evaluated on six complementing features, as given in Table 4.1. Soft criteria such as resilience, explain ability, scalability, hardware demand, and model complexity must be examined in addition to a performance metric. Depending on the application, the measurements can be weighted differently.

Table 4. 1. Quality measures of machine learning model

Performance	Performance metric on unseen data e.g., accuracy, AUROC, F1-score, mean square error (MSE), mean absolute error (MAE) etc.
Robustness	Model resiliency in the face of unanticipated inputs including adversarial assaults, out-of-distribution samples, anomalies, and distribution shifts, as well as problems in the underlying execution environment such sensors, actuators, and the computational platform.
Scalability	During training and retraining in the production system, the model's capacity to scale to enormous amounts of data. Study of the impact of complexity on execution time and hardware requirements dependent on the number of samples and feature dimension.
Explain ability	Direct or post-hoc explanations could be used to explain models. Explainable models' decisions can be double-checked, which would improve user acceptance. Furthermore, uncertainty and confidence estimates help with hesitant decisions.
Model complexity	On limited data sets, models with large capacity are easily overfit. Make sure your model's capability matches the complexity of the data, and utilise suitable regularisation.
Resource Demand	The model is limited by its memory and must be deployed on hardware. Furthermore, the inference time must be taken into account in relation to the application.

Source: Studer *et al.* 2021 (p.9)

Along with some of the quality measures mentioned in Table 4.1, this research used some specific performance metrics for evaluating regression algorithms. Performance metrics are used in ML regression trials to compare the trained model predictions with the actual (observed) data from the testing data set (e.g., Botchkarev, 2018a; Makridakis et al., 2018). The outcomes of these comparisons can have a direct impact on the decision-making process for which machine learning algorithms to use. Azure ML Studio has a designated module – Evaluate Model – to perform comparisons. This module shares a drag and drop functionality with other Azure modules. However, it has certain limitations.

For example, it has a limited number of the metrics implemented to evaluate prediction errors (Evaluate Model 2018):

- **Mean Absolute Error (MAE)**

It calculates the average of each truth value's absolute deviation from the forecasts (Guanga, 2019). It determines how close the forecasts were to the actual results (Singh, 2020). It is used as a model's average error size and has proven to be a more natural measure of error than other average error measures like root-mean-square error (RMSE). The better the model, the lower the MAE.

- **Root Mean Squared Error (RMSE)**

It is calculated using the square root of the average of the squared difference between the predictions and the ground truth. It generates a single value that sums up the model's inaccuracy. It calculates the model's average error in predicting the outcome of an observation (Kassambara, 2018). The squared difference between the predicted and target values is calculated for each forecast value. The model is better if the RMSE is low.

- **Relative Absolute Error (RAE)**

The mean difference is divided by the arithmetic mean to get the relative absolute difference between expected and actual values.

- **Relative Squared Error (RSE)**

It divides the total squared error of the predicted values by the total squared error of the actual values to normalise the total squared error of the predicted values.

- **Coefficient of Determination (R^2)**

It compares genuine values to the model's anticipated value and is used to determine how well future samples will be predicted. It's also a measure of how well the prediction matches the actual numbers. R2 is a regression model goodness-of-fit metric. The R2 value ranges from 0 to 1, with 0 indicating no fit and the target model performing similarly to the baseline, and 1 indicating excellent fit (Singh, 2020). It indicates how much variation between the dependent and independent variables is explained by the model.

4.4.5 Model selection

Multiple machine learning techniques for regression, classification, and clustering are supported by Microsoft Azure ML Studio. It enables for model customisation using Python and R. (Qasem et al., 2015). Microsoft Azure ML Studio allows you to link modules and datasets together by dragging and dropping them (e.g., ML algorithms, feature selection, and pre-processing). Experiments created in Microsoft Azure ML Studio may be trained and turned into predictive experiments, allowing users to create their own models (Ericson et al., 2016; Rajpurohit, 2014). In general, Microsoft Azure ML Studio is intended to serve as a learning environment for both experienced and novice data scientists. The next section goes over the supervised regression models utilised in this study and discusses how each one trained the previously established models.

The four models that have been implemented to train the two models are explained with a brief comparative analysis mentioned below in Table 4.2. Ghanbari (2019) highlighted the necessity of applying forecasting algorithms for regression problems, that is why the mentioned algorithms were chosen, so they could deal with the numerical data in the provided dataset and predict the targeted output. The selected regression algorithms, mentioned in Table 4.2; were chosen among other regression algorithms that existed in Azure ML Studio, based on their accuracy and training time as explained in Chapter 3, Figure 3.4 After the following regression algorithms were trained, two trained models would be the output of this phase so that they would be ready for the scoring step that would be followed by the evaluation phase (discussed in the next chapter).

Table 4. 2. Regression algorithms used in training the models

	Linear Regression	Decision Forest (DF) Regression	Boosted Decision Tree (BDT)Regression	Neural Network (NN) Regression
Average Predictive Accuracy	Low	High	Low	High
Training Speed	Fast training	Fast training	Fast training	Long training time
Prediction Speed	Fast	Fast	Fast	Fast
Advantages	-Simple to perform. -Useful and performs well if the simulation model is linear. -Easier to implement, interpret and very efficient to train.	-Easy to interpret. - Can work with missing values. -Works effectively with huge datasets and can handle both numerical and categorical data.	-Stochastic, which increases predictive accuracy -Can be utilised with a number of response types (binomial, gaussian, poisson) -Algorithm detects the best fit automatically -Model represents the influence of each predictor after accounting for the effects of other predictors -Robust to missing values and outliers	-Have strong fitting ability. -Able to tolerate noisy input. - When there is a complicated, non-linear pattern relationship between input and output, this method might be applied. -Have good prediction generally. -Incorporate the predictive power of different combinations of inputs.

Source:Adapted from (Liu and Lang, 2019; Naresh Kumar, 2019; Gupta and Kaushik, 2018; Ossianwo et al., 2017; Lidong Wang et al., 2017; Markham, 2015; Tappenden et al., 2004)

After the collected data has been prepared and it was split into two subsets, the model selection step was about choosing the algorithms that would be fed with the training dataset in both models: SPM and PPM. The model in each framework would process the data and generate a model able to find a target value in the new data. Supervised learning was used in this research to allow processing data with target values, and these values were mapped with historical data before the training began (as explained in detail in Chapter 3). In this research, the models are initially implemented on the training set list to forecast for the years (2014, 2015, 2016 and 2017). These forecasted values were compared with the test set list values of the year (2018) and the test accuracy of the models were computed. Once the test errors were computed, the entire data set list was inputted into the models to forecast for the following year.

As previously mentioned, the PPM was developed based on multiple regression models using different regression models and then the output predicted by each model was evaluated. These regression performance metrics were compared together in a predictive experiment in Azure ML Studio. The model below, shown in Figure 4.5, explains the data flow in the PPM, starting from the input parameters through to the output parameter. It reviewed the input variables to the model that were used by the four separate sub models. These sub models were trained by four different regression models, shown below in the Figure 4.5, so that the model would be able to predict the targeted value (EOQ).

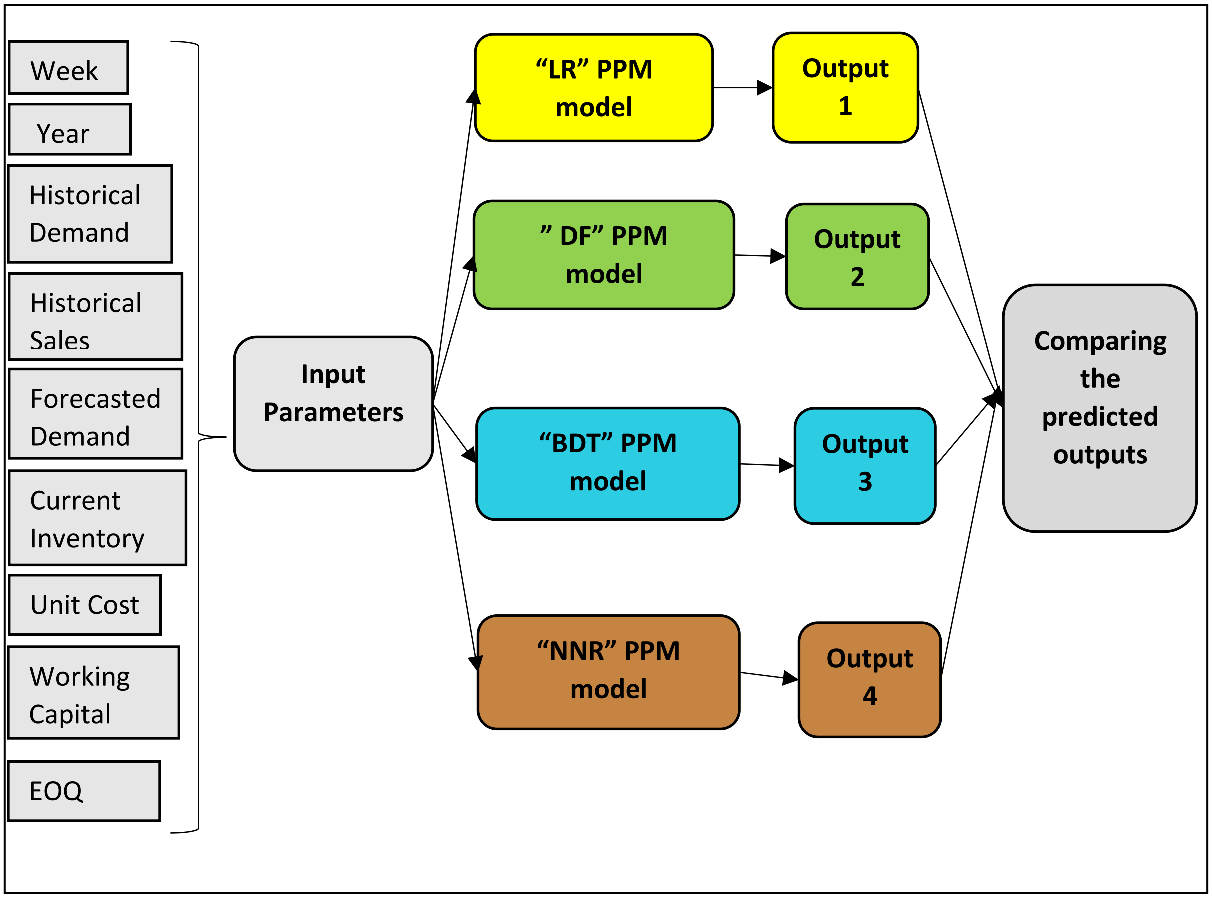


Figure 4. 6. Data flow diagram of the PPM

These models have been selected, as they were suitable for regression problems' implementation when estimating the value of a given output based on a set of inputs and target values. Each of the previous predictive sub model mentioned in Figure 4.6 forecasted the EOQ based on the training performed on the input dataset by each algorithm in the different models, (explained in detail in Section 4.4.3). The output of each network was evaluated through several regression performance metrics and other quality measures (explained earlier in this chapter). The performance metrics of the four models were compared against each other and then the results were illustrated showing which of the two models had the best and the most accurate forecast results.

The next data flow diagram, shown in Figure 4.7, explains how the SPM had been developed in detail. This model included four consecutive sub models linked in sequence, as the output of each sub model was added to one of the inputs in the following sub model. The first sub model used the “BDT Regression” algorithm to train the sub model, and the prediction of the first sub model was the weekly product sales, and this output was fed as one the inputs of the second sub model. The second sub model used the “BDT Regression” algorithm as well to train the sub model and the prediction of this sub model was the weekly product inventory levels and this output was fed as one of the inputs in the third sub model. The third sub model used the “BDT Regression” algorithm to train the sub model and its prediction was for the product weekly demand and this output which was fed as one of the inputs into the last and fourth model. The fourth sub model used the “NNR” algorithm to train the model based on the three predicted new inputs generated by the previous three sub models along with the already existing parameters in the dataset.

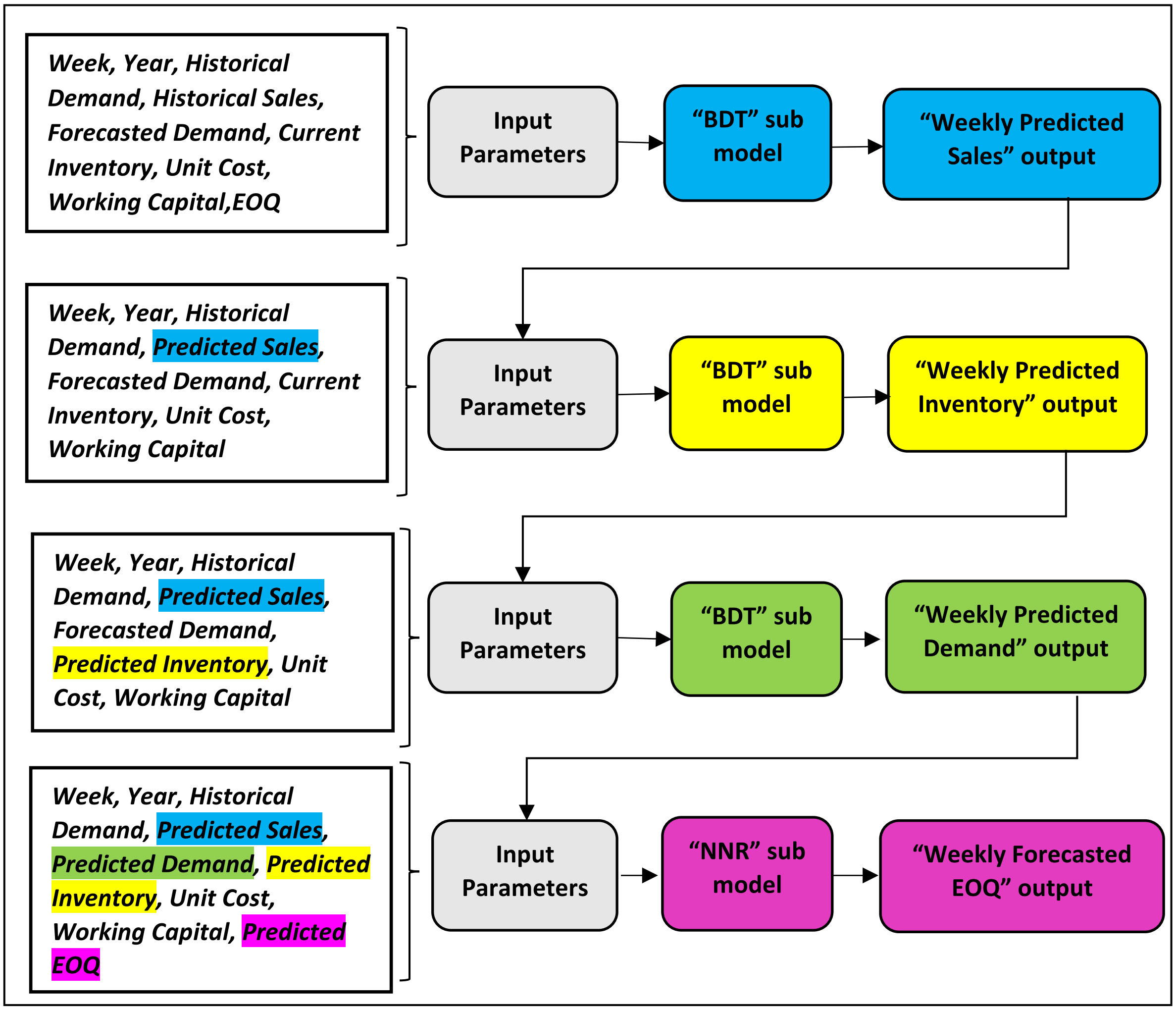


Figure 4. 7. Dataflow diagram of SPM

The three predictive sub models predicting the sales, inventory and demand have been trained by the "Train Model" module using the "BDT Regression" algorithm. The fourth sub model that forecasts the EOQ has been also trained by the "Train Model" module using the "NNR" algorithm. Each model was trained with 80% of the data provided. The "Score Model" module has been used for every predictive sub model to make the prediction on the test data set and that prediction/output named as Scored Labels, was used as one of the input parameters in the following neural network through the "Select Columns in Dataset" module. The remaining 20% of the data was scored by the "Score Model" module to see how well each sub model functions. The “Select Columns in Dataset” module was used at the beginning of the second, third and fourth sub model so that the output, highlighted in blue, predicted by each sub model can be implemented in the input of the following sub model. Based on the predictions generated from the test data set, the “Evaluate Model” module was applied only once at the end of the framework to compute the regression performance metrics for the whole model to be evaluated in the next chapter.

4.4.6 Model training

The second step in the modelling phase was the Model Training that provided the dataset which contained historical data and that data contained both the outcome (label) that was predicted, and related factors (variables). During the training process, the data was sorted by outcomes and the algorithm extracts patterns to train the model. To use the trained model in predicting new variables, it should be connected to the (Scoring the model) step with new input data. Scoring the model was a step included in the Model training phase that described the numeric value predictions that were generated based on the used regression algorithms implemented in the two developed predictive models.

As mentioned earlier in this chapter, different regression algorithms have been used to train the developed models. The PPM was built using LR, DF, BDT and NNR. To train this model, the tagged dataset and the regression algorithms were provided as inputs to the model. This enabled the trained model to predict the optimum EOQ. The “Train Model” module used in the predictive experiment was designed to provide the regression model with a trained dataset aimed at discovering patterns. The two inputs to this module were the four previously mentioned algorithms and the other one is the trained dataset. The trained model, shown in Figure 4.7, was the outcome that was used to create the predictive model used in predicting the EOQ of the FMCGs distributor. The following modules are the main modules included in building the predictive experiment developed in Azure ML studio for the PPM.

- **Training Dataset:** For the prediction of the EOQ, historical data over a span of five years were used. "EOQ" field from the "Weeks DS.csv" dataset was chosen as the training dataset.
- **Algorithms used:** Linear regression, DF, BDT and NNR were selected as the regression algorithms.
- **Train Model:** The model is trained with the training dataset and the selected algorithms.
- **Score Model:** This model is used to generate predictions using the trained model.
- **Evaluate Model:** A set of regression performance metrics are generated indicating the accuracy of the model.
- **Execute R Script:** It contains sample code that can be used as a starting point. To configure this module, a set of inputs and code were provided to be executed. It was used so that each corresponding network name can be added manually and the performance metrics.
- **Add Rows:** It is used to join two datasets together. The rows of the second dataset are added to the end of the first dataset, and so on, in concatenation.
- **Test Dataset:** A separate dataset was used in the initial phase to evaluate the forecast model's accuracy.

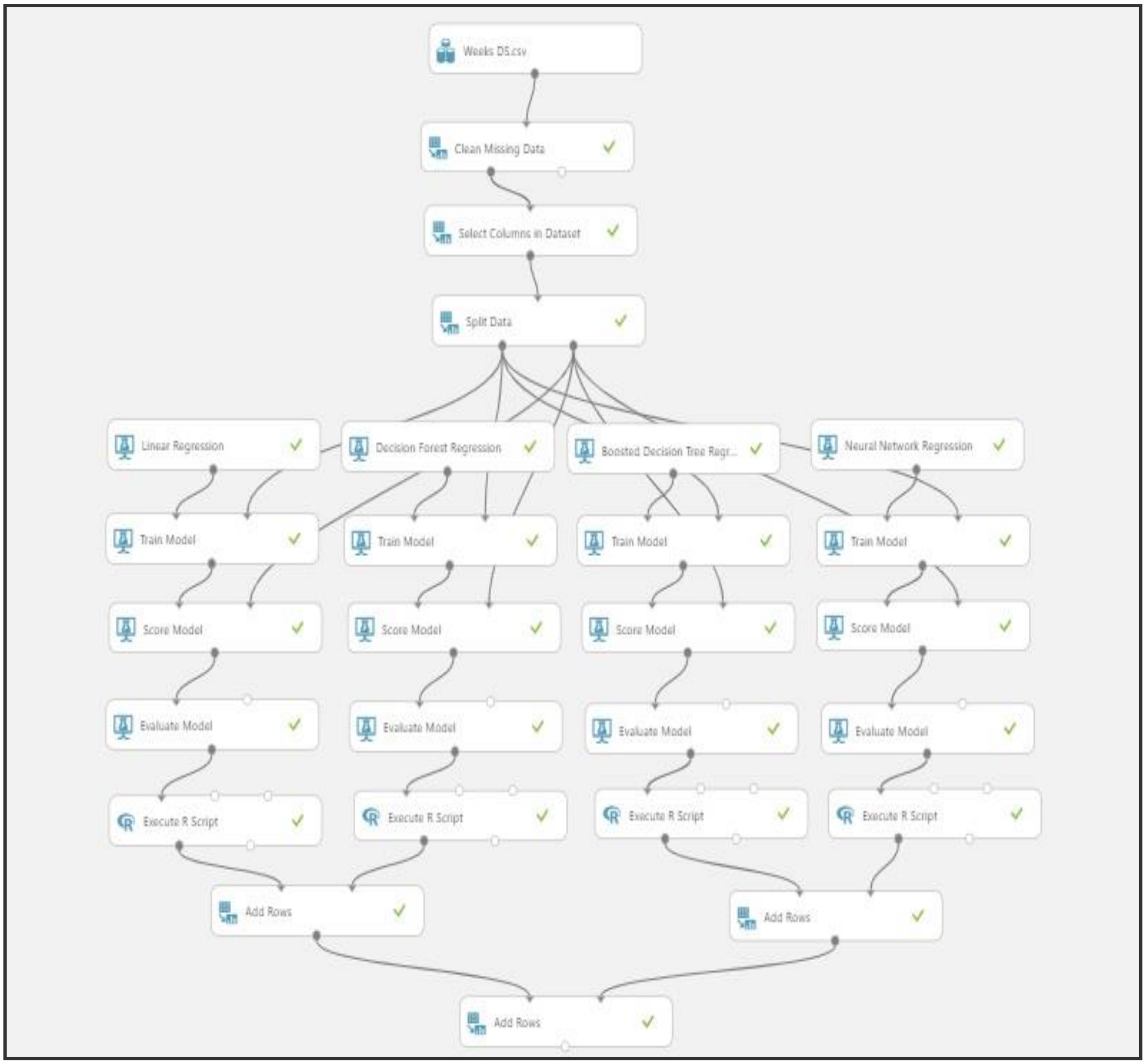


Figure 4. 8. PPM predictive experiment

The model is trained using the "Train Model" module, and then the "Score Model" module is used to generate predictions on the test data set. The "Evaluate Model" module was used to compute the regression performance metrics for the different models based on the prediction obtained from the test data set. Each predictive model in the system is now regarded as a fully trained regression model that was ready to score the new EOQ. Each network was trained with the 80% of the data provided. Next, 20% of the data was scored by the “Score Model” module to see how well each sub model functions.

And finally, the “Execute R Script” and the “Add Rows” modules are added so that all the regression performance metrics can be combined and compared together. These modules were added because the “Evaluate model” module produces a table with a single row only that contains various metrics, but in the “Execute R Script” module, the regression performance metrics are extracted, and the corresponding model name is added manually. All “Execute R Script” modules in this framework produced a table with a single row that contains model name and various metrics. The last step shown in the previous figure was adding the “Add Rows” modules to combine all regression performance metrics together generated by all the predictive models. The results of the baseline framework were obtained from the last “Add Rows” module shown in the previous figure, in the form of one integrated table from the four predictive models, where the first column labelled as the name of the machine learning algorithm used to train the network, and the remaining five columns are used to compute the regression performance metrics.

The SPM was built using BDT Regression and NNR. To train this model, the tagged dataset and the regression algorithms were provided as inputs to the model. This enabled the trained model to predict the optimum EOQ. The “Train Model” module used in the predictive experiment was designed to provide the regression model with a trained dataset aimed at discovering patterns. The two inputs to this module were the two previously mentioned algorithms and the other one is the trained dataset. The trained model, shown in Figure 4.9, was the outcome that was used to create the predictive model used in forecasting the EOQ of the FMCGs distributor.

The following modules are the main modules included in building the predictive experiment developed in Azure ML studio for the SPM.

- **Training Dataset:** For the prediction of the optimum quantity to order, historical data over a span of five years were used. “Sales”, “Inventory”, “Demand” and “EOQ” field from the “Weeks DS.csv” dataset was chosen as the training dataset.
- **Algorithms used:** BDT Regression and NN Regression were selected as the regression algorithms.
- **Train Model:** The model is trained with the training dataset and the selected algorithms.
- **Score Model:** This model is used to generate predictions using the trained model.
- **Evaluate Model:** A set of regression performance metrics are generated indicating the accuracy of the model.
- **Test Dataset:** A separate dataset was used in the initial phase to evaluate the forecast model's accuracy.

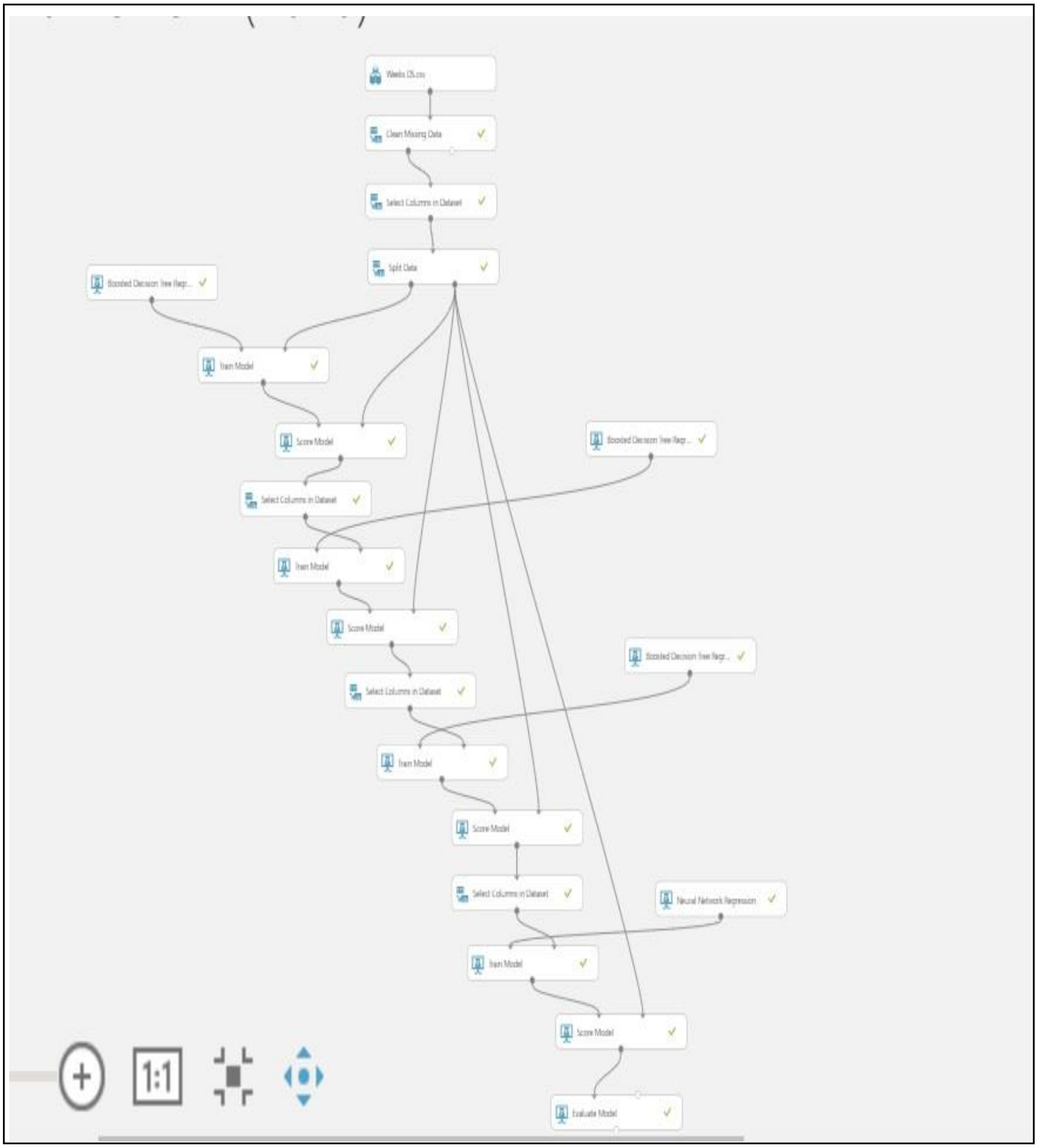
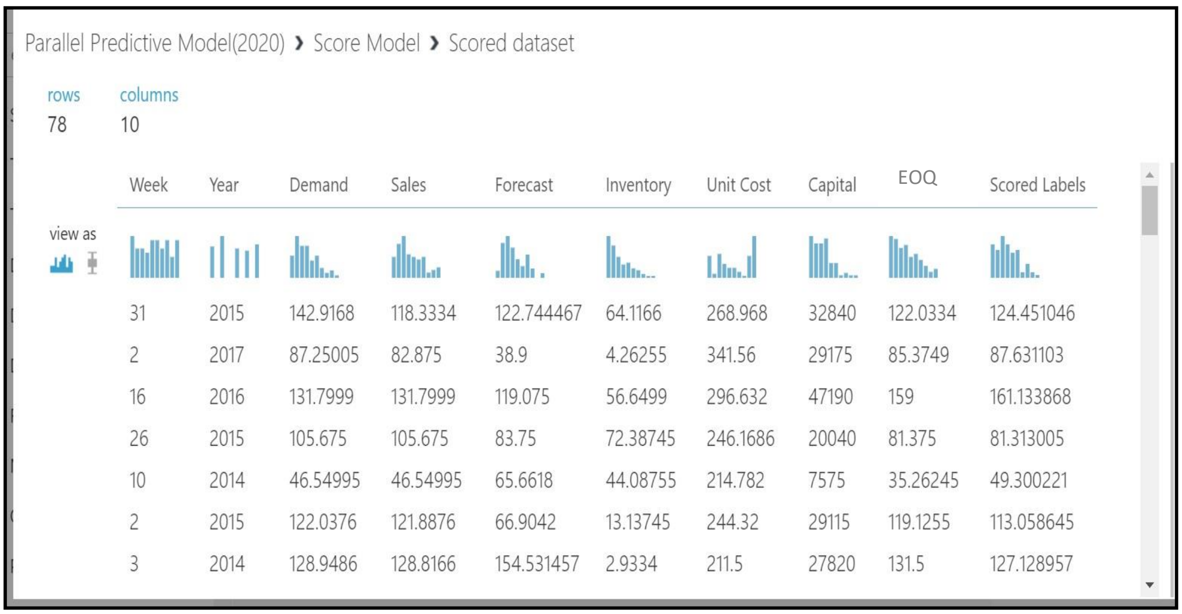


Figure 4. 9. SPM predictive experiment

Now the two trained models shown in Figure 4.8 and 4.9, are ready to be used as inputs to the “Score Model” module which was used to produce predictions of the trained models. The “Score Model” module had a trained dataset and trained models as inputs, and a set-aside dataset for model testing. This “Score Model” module generated predicted values and its output datasets will be evaluated in the next chapter. As shown in Figure 4.8, there were four scored datasets for the four separate sub models. These four datasets were evaluated and then the results were integrated together to be reviewed in one table. Figure 4.10 showed the scored datasets of the PPM and SPM.


Parallel Predictive Model(2020) › Score Model › Scored dataset

rows 78 columns 10

view as

Week	Year	Demand	Sales	Forecast	Inventory	Unit Cost	Capital	EOQ	Scored Labels
31	2015	142.9168	118.3334	122.744467	64.1166	268.968	32840	122.0334	124.451046
2	2017	87.25005	82.875	38.9	4.26255	341.56	29175	85.3749	87.631103
16	2016	131.7999	131.7999	119.075	56.6499	296.632	47190	159	161.133868
26	2015	105.675	105.675	83.75	72.38745	246.1686	20040	81.375	81.313005
10	2014	46.54995	46.54995	65.6618	44.08755	214.782	7575	35.26245	49.300221
2	2015	122.0376	121.8876	66.9042	13.13745	244.32	29115	119.1255	113.058645
3	2014	128.9486	128.8166	154.531457	2.9334	211.5	27820	131.5	127.128957

Figure 4. 10. A scored dataset from the PPM

Both diagrams showed their predicted output, EOQ, which was labelled as the “Scored Labels”. The scored datasets of both models, PPM, and SPM, would be used as inputs for the “Evaluate Model” module. This evaluation step will be outlined along with the deployment phase in the next chapter. In the previous figure, the targeted output was the predicted EOQ.

4.8 Chapter summary

This chapter covered the data preparation and the modelling phases for the models, SPM, and PPM, that were developed in Azure ML Studio. These two models were trained to forecast the EOQ of the FMCGs distributor. The models were trained on how to detect the patterns found in the dataset, and finally setting them as predictive models to detect and identify the targeted output; EOQ. The two predictive supervised regression models were implemented based on regression algorithms; LR, BDT, DF and NNR. The models were trained using the real dataset named "Weeks DS" from the distributor. This was done after subjecting the dataset to a preparation phase which involved data cleaning, feature engineering and data splitting. After that, the models were trained, and the data sets were scored to be ready for the evaluation and deployment phases described in Chapter five. The next chapter will analyse the results of running the two models' post-evaluation, and the regression performance metrics will be viewed to identify the best algorithm with the best performance so that it would be ready for validation and deployment.

Chapter Five

Model Validation and Deployment

5.1 Chapter overview

In the previous chapter, a detailed description of the developed supervised regression predictive model with its two scenarios was given. The next step is to evaluate both scenarios and choose the one with the better performance metrics to be deployed as a predictive experiment. The chapter starts with an introduction that defines the models' evaluation strategy with a detailed illustration of the model performance validation. The following section includes the robustness test performed on the developed model followed by a section that discusses the relative importance of the input features of the model. Then the following section presents the deployment strategy for the developed model and publishing the model as a web service on the cloud. Finally, the last section discussed how the developed model would be monitored to maintain its predictive performance for the long term.

5.2 Introduction

Three phases have already been accomplished in the previous chapters; the first phase was explained in Chapter Three and the second and third phases were explained in Chapter Four. The remaining three phases of the predictive ML model development methodology will be explained in this Chapter with their sub-processes shown in Figure 5.1. This chapter starts with the evaluation phase that was responsible of evaluating the ML predictive model through validating the performance of the model and determining its robustness. The following phase, deployment phase, explains how the evaluated model was deployed from the previous phase to the testing dataset and how its behaviour was evaluated in the real-world environment. Then the chapter concludes with the monitoring and maintenance phase that managed the

ML predictive model to assure its quality during its life cycle and to avoid the degradation of its performance over time.

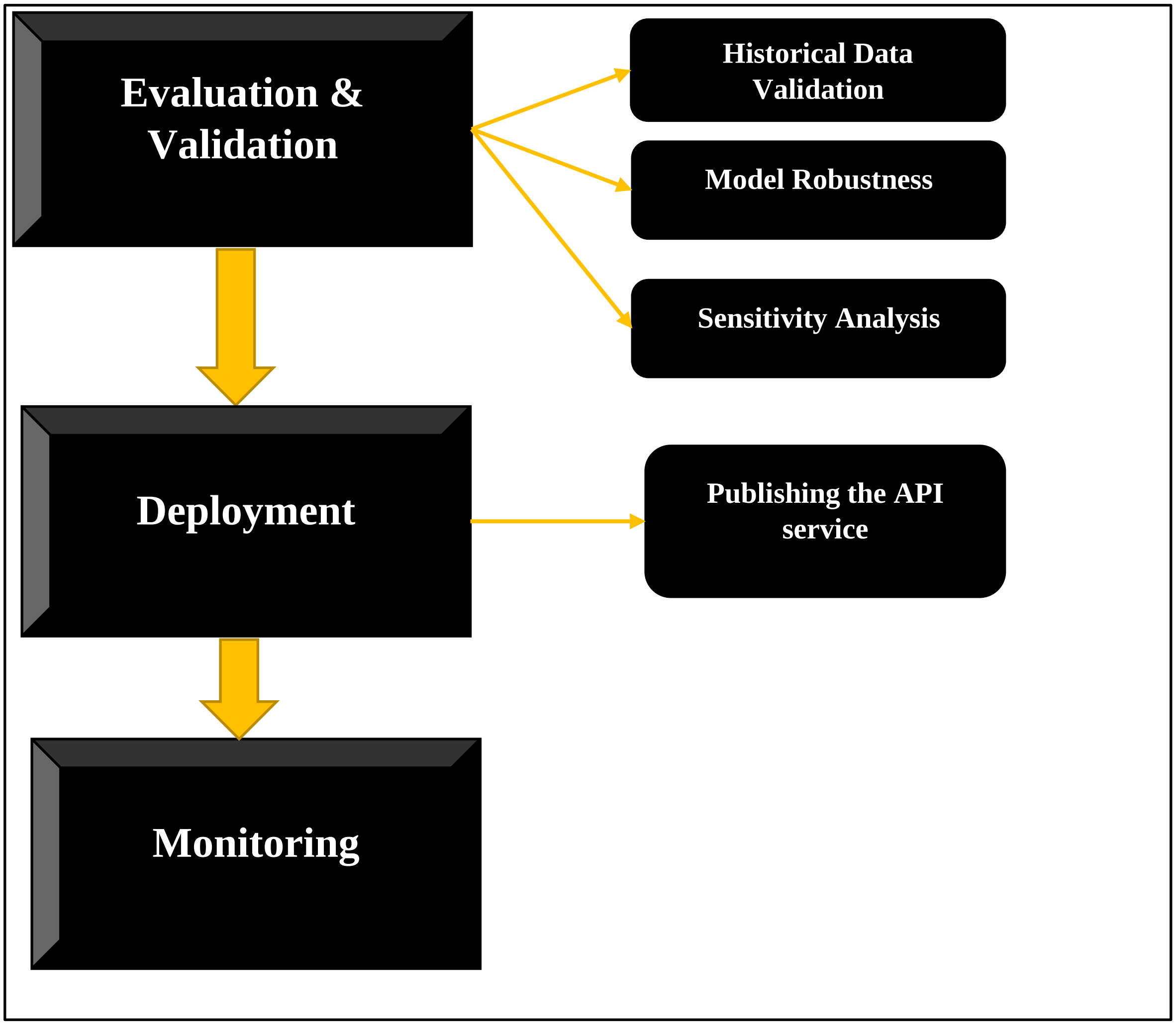


Figure 5. 1. Evaluation, deployment, and monitoring phases of the proposed model

The following sections illustrate the phases mentioned in Figure 5.1 and are explained in detail to give a full and clear explanation of the last three phases of the model development methodology used in this research.

5.3 Evaluation and validation

This phase evaluated the ML predictive model through standard regression performance metrics to measure the accuracy of the predictions, the number of errors and asses the model fit. This evaluation and validation phase consisted of two major tasks that covered the performance validation of the proposed model and determined the robustness of the model by monitoring its behaviour and generalization ability when it was exposed to different training and validating sets. There are various approaches for validating and verifying models, some of which are described below based on literature (Sargent, 2013). The next section defines the key techniques employed throughout this study and explains how they are applied to the research case study.

1. Historical data validation: where part of the historical data is utilised to construct the machine learning predictive model and another portion is used to verify whether the model behaves like the real system.

2. Multistage validation: There are three stages involved. First, the model must be developed in accordance with theory and observations. Second, the model must be validated against empirical data. Third, the outcomes of the model should be compared to those of a real system.

Sensitivity analysis is used to explain how changing the value of a model's input or parameter affects the output or outcome of the model. This method can be used to double-check both qualitative and quantitative results. The output of the model is greatly influenced by these sensitive factors. This followed to the scenario analysis stage when each suggested scenario's sensitivity analysis was examined. According to Law (2005), a simulation model is valid if the findings are as similar to the actual system as possible. Brookes et al. (2004) mentioned the principles of a sensitivity analysis as follows:

a) to allow the investigator to quantify the uncertainty in a model,
b) to test the model of interest using a secondary experimental design, and
c) to determine the overall sensitivity of the model of interest using the results of the secondary experimental design. The sensitivity analysis is justified by the fact that when a model is evaluated on the dataset from which it was derived, it always performs better.

The following section demonstrates how the ML prediction model constructed in this study was checked and validated. It outlines the most common strategies and explains how to apply them to the prediction model.

5.3.1 Historical data validation of the model

To validate the developed model, a run was conducted for a period of 12 months which was across the year 2018. A detailed explanation of the results of running the two scenarios of the predictive model for one long run will be reviewed in the coming two sections. The goal is to compare the model outputs to the data acquired from the example company to see how closely the model resembles the real system.

5.3.1.1 Performance validation

A danger arises during the validation of the performance by optimising the model using feedback signals from the test set. To avoid this, it's a good idea to have a separate test set separate from the training set, which is only utilised for a final review and never shipped to any partner for performance metrics measurement. To avoid biassing a model's performance, the test set should be built to encompass the whole input distribution and account for any data invariances. The previously stated performance metrics should then be assessed on that test set. When evaluating an ML model and studying its behaviour on incorrect inputs, Studer et al. (2021) addressed the need of ensuring the validity of the results. When testing, keep in mind that the non-linear nature of the data, which results in label noises, limits test accuracy from the top down, implying that 100 percent test accuracy is unlikely.

The accuracy of the trained models' performance was measured in the evaluation step. The "Evaluate Model" was utilised as an evaluation tool for the two ML prediction model scenarios in this study. This phase took the scored datasets from both situations as input. This model supplied the metrics scores that were used to compare the two models. The "Evaluate Model" module provided an estimate of the trained models' accuracy. The “Evaluate Model” module depends on the type of the model being evaluated whether it’s a classification, a clustering, or a regression model. The models being evaluated in this research have been trained by different supervised regression algorithms. The performance metrics generated from each evaluation scenario would be compared in the coming sections so that both would be assessed and the one with the better and more accurate performance metrics would be chosen as the proposed model and get prepared for the deployment phase. In the parallel model scenario, the “Evaluate Model” module was used four times in parallel because it was evaluating four separate regression algorithms. But in the sequential model scenario, the “Evaluate Model” module was used once at the last phase of the model because the algorithms used were predicting features in a sequential form until, they reach the prediction of the targeted value then perform the evaluation step on it.

Going through the literature about the performance regression metrics used by researchers, it was obvious that most of the researchers depended on R^2 and the RMSE as the performance metrics for their models' evaluation as mentioned before. MAPE, MSE, and R2 are the tools used by Kok et al. (2017). RMSE, MAE, and R2 are employed by Yacim and Boshoff (2018). RMSE, MAE, MAPE, and CC are used by Peterson and Flanagan (2009) and Zurada et al. (2011). Bogin and Shui (2018) assess the performance of Automated Valuation Models using RMSE and R2, whereas Bajari et al. (2015) compare approaches for predicting grocery store sales using RMSE. The Adjusted R2, RMSE, AIC, and BIC are the most relevant measures, according to Kassambara (2018). The performance metrics for evaluating regression models in Microsoft Azure ML studio, which was employed in this study, include MAE, RMSE, RAE, RSE, and R2. Tables 5.1 and 5.2 would list all of the previously specified measures, with the RMSE and R2 serving as the primary performance indicators for comparing the two situations. The performance of these metrics would then be demonstrated by using them to estimate the EOQ using parallel and sequential models.

The score values of the selected trained algorithms were represented by these performance indicators. Fitting the models with the trained data set and then applying the fitted models to the test data set were used to assess these. The fitted models' predictions are then compared to the actual values of the test data set's target label. The existing data was split into train and test sets according to the 80-20 rule to measure the accuracy of each of the models over a five-year period (2014-2018). Data from January 2014 to December 2017, accounting for 80% of the dataset, was used as the training set for the model, while data from January 2018 to December 2018, accounting for 20% of the dataset, was utilised as the validation set for assessing the model's prediction performance. The percentage inaccuracy was derived by comparing the actual value to the projected value. To construct a better model and reduce the danger of overfitting, the algorithm would split the training data set into a train and validation dataset while fitting the model. Furthermore, the computational performance of the model was assessed during both its fitting and prediction of the test set.

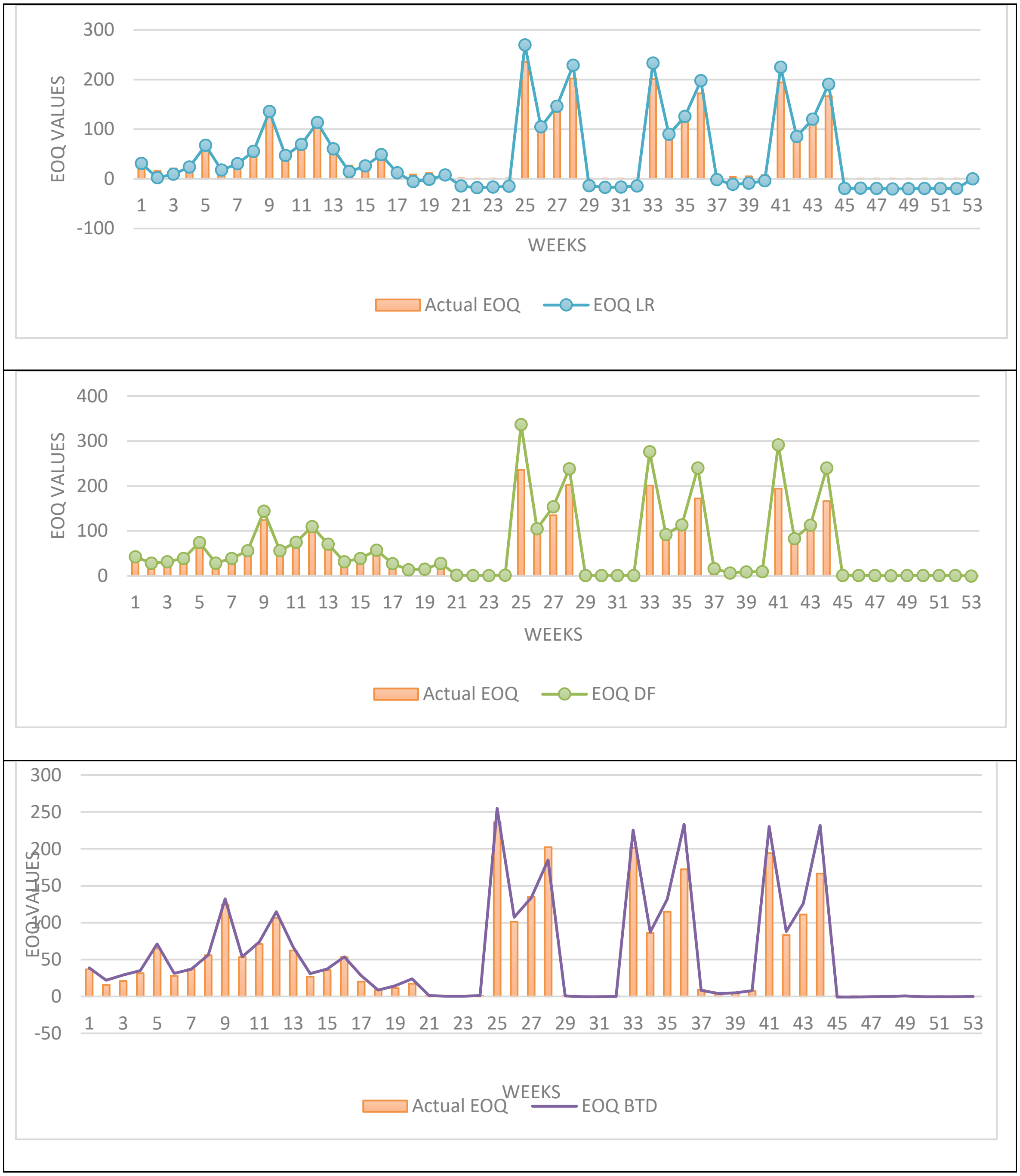
1. **Evaluating the parallel model scenario**

In this phase, each scenario was evaluated independently to assess the accuracy of the predictions generated by each predictive experiment. As aforementioned in Chapter Four, the parallel model was built in Azure ML Studio using four different algorithms: LR, DF regression, BDT and NNR. After the model was trained, the scored dataset with the predicted EOQ was ready to be evaluated. The evaluation results of the PPM are shown in Table 5.1 listing the regression performance metrics based on each of the four algorithms. The results showed that the DF algorithm had the lowest R^2 value (0.82158) and highest RMSE with value (27.211456) while the NNR algorithm scored the highest R^2 value (0.972723) and the lowest RMSE value (10.639746).

Table 5. 1. Performance metrics evaluation of the PPM

Algorithm	Quality Measures				
	MAE	RMSE	RAE	RSE	R^2
Decision Forest	12.253354	27.211456	0.235726	0.17842	0.82158
Linear Regression	13.658502	15.731748	0.262758	0.059634	0.940366
Boosted Decision Tree Regression	6.811415	14.920812	0.131036	0.053644	0.946356
Neural Network Regression	9.485885	10.639746	0.182487	0.027277	0.972723

The LR and BDT performance metrics results were close to each other and related to the other algorithms with a small range of difference between the RMSE and R^2.


EOQ VALUES
WEEKS
Actual EOQ
EOQ LR
EOQ VALUES
WEEKS
Actual EOQ
EOQ DF
EOQ VALUES
WEEKS
Actual EOQ
EOQ BTD

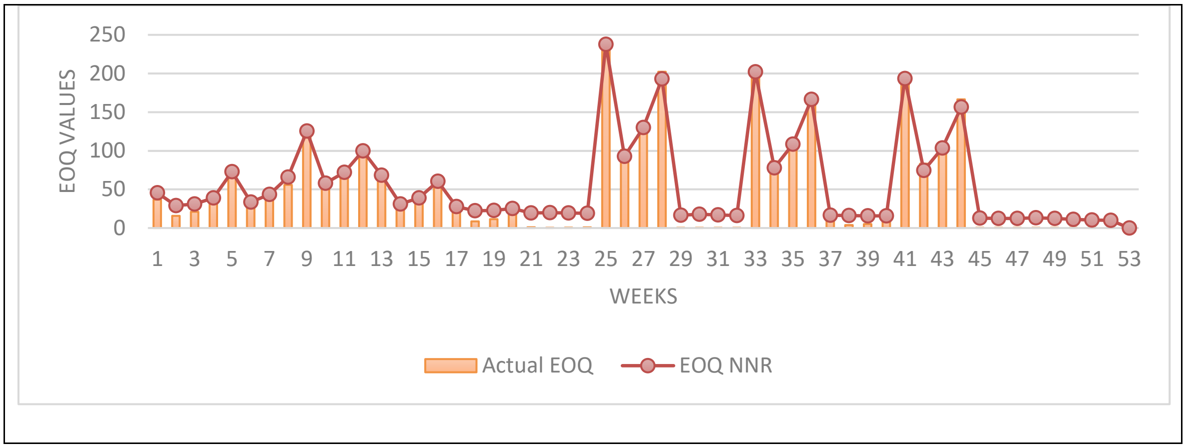
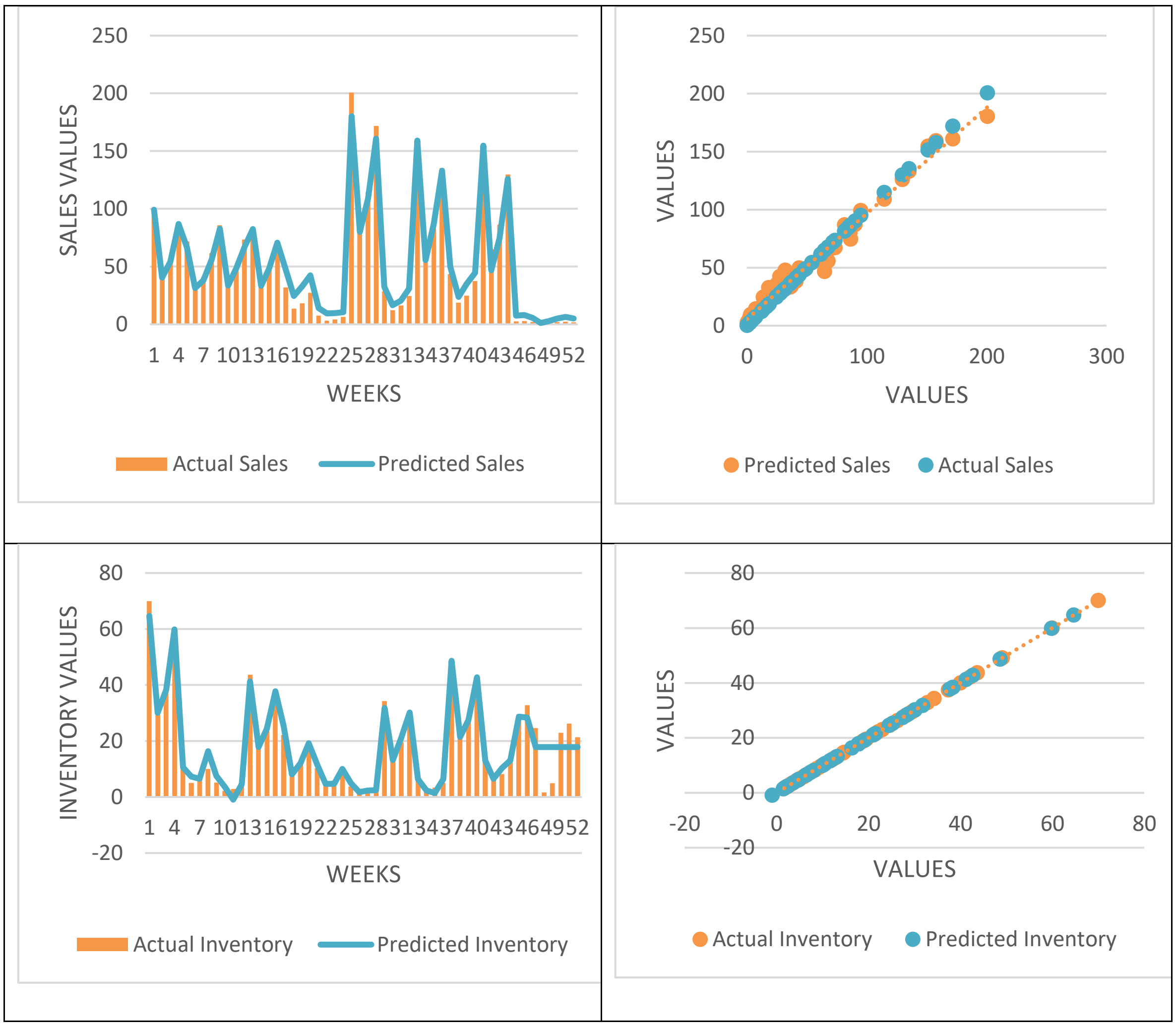


Figure 5. 2. Actual EOQ vs predicted EOQ with LR, DF, BDT and NN algorithm

Another way of evaluating the performance of the parallel model was to compare the actual EOQ provided in the original dataset with the EOQ predicted by the four regression algorithms separately, as shown in Figure 5.2. The graphs plotted the actual vs the predicted EOQ, and the results were consistent with those shown in Table 5.1. The DF algorithm showed the most noticeable difference between the actual and the predicted EOQ and this difference slightly decreased until it almost disappeared in the NN algorithm graph. The EOQ predicted by the NN algorithm showed remarkable consistency with the actual EOQ followed by the BDT algorithm. The next section will review the evaluation process of the other scenario followed by a comparison between both scenarios and then a decision would be made for choosing one of the scenarios over the others.

2. Evaluating the sequential model scenario

The sequential model was built using only two algorithms; BDT regression and NN regression (as mentioned before in Chapter Four). Choosing the BDT and NN algorithms specifically for building the sequential model also proved to be correct based on the performance metrics results shown in Table 5.1 that showed the higher EOQ prediction accuracy of these two algorithms other than the rest algorithms (LR and RF) and the baseline. This model predicts three main features before predicting the EOQ. It starts with predicting the sales, the inventory then the demand and these three phases were trained by the BDT algorithm. Then the last phase was trained by the NN algorithm for predicting the EOQ. Figure 5.3 focused on the actual values vs the predicted values of the sales, inventory, and demand respectively.



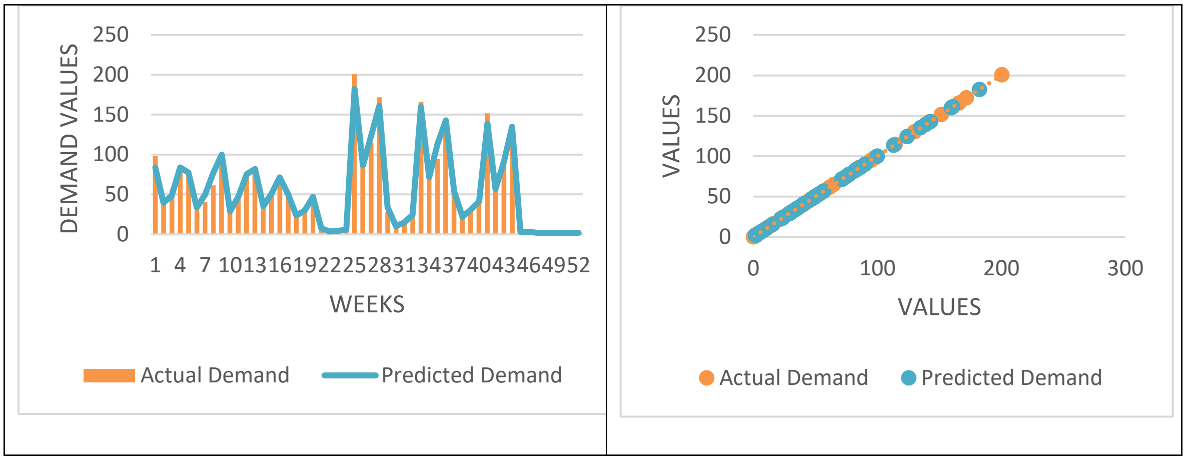


Figure 5. 3. Actual sales, inventory and demand vs predicted values scatter plots

It was obvious from the sequence of the graphs that the graph of the predicted sales was a bit far from the actual values. The following graph related to the inventory was a slightly better fit, but it showed a major deviation in the period starting from week 46 to week 52. Then the last graph showed a better consistency between the actual demand vs the predicted demand. The main reason behind predicting these features before the target feature, EOQ was to give this model more credibility and generalization ability when it is trained on different datasets. Some datasets might not include all the features necessary to predict the EOQ. Others might contain some null or false inputs in these features records. That is why this model predicts the sales, inventory, and demand to avoid any of the previous obstacles that might prevent it from predicting the EOQ. For assessing the quality and the accuracy of both models, the parallel and the sequential, a comparative analysis between the performance metrics of both models is shown in Table 5.2. As mentioned before in Table 5.1, the NN algorithm had the best predictive performance and least errors among the rest of the algorithms with RMSE (10.639746) and R^2 (0.972723).

Table 5. 2. Comparing the PPM and the SPM performance evaluation metrics

Method used		Quality Measures				
		MAE	RMSE	RAE	RSE	R^2
PPM	LR	13.658502	15.731748	0.262758	0.059634	0.940366
	DF	12.253354	27.211456	0.235726	0.17842	0.82158
	BDT	6.811415	14.920812	0.131036	0.053644	0.946356
	NN	9.485885	10.639746	0.182487	0.027277	0.972723
SPM		0.887657	1.134558	0.017076	0.00031	0.99969

The evaluation of the predictive models was governed by the RMSE and the R^2 value. The model with a lower value of RMSE and an R^2 value closer to 1 was considered preferable. Going through the results produced from both models, the SPM is showing the highest R^2 and the lowest RMSE unlike the PPM that has very high values of RMSE but moderate values of R^2. It has been observed that the SPM is performing better than the PPM with RMSE (1.134558) and R^2 (0.99969) while predicting the targeted output (EOQ). Conversely, the PPM generated the biggest error with RMSE (27.211456) from the DF algorithm and R^2 (0.82158). The difference between the errors is large which led this research to conclude that SPM was a better and more optimized multi-step predictive model than the parallel model. The sequential model would best fit the research aim of predicting more accurate EOQ of the FMCGs distributors. Afterwards, this sequential model would be presented as the research proposed model that would be tested and validated ready for the deployment phase. This is outlined in the following sections.

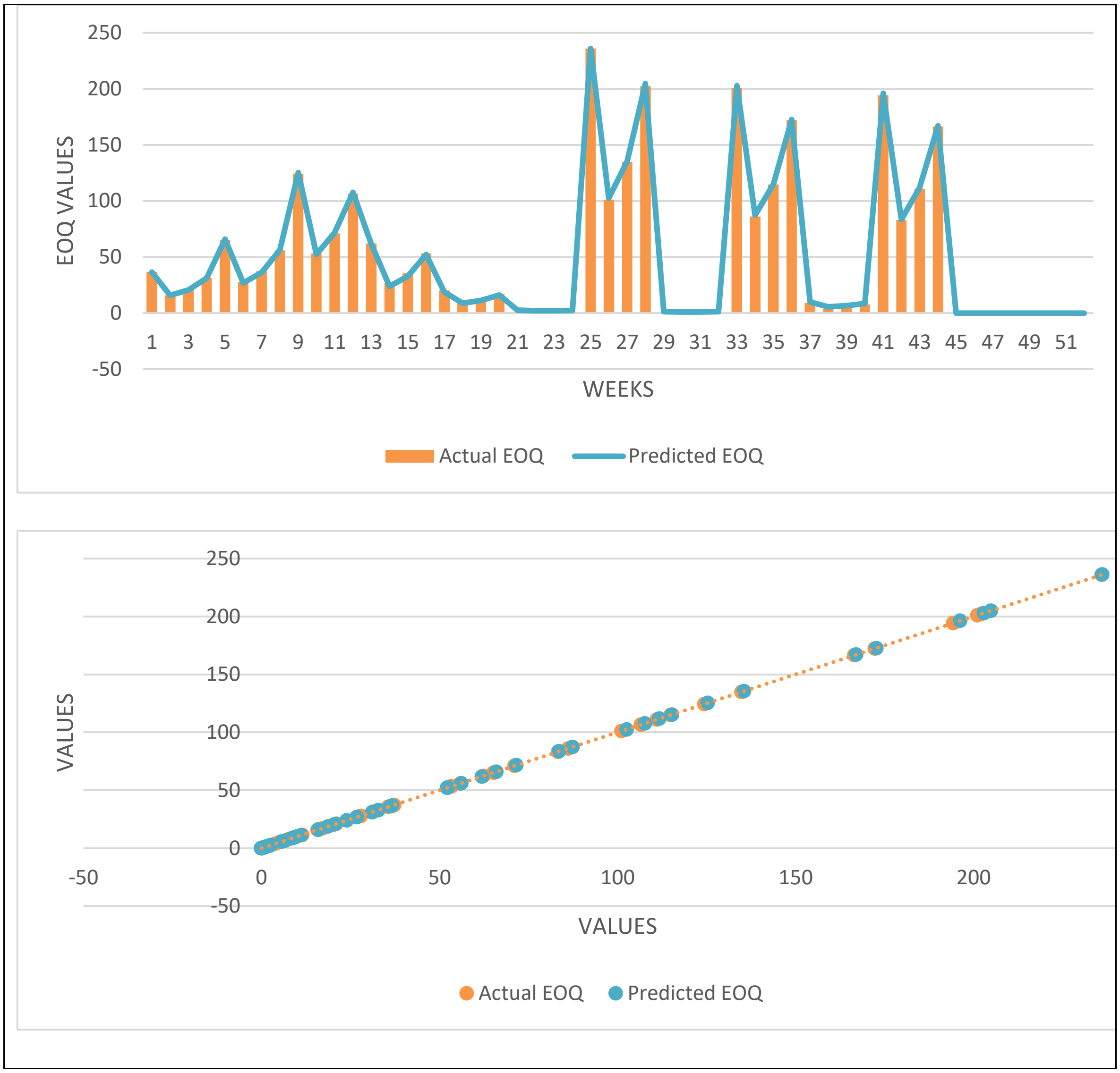


Figure 5. 4. Actual EOQ values vs EOQ predicted values with SPM

Figure 5.4 showed the comparison between the EOQ values predicted by the SPM and the actual values for the EOQ. It was clear that the SPM can predict values which are closer to the actual values for the output parameter than the values generated by the PPM. The results conclude than the SPM can be efficiently used to predict the EOQ of the distributors in a non-linear environment and with more accurate performance.

This section showed how the different structure of both scenarios have affected the performance of the model and the prediction accuracy. The PPM showed that the performance of the algorithms in a parallel way had a slight improvement on the performance of the results unlike developing the model in multi-step predictive way. Therefore, the sequential architecture was selected as the optimum proposed model suitable for fulfilling the research aim. The proposed model was tested on the data for the year 2018 due to the small size of the dataset available for that year. The NN algorithm would work better than the rest of the regression algorithms tested according to the previous figures and quantifiable results. The EOQ values predicted by the SPM captured in Figure 5.4 showed fewer deviations from the actual EOQ values at some weeks than the deviations generated by the PPM. This improvement was achieved because the predicted features (sales, inventory, and demand) were more accurate and more optimized after being predicted one after the other in the sequential model. On the other side, those features have been used as inputs to the parallel model in a raw form without any optimization process performed on them. That is why some graphs in the parallel model showed a larger deviation in the results than the actual EOQ. As shown in Table 5.2, most of the performance measures resulting from the SPM are very close to the real (baseline) EOQ which gave an insight that the developed model is reasonable, representative, and can be reliable for further investigation.

5.3.1.2 Proposed model forecasting accuracy

The weekly data of the distributor, between the years 2014-2017 was used to train the proposed model, and then the EOQ pattern prediction was made for 12 months across the year of 2018. In our case, the data from year 2014 was considered as the base year data to calculate next year data for year 2015, but that data was available and at the same time it could not be considered as a forecasting data, and it would only be considered as target data.

The same scenario would go with the rest of the years up to the data for year 2017 would be used as a base data to forecast data of year 2018 which was used as the test data of the proposed model. To calculate the forecasting error and the percentage of the forecasting error as shown in Figure 5.5, the following equations was used.

Forecasting Error = Actual EOQ – Predicted EOQ

Percentage of Forecasting Error = (Forecasting error/ Actual EOQ) * 100

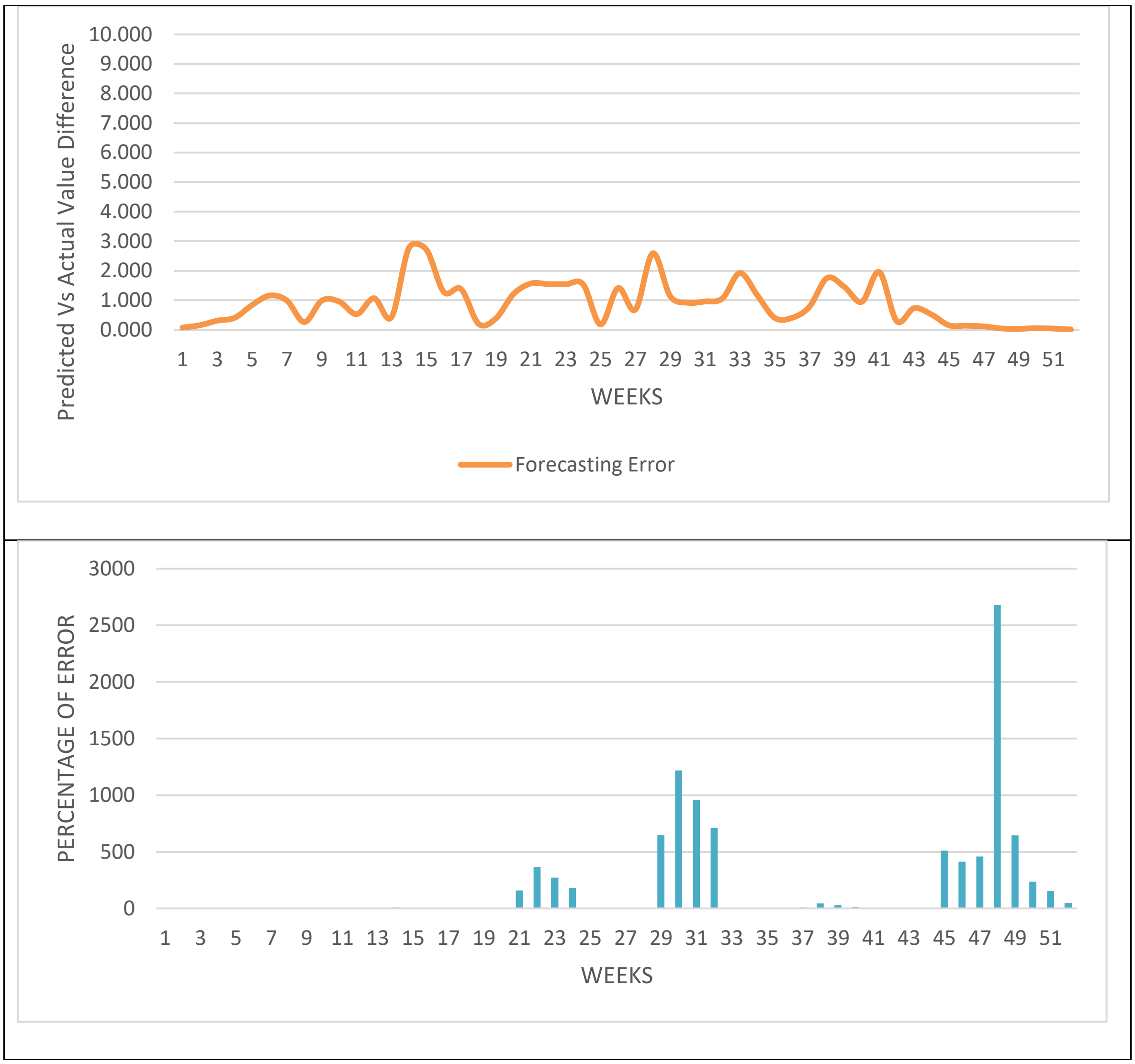


Figure 5. 5. Proposed model forecasting error vs forecasting error percentage

The previous figure reveals that the percentage error throughout the 52 weeks of the year 2018 was high during three main phases: from week 21-24, week 29-32 and week 45-51. Going back to the detailed data in the main dataset for year 2018, it was found that during these weeks, the working capital feature was very low and insufficient to purchase any orders to fulfil the EOQ. This huge gap between the available working capital during these weeks made it hard for the distributors to issue any orders to purchase the needed amount resulting in the large forecasting error percentage plotted in Figure 5.5.

5.3.2 Validation

Data validation is a technique for ensuring that a model will behave similarly under different testing settings. The investigator's primary task is to determine the model's fitness for the data (Salciccioli et al., 2016). The basic goal of data validation is to assess and monitor data quality throughout the ML life cycle (Vadavalasa, 2021). The validation has been carried out in this research by first developing the model in accordance with the collected data then it was validated against the company's empirical statistics.

5.3.2.1 Model robustness

The basic goal of machine learning is to build a computational model that can generalise well. During the training process, a model is fitted to the input data samples. The model's capacity to predict data that was not seen during the training phase is then tested, which is known as generalisation (Ma, 2019). As illustrated in Figure 5.6, poor prediction outcomes in test data can be characterised as underfitting or overfitting. When the trained model fails to detect the underlying trend in the data, this is known as underfitting. This could be due to a too basic model or a lack of often utilised features. Overfitting, on the other hand, occurs when a model is trained too effectively on training data and so does not apply to fresh data.

A model's capacity to generalise is harmed when it learns too much of the noise and random fluctuations in the training data. The most common causes of overfitting include a too sophisticated model, too much noisy data, or insufficient training data.

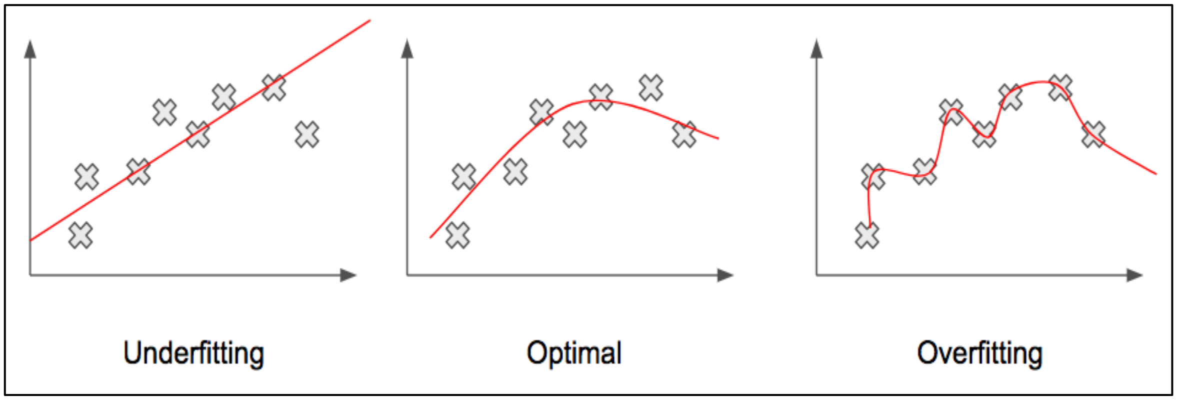


Figure 5. 6. Underfitting and overfitting (Source: Tanwar, 2018)

Ma (2019) highlighted that the robustness of an ML model may be verified using k-fold CV, where the algorithm is repeatedly verifying by holding disconnected subjects of the data out of the training data as validation data. The cross-validation mean performance and variance can be examined to see if the model can generalise to different data sets. Furthermore, whether introducing various types of noise to the data, modifying the hyper-parameters that indirectly characterise the model, or giving the model incorrect inputs, resilience should be tested. K-fold cross-validation is a well-known and often used ML method evaluation (Tryman, 2019). Moskalev (2019) described cross validation as a process that divides the dataset into numerous equal-sized portions, known as folds, as shown in Figure 5.7, and then picks one-fold as a validation/test set while merging all other folds into one training set. This method is carried out once for each of the folds. The final accuracy measure is determined as an average over all folds once all folds have been used as the test set. The validation set is used to evaluate the model's performance, whereas the training set is used to fit the model.

This validation set evaluation is used to determine how well the model performs on unknown data.

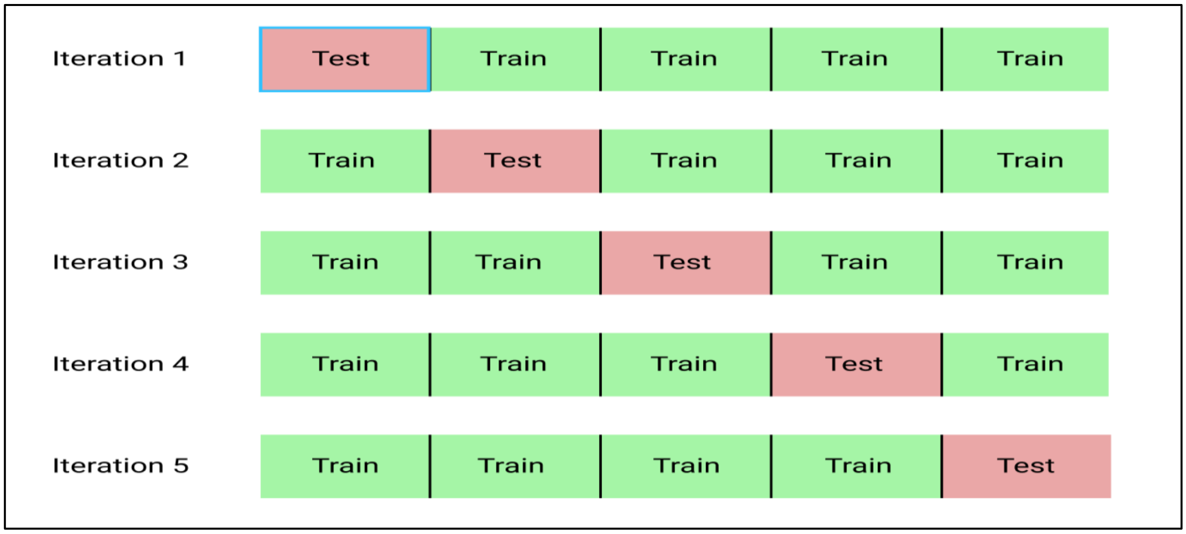


Figure 5. 7.K-fold cross validation iterations (Source: Shaikh, 2018)

Cross-validation is a common ML approach for assessing the variability of a dataset as well as the reliability of any model trained on it. The 10-fold cross-validation approach is the most widely used cross-validation strategy, with good results in practise (Kohavi 1995; Hu et al. 1999) and theoretical support (Bengio and Grandvalet, 2004). 10-fold cross validation gives better results in the parameter search by making better use of the training data because a prediction is made once for each instance, as opposed to only the test instances in expanding window cross validation (Tryman, 2019). Moreover, Emmert-Streib and Dehmer (2019) highlighted the main advantage of the k-fold CV as it provides a direct estimate of the prediction error, and every data point is used for both training and testing.

This research applied the 10-fold cross validation to test the robustness of the proposed model. The “Cross-Validate Model” module, as shown in Figure 5.8, takes a labelled dataset as input, together with the untrained NNR algorithm to train the proposed model with. It divides the training data into many folds at random and then returns a set of accuracy statistics for each fold. The data in fold 1 is set aside for validation, while the remaining folds are used to train a model. Multiple accuracy statistics are considered during model testing for each fold. After all folds have been built and evaluated, the "Cross-Validate Model" module generates a set of performance metrics and scored results for all of the data.

Figure 5. 8. Cross validation for the proposed predictive model

The two most prevalent strategies for minimising variance and preventing overfitting are repeated cross validation and 10-fold cross validation (Ghanbari, 2019). The quality of the data set can be analysed and if the model is subject to variations in the data by comparing the accuracy of the statistics for all folds. The "Cross-Validate Model" module also offers anticipated results and probabilities for the dataset, allowing you to examine the accuracy of the predictions. On the pre-processed dataset, the proposed model was cross validated using the NNR technique. The “Cross-Validate Model” module is computationally more intensive than the modules (Split Data, Train Model, Score Model and Evaluate Model) and can replace them when developing a model. One main advantage of the “Cross-Validate Model” module is that it minimizes the risk of the model overfitting, in addition to scoring the entire dataset instead of scoring only the remaining percentage of the test data (Azure ML, 2019).

Table 5. 3. Performance metrics of the proposed model vs the cross validated model

	Proposed Model	Cross Validated Model metrics for each fold									
		0	1	2	3	4	5	6	7	8	9
MAE	0.8876	0.7425	0.8529	0.7135	0.6800	0.7708	1.3042	0.8357	0.9638	4.3341	1.0066
RMSE	1.1345	1.0063	1.0188	0.9196	0.8984	0.9332	1.5795	1.0479	1.1549	15.796	1.4618
RAE	0.0170	0.0220	0.0177	0.0119	0.0125	0.0166	0.0271	0.0222	0.0168	0.0785	0.0240
RSE	0.0003	0.0004	0.0002	0.0001	0.0001	0.0002	0.0006	0.0005	0.0002	0.0347	0.0006
R^2	0.9996	0.9995	0.9997	0.9998	0.9998	0.9997	0.9993	0.9994	0.9997	0.9652	0.9993

A comparison of performance measures between the proposed model and the cross validated model can be seen in Table 5.3. This table provides the result of the k-fold cross validation of the proposed model that reviewed the 10 folds that were created and evaluated. Nine of these ten-fold were used, and only one-fold was set aside to be used for validation while the other nine folds would be used. The “Cross-Validate Model” module would randomly select these samples out of the existing dataset and that is how it improved the ability to avoid overfitting of the model.

Any supervised machine learning method aims for minimal bias and low variance in order to obtain strong predictive performance. Raschka (2018) defined prediction model behaviour by claiming that if the model is too simplistic and has few parameters, it would have a large bias and low variance. On the other hand, if the model contains a large number of parameters, the variance and bias will be considerable. Understanding bias and variance is therefore essential for comprehending the behaviour of prediction models. It could be concluded that there is a consistent performance and close accuracy measures results between the proposed model and the cross-validated model, as shown in Table 5.3. This means that the proposed model proved that it has low variance and high bias due to the small size of the dataset used for developing the model. This behaviour might have changed if the proposed model has been provided with a larger dataset. The next section lists the input features of the proposed model with their importance scores and that would be the last section of the evaluation phase.

5.3.3 Sensitivity analysis

Users of mathematical and simulation models can use sensitivity analysis to understand how the model output is dependent on the model input and to study how essential each model input is in deciding the outcome (Looss and Saltelli, 2015). To put it another way, sensitivity analysis determines how "sensitive" the model is to changes in the parameters and data it is based on. The results of sensitivity analysis can have significant ramifications at many phases of the modelling process, including identifying model mistakes, directing model parameter calibration, and studying the relationship between the model's inputs and outputs more widely (Salciccioli et al., 2016). When making decisions, sensitivity analysis can also be utilised to provide insight into the robustness of model results. Sensitivity analysis is a validation technique that shows the influence of changing the value of a model's input or parameter on the model's output or outcome (El mesmary, 2015). The sensitivity analysis in this study will be detailed in the following sections through the feature importance and scenario analysis techniques done on all of the model's input variables.

5.3.3.1 Feature importance

Feature selection is the process of selecting the most essential features from a dataset. In many circumstances, feature selection can improve a learning model's performance (Shroff and Maheta, 2015). This section explains how the proposed model's "Permutation Feature Relevance" module was used to score the importance of each input feature. This module assists in choosing the optimal characteristics to utilise in the model by changing the values of each feature at random, one column at a time, before evaluating the model. This module measures how much each feature influences the model's predictions. The input factors examined in the proposed model have an impact on EOQ prediction accuracy as well as distributor ordering decisions. The impact of the inputs on the EOQ is unpredictable; it might not be what you expect. Table 5.4 shows the relative importance of these choice factors as determined by the "Permutation Feature Importance" module in Azure ML studio. The relative significance values depict each input's contribution to the model; physical consequences may or may not be obvious. The relative relevance of input values is a measure of the importance of each input in the predictive model. Higher values are linked to more significant variables (inputs). An input variable with a greater relative relevance value is simply more important than the rest.

All conserved factors influence the output, which is the distributor's EOQ, as shown in Table 5.4. It is a supervised learning method because both the input and output values are supplied to train the network. The "Permutation Feature Importance" module is added to the SPM predictive experiments and the model was run again to get the new scored dataset with new values for each feature. The scores produced by the model represented the change in a trained model's performance after permutation. Important features are usually more sensitive and that is why they result in higher scores.

Table 5. 4. Relative importance of inputs

	Score of input features						
Prediction Phases	Week	Year	Demand	Inventory	Forecast	Unit Cost	Capital
Sales	-0.00046	0	1.5587	-0.0013	-0.00145	0	0.02627
Inventory	0.09283	0	1.0501	Predicted	0.34082	0.0574	3.13945
Demand	0.19619	0	Predicted	Predicted	0.27226	0.0795	0.9168
EOQ	0.000317	0	Predicted	Predicted	0.00002	0.0011	2.0148

The previous table showed different scores of the features throughout the multi-prediction phases of the proposed model. As explained before, the sales, inventory and demand features were predicted simultaneously before the prediction of the EOQ. This explained the different scores of the same features during each phase. The "Year" feature has no influence on the EOQ during the four phases. During the sales prediction phase, the "demand" feature was the one with the highest importance. During the inventory prediction phase, the working capital and historical demand recorded high scores while the unit cost was the least important feature. During the demand prediction phase, the working capital showed highest score while the unit cost continued to be the least important feature. During the final and most critical phase, the EOQ prediction phase, it has proven that the working capital still showed the highest score which made it the most influencing feature among the rest of the features on the EOQ prediction. These findings assured what was mentioned before in Section 5.1.1.3. When the model was tested, three major points through the year were found to have a high percentage of error because during these weeks, the working capital was very low at the time. That was compatible now with the findings in Table 5.5, that confirmed how the important and influencing the working capital feature is on the predicted EOQ.

5.3.3.2 Scenario analysis

Scenario analysis approaches are known for combining quantitative and qualitative data to create different scenarios or alternative future pictures (Nguyen & Dunn, 2009). The influence of each suggested scenario on the entire process is measured and reported using scenario analysis. The proposed model serves as a foundation for creating numerous scenarios to test and assess the influence of various forecasting uncertainties and input combinations on EOQ prediction and overall forecasting performance. These scenarios are primarily intended to suggest improvements and viable solutions for improving the example company's overall performance. Six scenarios have been suggested and tested on different working capital ranges starting from 1 to 100,000 Egyptian pounds. Each scenario had six testing points (six different weeks) with different input parameters to monitor the performance of the developed model in each case and how the EOQ prediction is affected in each scenario as follows:

- Scenario A: The impact of inputting a capital range of 1-1000 (as input parameter), on the EOQ (an output of the model).
- Scenario B: The impact of inputting a capital range of 1000-10,000 (as input parameter), on the EOQ (an output of the model).
- Scenario C: The impact of inputting a capital range of 10,000-25,000 (as input parameter), on the EOQ (an output of the model).
- Scenario D: The impact of inputting a capital range of 25,000- 50,000 (as input parameter), on the EOQ (an output of the model).
- Scenario E: The impact of inputting a capital range of 50,000-80,000 (as input parameter), on the EOQ (an output of the model).
- Scenario F: The impact of inputting a capital range of 80,000-100,000 (as input parameter), on the EOQ (an output of the model).

The six testing points in each scenario have been chosen randomly to cover several weeks in different quarters of the year. Each scenario had a specific range of the working capital that has two specific points that were tested on the chosen weeks as shown below in Table 5.5, 5.6, 5.7, 5.8, 5.9 and 5.10 that showed the details of the six scenarios with their testing points. The testing points are repeated in the same order in each scenario as follows along with the other model inputs (Forecast, Unit cost, Net in):

1. **Week 5:** Sales, demand and inventory are all requested to be inputs.
2. **Week 19:** Demand and inventory are requested to be inputs with no sales
3. **Week 25:** Demand is requested to be an input with no Sales and no inventory.
4. **Week 38:** Inventory is requested to be an input with no Sales and no Demand.
5. **Week 44:** Sales is requested to be an input with no Demand and no Inventory.

6. **Week 52:** No Sales or Demand or Inventory are requested as inputs to the model.

The columns highlighted in yellow represent the input parameters of the model and the green columns represented the model outputs. The records filled in Tables 5.5,5.6,5.7,5.8,5.9 and 5.10, represent a sample taken from the original dataset that have similar capital ranges as those chosen for the testing points in each scenario.

Table 5. 5. Scenario A results

W/Capital	Sales	Predicted Sales	Demand	Predicted Demand	Inventory	Predicted Inventory	Actual EOQ	Predicted EOQ	% of Error
5/20	2.07	12.19	2.10	26.11	24.64	8.91	0.02	1.69	8350%
19/20	0	7.27	16.35	25.29	19.58	13.86	0.10	1.23	1130%
25/20	0	4.41	12.26	13.97	0	18.65	0.08	1.07	1237.5%
38/20	0	17.43	0	30.16	29.38	15.99	0.15	0.65	333.33%
44/20	2.77	2.84	0	16.04	0.00	16.73	0.03	0.51	1600%
52/20	0.00	-0.35	0	-0.71	0.00	15.62	0.02	0.32	1500%
5/385	190.2	163.82	190.2	26.81	251.18	151.36	1.75	2.59	48%
19/385	0	5.98	8.05	24.87	10.24	7.97	0.10	2.13	2030%
25/385	0	4.41	4.60	13.55	0	12.91	0.57	1.96	243.85%
38/385	0	17.02	0	29.40	107.65	15.69	0.75	1.55	106.66%
44/385	51.85	2.84	0	15.28	0	16.43	1.52	1.40	7.89%
52/385	0	-0.35	0	-1.47	0	15.32	0.61	1.21	98.36%

Table 5. 6. Scenario B results

W/Capital	Sales	Predicted Sales	Demand	Predicted Demand	Inventory	Predicted Inventory	Actual EOQ	Predicted EOQ	% of Error
5/1820	13.7	11.63	22.3	28.93	9.49	16.38	8.60	6.26	27.21%
19/1820	0	35.82	52.56	35.39	49.12	31.92	8.95	5.80	35.19%
25/1820	0	18.43	30.03	22.95	0	20.26	5.12	5.62	9.76%
38/1820	0	16.31	0	31.43	42.10	9.42	7.67	5.21	32.07%
44/1820	0.68	3.80	0	14.35	0	9.75	4.07	5.05	24.07%
52/1820	0	0.61	0	6.65	0	7.35	8.59	4.84	43.65%
5/6060	40.71	44.88	42.06	30.7	29.99	26.58	15.75	18.04	14.53%
19/6060	0	60.92	65.92	45.45	44.22	39.70	23.80	17.64	25.88%
25/6060	0	31.04	52.03	29.35	0	24.12	20.07	17.43	13.15%
38/6060	0	21.66	0	38.39	18.98	7.32	17.20	17.15	0.29%
44/6060	77.37	8.83	0	31.79	0	8.58	24.12	16.93	29.8%
52/6060	0	5.65	0	22.58	0	6.59	24.00	16.69	30.45%

Table 5. 7 Scenario C results

W/Capital	Sales	Predicted Sales	Demand	Predicted Demand	Inventory	Predicted Inventory	Actual EOQ	Predicted EOQ	% of Error
5/12915	95.00	94.84	98.15	40.80	69.97	50.61	36.75	38.24	4.05%
19/12915	0	41.53	48.25	49.72	24.93	23.25	35.58	38.10	7.08%
25/12915	0	36.03	47.41	37.05	0	13.51	35.74	37.83	5.84%
38/12915	0	25.14	0	49.08	19.08	6.75	37.06	38.03	2.62%
44/12915	28.64	11.75	0	41.11	0	5.82	37.65	37.64	0.026%
52/12915	0	8.39	0	46.25	0	4.31	43.16	37.35	13.46%
5/22890	71.78	70.03	71.78	71.97	11.73	15.34	65.16	67.02	2.85%
19/22890	0	98.95	104.73	96.71	13.83	37.92	95.45	67.25	29.54%
25/22890	0	59.4	65.8	72.81	0	12.27	79.50	66.80	15.97%
38/22890	0	28.84	0	100.24	33.38	7.05	108.60	67.78	37.58%
44/22890	116.35	15.36	0	91.14	0	5.75	109.70	67.00	38.92%
52/22890	0	12.61	0	74.46	0	2.22	84.40	66.51	21.19%

Table 5. 8 Scenario D results

W/Capital	Sales	Predicted Sales	Demand	Predicted Demand	Inventory	Predicted Inventory	Actual EOQ	Predicted EOQ	% of Error
5/37500	162.52	167.13	162.72	115.35	17.52	44.43	158.83	109.88	30.81%
19/37500	0	106.72	116.33	113.83	5.68	31.93	113.83	110.05	3.32%
25/37500	0	105.62	115.80	100.38	0.00	17.74	109.23	109.18	0.045%
38/37500	0	28.22	0	93.39	4.37	5.20	106.58	110.54	3.71%
44/37500	70.33	19.10	0	85.98	0	5.24	108.38	109.08	0.64%
52/37500	0.00	21.70	0	104.91	0	4.05	166.25	108.02	35.02%
5/47380	225.43	198.88	225.66	143.70	5.13	33.81	230.13	138.51	39.81%
19/47380	0	141.45	154.96	165.61	116.38	55.91	189.70	138.48	27%
25/47380	0	133.80	131.80	135.39	0.00	18.16	159.00	137.40	13.58%
38/47380	0	49.67	0	120.34	168.90	5.54	189.88	138.74	26.93%
44/47380	114.60	39.83	0	92.75	0	2.63	134.83	137.00	1.609
52/47380	0	37.51	0	111.28	0	3.50	146.88	135.68	7.62%

Table 5. 9 Scenario E results

W/Capital	Sales	Predicted Sales	Demand	Predicted Demand	Inventory	Predicted Inventory	Actual EOQ	Predicted EOQ	% of Error
5/60570	243.78	199.10	244.08	179.32	26.27	5.49	238.25	173.77	27.06%
19/60570	0	196.79	174.50	168.17	8.53	18.09	170.75	173.44	1.57%
25/60570	0	195.12	166.51	178.57	0	18.09	175.50	172.21	1.87%
38/60570	0	55.63	0	159.79	4.81	-0.50	199.83	173.36	13.24%
44/60570	135.2	47.46	0	135.82	0	0.67	172.30	171.46	0.48%
52/60570	0	45.15	0	133.43	0	0.50	166.52	169.98	2.07%
5/71070	284.4	202.39	284.75	179.32	30.65	5.49	277.96	199.65	28.17%
19/71070	0	196.79	203.58	194.24	9.95	8.67	199.21	198.92	0.145%
25/71070	0	195.12	200.33	194.56	0	11.83	231.35	197.49	14.63%
38/71070	0	55.63	0	159.79	3.26	-0.50	202.25	198.33	1.93%
44/71070	157.73	47.46	0	151.82	0	-1.51	201.02	196.25	2.37%
52/71070	0	45.15	0	152.57	0	1.10	194.28	194.57	0.15%

Table 5. 10 Scenario F results

W/Capital	Sales	Predicted Sales	Demand	Predicted Demand	Inventory	Predicted Inventory	Actual EOQ	Predicted EOQ	% of Error
5/82915	200.55	198.88	200.55	179.32	3.82	5.49	235.96	228.18	3.29%
19/82915	0	189.24	233.71	194.24	42.18	8.67	269.91	226.79	15.97%
25/82915	0	148.82	132.73	194.56	0	-1.47	266.43	224.95	15.56%
38/82915	0	55.63	0	159.79	8.54	-0.50	198.64	225.36	13.45%
44/82915	153.67	47.46	0	151.82	0	-1.51	199.23	222.84	11.85%
52/82915	0	45.15	0	152.57	0	1.10	193.34	220.71	14.15%
5/95000	226.30	199.10	232.28	179.32	11.23	5.49	266.26	259.34	2.59%
19/95000	0	196.28	199.10	194.24	12.65	8.67	199.65	257.13	28.79%
25/95000	0	195.12	200.55	194.56	0.00	11.83	235.96	254.69	7.93%
38/95000	0	55.63	0	159.79	9.67	-0.50	198.12	254.69	28.55%
44/95000	150.56	47.46	0	151.82	0	0.67	188.37	251.43	33.47%
52/95000	0	45.15	0	152.57	0	1.10	185.32	248.56	34.12%

The last column in each table showed the "Predicted EOQ" with differed values for each testing point and that was due to the different inputs to the model in each of the testing points. The results viewed in the previous table confirmed the direct effect the working capital have on the target output (EOQ) of the model. Scenario A and B were tested using low capital ranges and that explains the low values of the EOQ predicted in these scenarios. The rest of the scenarios had higher capital ranges which have a proportional relationship with the higher values of the predicted EOQ. Another observation from the previous table, was the close values of the original EOQ and the targeted EOQ which confirmed the stability of predictions and the accuracy of the developed model as well. The stability of the predictions was not affected when some of the inputs had null values as in week 19, 25, 38, 44 and 52. The values remained optimal during most of the testing scenarios but some distance from the original values in other areas, and this explains the high error percentage reported before in Section 5.3.1.2.

The developed model showed some overfitting areas in Figure 5.9, and that was due to the limited size of the dataset and the fact that the model was trained too well with the training data.

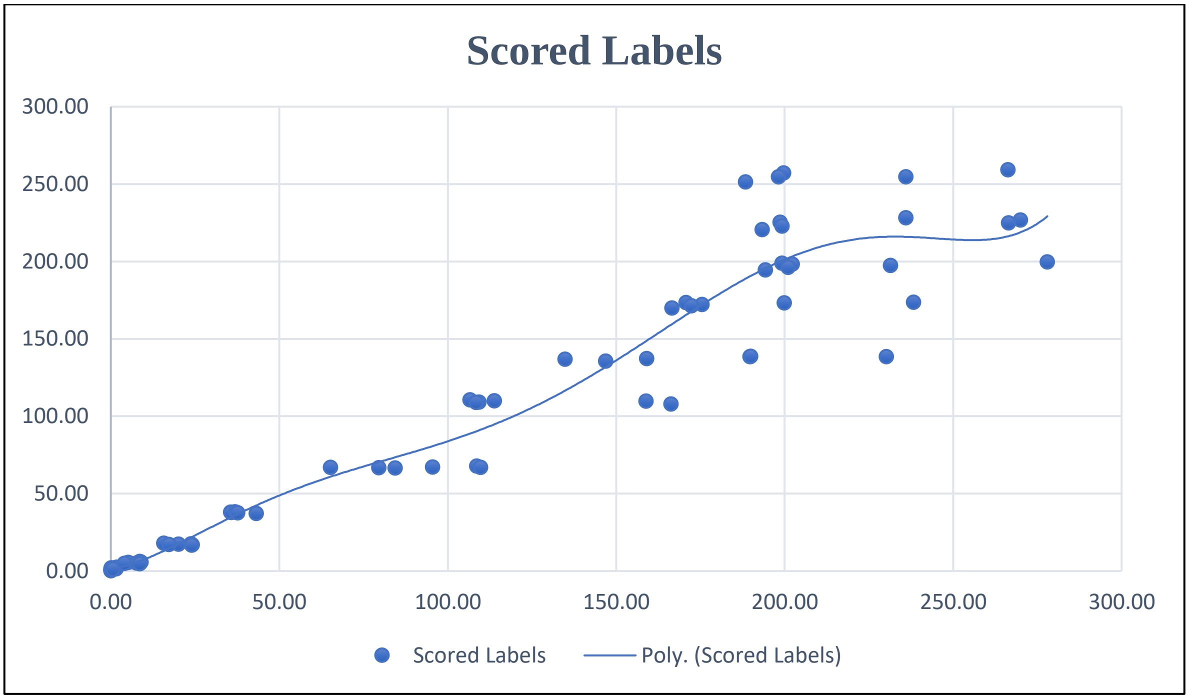


Figure 5. 9. Generalization of the developed model

The basic goal of machine learning is to build a computational model that can generalise well. During the training step, the created model was fitted to a sample of input data from the original dataset. When a model learns too much of the noise and random fluctuations in the training data, its ability to generalise suffers. With certain minor stages that revealed overfitting circumstances, the created model is said to have a decent generalisation capacity to forecast. The previous analysis revealed expected bottlenecks at some stages of the process under certain circumstances in some scenarios. That would help in providing potential solutions for expected problems in other scenarios and would also help in presenting managerial insights for improvement and better performance of the decisions taken by the distributors in other possible scenarios that will be discussed in the next chapter.

After being evaluated and validated, the developed model was ready now to be deployed. The deployment phase will be thoroughly explained in the next section along with how the model would be published as a web service so that anyone can access it through its API.

5.4 Model deployment

The model is ready to be deployed once it has successfully passed the evaluation state. The practical use of a machine learning model in the selected field of application defines the deployment phase. The size and inference time of models implemented on embedded systems are limited. While cloud computing provides enormous computing capacity, a consistent, lag-free, and stable connection is required. Complementary devices near the cloud's edge have restricted access to giant data centres, and while they can communicate with them, calculations must be done locally. Such devices can periodically download the most recent ML models and be maintained by the ML deployment team. It is recommended practise to deploy a model to a small fraction of current apps first and test its behaviour in a real-world context before rolling it out to all existing applications. The expense of correcting errors and the consequences of such erroneous deployments should be kept to a minimum. If the canary deployment goes well, the model can be deployed to all users.

The training experiment was transformed into the EOQ prediction predictive experiment. As illustrated, the predictive experiment was deployed as an Azure web service to take user input in Figure 5.9. The evaluated experiments were deployed as a web service. The web service was published as a request response Application Program Interface (API) on Microsoft Azure Cloud. Where user data enters the pipeline is indicated by the Web Service Input module. In a real-time inference pipeline, the Web Service Output module indicates where user data is returned.

The input and output parameters of the API are shown in Figure 5.10. The web service is published on Microsoft Azure cloud. The input of the API shows the variables that should be available in the input data of the model.

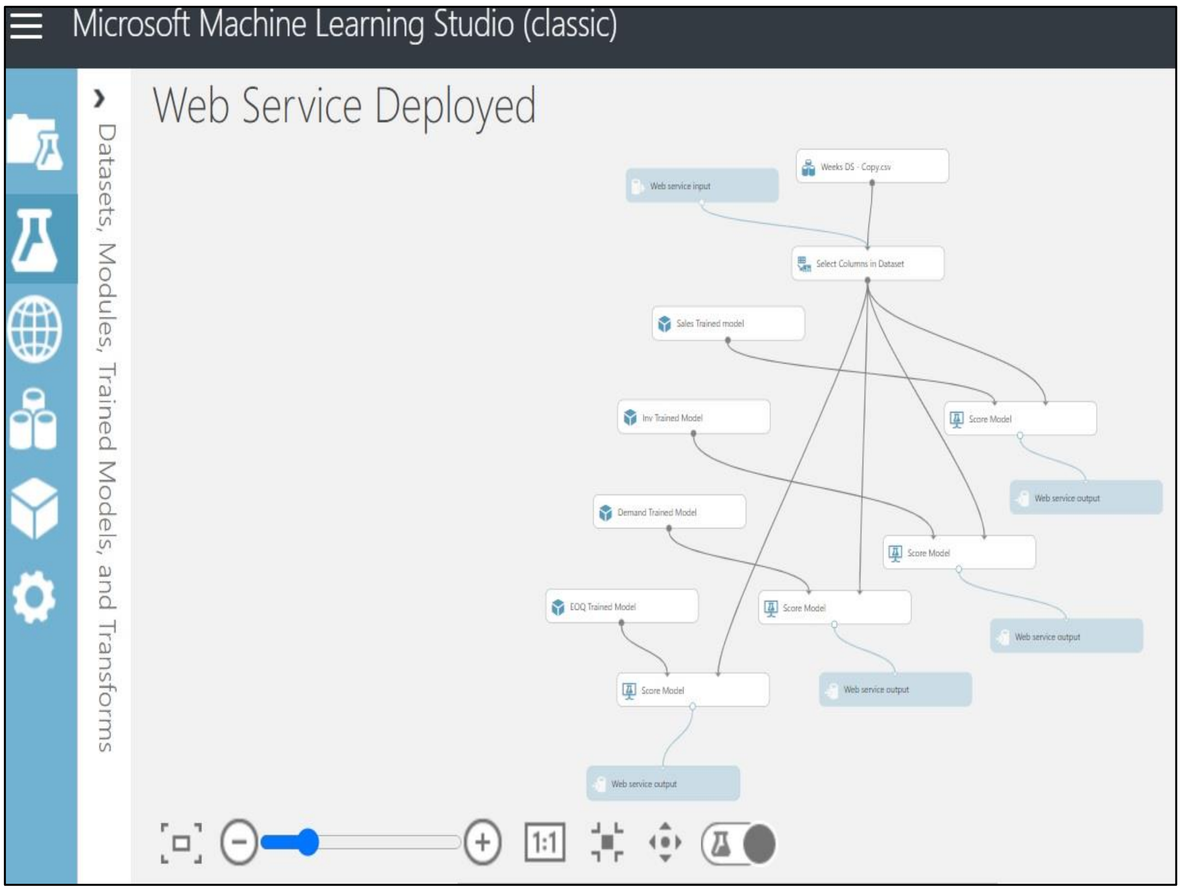


Figure 5. 10. The proposed model web service

Figure 5.10 shows two scenarios of inputs to the model, one with all the variables available and the next one with all the variables available except the sales, inventory, and demand variables with null values. The output of the API in both scenarios showed the aim of the model which is to predict the sales, inventory, and demand variables first then predict the EOQ as the final output in case they were unavailable in the input data provided.

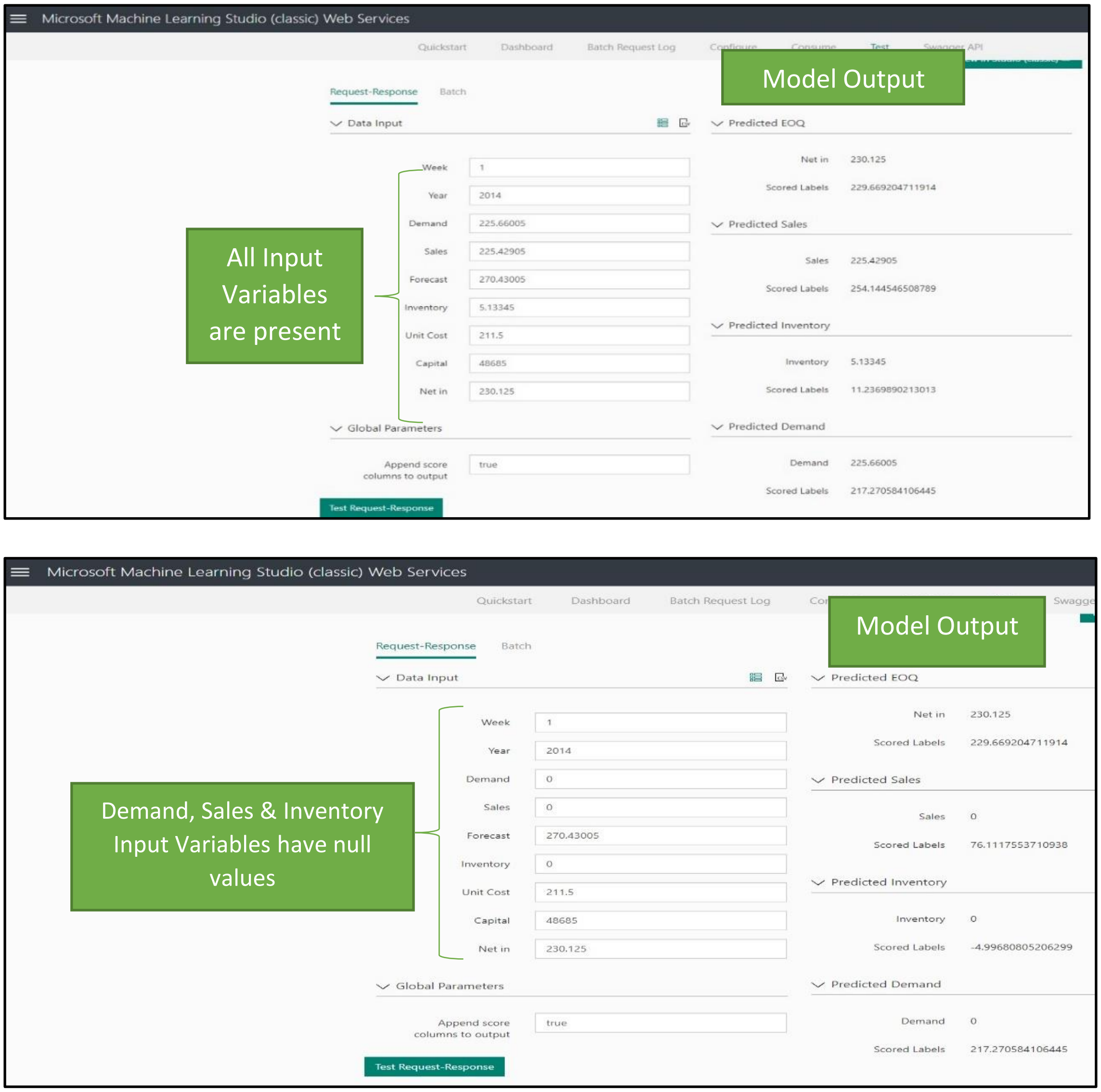


Figure 5. 11. Input and output parameters of EOQ prediction API

The published request/response web service can be used through any web application as well as through the Azure Machine Learning plugin for Microsoft Excel.

5.5 Monitoring the developed ML predictive model

The monitoring phase is the final phase in the life cycle of the ML model that enables developers to understand what data is being sent to your model and the predictions that it returns (Microsoft Azure ML,2020). Jordan (2021) described the monitoring phase as a well-accepted practice to monitor software systems so that developers can understand performance characteristics and react quickly to system failures. Monitoring is a non-automated procedure for most businesses that involves examining the impact of a model from a business standpoint and then deciding whether the existing model needs to be updated (Christopher, 2020). The monitoring phase has many scenarios, one of the most common scenarios is the model deployment which was described in Section 5.4 which determined whether the developed model changes had the desired effects.

Because quality assurance procedures cannot prevent all errors that could lead to software failure, development teams have developed monitoring practises to track how software performs. The magic of machine learning is in how it generalises from previous experience and reacts to new data without humans having to describe each situation. Testing for all possible scenarios that a machine learning system may encounter is impossible, which is why the system must be monitored continuously to ensure that it is functioning properly (Patruno, 2021). Because ML systems are software systems, it's still vital to keep an eye on their performance indicators to verify that the ML serving system is up and running and producing predictions with a reasonable amount of latency. However, because monitoring ML systems is about measuring the quality of decision making that the system supports, these metrics are only a subset of the metrics that should be observed.

Quality assurance is carried out in this research to assure the quality of predictions of the developed model through the following points:

- The quality of the data fed to models at inference time.

  Monitoring an ML system entails not just monitoring the model itself, but also all of the data sources input into the model. Any of these systems can have a negative impact on the accuracy of a model's predictions. In this research, this step was undertaken in the data cleaning phase in Chapter 4, Section 4.3.2, to make sure that all the data fed into the model was clean, did not contain any null values and ready to be processed in the predictive model.

- Modelling assumptions remaining relatively constant.

  From historical data, models understand links between inputs and outputs. Because the real world is dynamic, these relationships are always changing, causing model performance to deteriorate with time. Models must adapt to changing situations, but identifying these changes requires rigorous, continuous monitoring, which in this study might be accomplished by deploying the model continuously (as discussed in Section 5.4) through the web service, to detect any areas that might have high rates of percentage of error.

- The robustness and stability of predictions.

  Model output can be affected by changes in any aspect of the system, including hyperparameters, sampling methods, learning settings, and data selection.Monitoring solutions are needed for the ML models to ensure proper business performance. To test the robustness of the developed ML, a cross validation test was discussed in

Section 5.3.2.1, and the results proved that the developed model has stability of predictions.

ML models have a life cycle that must be managed, and ML model maintenance ensures that the model's quality is maintained throughout its life cycle. The risk of not updating the model is that its performance will deteriorate with time, resulting in inaccurate forecasts and possibly causing faults in future systems. Furthermore, the model must adapt to changes in the environment (Sugiyama et al., 2007). Baylor et al. (2017) recommend that all input signals be registered and that the model be notified when an update occurs. Input signal updates could then be handled either automatically or manually. The schema defined in Chapter 3, Section 3.1.5, can be used to ensure that incoming data is correct. Inputs that do not conform to the schema can be classified as anomalies, and the model will reject them. Coming to the end of the monitoring phase of the developed ML predictive model means the successful accomplishment of the CRISP-ML(Q) methodology across its six phases that had been followed in this research.

5.6 Chapter summary

This chapter has represented the evaluation, validation, and deployment processes for the proposed ML predictive model. It highlighted some performance metrics reviewed in the literature and addressed how they were used in evaluating the performance of different ML models. The chapter then discussed how the evaluation process was carried out on both scenarios, compared the results, and chose the scenario with more accurate results. Then some of the main validation techniques that were used to validate ML models were reviewed and the used one in the research was explained in detail. The 10-fold cross validation technique used in the research focused on scoring the whole dataset instead of depending on the assigned training and testing partitions of the dataset to achieve the objective of validating a reasonable, reliable, and sensitive proposed ML predictive model. The chapter then outlined the deployment phase of the proposed model and showed how the API was accessed through the Microsoft Azure ML cloud service. The chapter ended by discussing some points about the model monitoring and how to maintain the model to get a sustainable predictive performance.

Chapter Six

Discussion

6.1 Chapter overview

The previous two chapters (Four and Five) presented a comprehensive analysis for the proposed supervised regression predictive model and the two scenarios for its development. The suggested scenarios addressed different ranges of the working capital used in the developed model. The results of all scenarios were tested, analysed, and interpreted. This chapter starts with an introduction then it briefly reviews the main research gaps and how they were closed. The rest of the chapter explains how the study questions and objectives were addressed by detailing the research framework and methods used.

6.2 Issues discussed

In this study, the literature review was organized as follows: firstly, an overview of the distribution process was provided, which includes the main activities of distribution and an overview of the FMCGs industry and its effect on the economy. Secondly, the literature explaining the significance of demand forecasting and EOQ determination, forecasting tools and their applications in the recent past was reviewed. Thirdly, an overview of the ML techniques in supply chains was provided which highlighted the supervised regression techniques in detail and their applications in EOQ and demand forecasting. Then the research gaps were identified, followed by the research questions imposed by the research.

This research targeted the distribution sector of the FMCGs supply chain, and it focused mainly on determining the EOQ through a supervised regression predictive model to allow appropriate inventory management and inventory levels optimization. This research compared different supervised ML regression techniques and applied the models that were suitable for achieving the research aim. This study proposed two scenario implementations for the EOQ prediction in Chapter Four and their results have been discussed in Chapter Five. The sequential model improved the accuracy of the prediction results over those provided by the parallel model and the baseline model (provided by the case company). The improved forecasts directly resulted in better operational and financial performance for the targeted FMCGs distributor through measuring and comparing some of the calculated KPIs (ATP, OCF, ITR and OFR) with the baseline KPIs later in this chapter. The goal behind conducting this research was to select an optimum combination of supervised ML regression algorithms which would produce least error measures along with predicting the optimal weekly EOQ for the distributor based on newly added variables that were not covered in the previously published EOQ prediction models.

The computation of EOQ is a well-known and a widely used method of inventory management. There was a wide range of models which consider various environments and constraints (Banyai et al., 2020). The added value of this research is the modelling of an EOQ problem in the deterministic and stochastic environments, where the working capital as a main constraint was considered. This research covered the building, training, testing, and comparison of supervised ML regression algorithms for predicting the EOQ. Among the tested models, the most accurate algorithms were the BDT and the NNR models that were used for building the supervised regression predictive model. The BDT and NNR showed similar accurate prediction results which was opposite to references (Dey and Ghose, 2019; Sremac et al., 2019; Pezente, 2018).   It has been found that the ATP by using the proposed EOQ model has been improved by 83% over the baseline used by the case company which would decrease the occurrence of overstock situations. It has also been found that the OCF was improved by 66% over the baseline and that would save the distributor from running into financial issues and ordering products while having no cash to pay for them. Managerial decisions can be influenced by the results of this research because the analysis presented in this research makes it possible to support managerial decisions regarding inventory strategies.

The research gaps were investigated and explained in Chapter Two. Throughout the research, these gaps were considered in different chapters and have been closed fulfilling the main aim of the research. The following points explain how the original research gaps have been closed. The first gap, addressed in this research, concerned investigating the influence and relationship of adding the working capital parameter to the developed supervised regression predictive model. Very few previous research studies have emphasized the relationship between working capital as an influential factor of determining EOQ. Only Serrano et al. (2017) investigated how the cost of capital and the inventory decisions can change through an EOQ model with deterministic demand only. They concluded that the additive and the multiplicative noise functions were irrelevant to compute the optimum inventory level and the EOQ allowing a small loss of accuracy in most practical cases. Oppositely, this research evaluated the importance and the effect that the working capital parameter had on the EOQ prediction in the deterministic and uncertain environments among the other parameters in the model, giving managers insights for more efficient decisions on the optimum quantities they should order (as discussed in Sections 5.3.3.1 and 5.3.3.2) in Chapter Five. Adding this parameter to the model showed a direct impact on the EOQ prediction results over other models mentioned before that didn’t consider measuring the effect in values but just proved how the working capital is an essential driver in managing inventory levels in companies.

This research studied the effect that working capital had on the EOQ prediction results through the developed model. The working capital variable was compared to the other input variables through a feature importance analysis that was carried out in Chapter Five and the results showed that during all the phases of the model prediction, the working capital variable showed the highest score which made it the most influencing feature among the rest of the features on the EOQ prediction. Also, the scenario analysis results viewed in Chapter Five confirmed the direct effect the "working capital" variable had on the EOQ prediction results of the model. Some scenarios were tested using low capital ranges and that resulted in low and inaccurate predicted values for the EOQ. The rest of the scenarios that had higher working capital ranges showed higher and more accurate predicted values for the EOQ predicted these values had a proportional relationship with working capital.

The second gap addressed in this research involved using specific supervised ML algorithms that would develop a predictive model that could accurately predict the EOQ of the FMCGs distributor. Concerning the existing EOQ models reviewed in the literature, most of them focused on determining the EOQ either through mathematical approaches, modifying existing formulas or applying calculation techniques (Senthilnathan, 2019; Nestorenko et al., 2020). Limited research has targeted the prediction of EOQ through supervised ML algorithms but instead the previous studies determined the EOQ through common formulas and numerical methods. Table 6.1 reviewed a comparison between EOQ models developed with different methods highlighting the objectives and conclusion from each model showing how the developed model in this research is different than the others.

Table 6. 1. Comparison of developed EOQ models in the literature

<table>
<tr><th>Method for determining EOQ</th><th>Referenced work</th><th>This research</th></tr>
<tr><td>Numerical Method</td><td>Huang and Wu (2016)

Minimized operational cost by 6%.</td><td rowspan="4">-Improved the ATP and decreasing the occurrence of overstock by 83%.

-Improved the OCF by 66%.

-Improved the ITR & OFR by 33%.</td></tr>
<tr><td>Probabilistic EOQ</td><td>Dania et al. (2019)

-Reduced ordering cost by 15.6%.

-Decreased of inventory cost by 0.14 %.</td></tr>
<tr><td>Multi-objective particle swarm optimization (MOPSO) and Multi-objective bat algorithm</td><td>Sarwar et al. (2020)

Minimized total inventory cost by 23%.</td></tr>
<tr><td>Sequential structure of supervised ML algorithms (BDT and NNR)</td><td>This research</td></tr>
</table>

This research considered developing a supervised regression predictive model that predicts the weekly EOQ of the FMCGs distributor. The sequential structure of the model concluded in better prediction results for EOQ over the EOQ calculated by the case company. During the development of the predictive model, the NNR model was superior and showed the most accurate results with (high R^2 and low RMSE) followed by the BDT model that showed close results to the NNR model. The PPM and SPM, discussed in Chapter 4, had a common feature that they were determining or predicting the EOQ either in the deterministic or the stochastic environments. But these models were developed using different methods which resulted in different prediction results. Most of them showed a decrease in the inventory cost and stock shortage. The model developed in this thesis showed more improvements in additional KPIs that were not covered in other EOQ models, such as OTP and OFR, making it more a reliable model for predicting EOQ. Since all the parameters of the model were predictable in a sequential order, this made the model more flexible and adaptable to uncertain and non-linear conditions. The prediction results of the predictive model showed the highest R^2 (0.99969) and the lowest RMSE (1.134558).

The third gap addressed the growing need for research in the areas of demand forecasting and EOQ determination using advanced supervised regression techniques, with specific applications in the Egyptian distribution and retailing sectors, as they depended on traditional forecasting techniques in their operations and needed to raise the performance level of their demand forecasts to enhance the overall supply chain performance. This research considered a case study application to an Egyptian FMCGs distributor (QEBAA) and it used real data from the company to evaluate the developed EOQ predictive model. Apart from being scientific, the developed model includes a practical aspect, as it has been tested in a specific FMCG company. The proposed model was tailored to the needs of the observed company's business, but it may be applied to any organisation that deals with the flow of commodities with minor adjustments.

6.3 Overview of the research methodology and framework

The case study method was used in this study for two reasons. For starters, case study methodologies are a simple way to analyse how and why research questions (Dinwoodie and Xu, 2008), which matched the study's research questions (as summarised in Chapter Two). Second, this strategy is appropriate for the study's nature as well as the goals and objectives (as listed in Chapter One). Note that modelling the distributor's EOQ forecast process necessitates a high degree of information, including both statistical and operational data. The case study approach was acceptable in that it allowed the research to focus on a single

FMCGs distributor in order to collect enough operational data to develop the model. This study used both qualitative and quantitative methodologies in its methodology. The researcher gathered primary data and retrieved secondary data from the company's records.

6.3.1 Achievement of research objectives:

This research was based on four objectives that were fully achieved throughout the whole research phases, starting from reviewing the literature related to the stated research problem, followed by the supervised regression model development, and finally validating the model and comparing its accuracy with the already existing inventory management techniques in the case company. The research objectives were listed as follows:

Research objective 1: To review the literature relevant to the ML (supervised regression) techniques in the supply chain demand forecasting and EOQ determination domain.

A review of published research on ML (supervised regression) approaches was used to achieve this goal, focusing on the supervised regression models, and how they were applied in the demand forecasting and EOQ determination area. The review of literature revealed that traditional forecasting methods use only limited factors and linear variables to create forecasts. Many authors have applied ML to demand forecasting and compared forecast accuracy against the accuracy of traditional forecasting methods. The results showed that advanced ML approaches were more accurate and could be applied in demand forecasting and be used to improve forecasts when demand is intermittent (Hribar et al., 2019; Saloux and Candanedo, 2018; Amirkolaii et al., 2017; Vargas and Cortes, 2017). The ML integrated approaches applied in other studies, related to the FMCGs, indicating their ability to achieve better results compared to traditional approaches, due to the strong relationship these integrated approaches establish between the input and the output values of the training data. This research depended on linear regression, decision forest, gradient boosting and neural networks that have been applied in the literature for FMCGs demand forecasting (Priyadarshi et al. ,2019; Granda et al., 2019; Goli et al.,2019; Pezente, 2018; Mupparaju et al., 2018; Liu and Frick,2018; Mahbub et al.,2013; Kandananond,2012; Paul and Azeem,2011). These were used as a base to construct the framework of the predictive model.

As previously mentioned in Chapter Two, most of the inventory management control models reviewed in the literature determined EOQ through mathematical models and basic statistical formulas. This research objective has been fully achieved through gathering clear knowledge about whether supervised regression techniques were intensely used for determining EOQ or not. A limited number of studies have been conducted to investigate the importance of ML techniques in predicting the EOQ. Most of the ML techniques covered in the literature were concerned with developing inventory control and optimization models giving a minimal contribution of using supervised regression models in specifically predicting the EOQ. Limited research focused on the supervised regression techniques specifically for EOQ prediction. Only Dey and Ghose (2019) and Sremac et al. (2019) highlighted the importance of using neural networks models for determining EOQ through the accurate prediction results they got from the models developed. This research got into deep investigation of other supervised regression models that were not used by models in the literature other than neural networks for the EOQ prediction. These models were compared and the NNR was still superior over the other three models, but another model (BDT) showed very close accurate results like the NNR.

Research objective 2: To analyze the existing developed ML (supervised regression) predictive models to identify the key input variables that affect the distributors' EOQ. The literature related to this issue was thoroughly searched and studied and consisted of various traditional, statistical, and ML-based forecast methodologies for supply chain which explore the array of methodologies adapted for FMCGs forecasting. After viewing the demand forecasting models created in previous studies, this research used the variables that suited the aim of the research and affected the distributor's performance in managing the inventory. The previous models developed by (Paul and Azeen, 2011; Sustrova, 2016; Chai et al. 2018; Bottani, 2019) focused on most of the variables targeting the demand forecasting like demand, unit cost, available inventory, sales, and transport cost. The analysis of well-known researchers' works in the field of inventory management (Sarwar et al. 2020; Dania et al. 2019; Agada and Ogwuche, 2017; Sustrova, 2016; Yousefli and Ghazanfari, 2012) revealed they key parameters in their proposed EOQ models, namely: demand, holding cost, shortage cost, ordering cost, setup cost, order quantity, reordering point, stockout cost and budget. Additionally, This research aimed to identify the variables that influenced the distributor's decision on the appropriate quantity to order, as well as to develop a model that can incorporate inputs from all of those variables and use them as inputs to the predictive model.

During the interviews conducted with the case company, the managers highlighted the importance of the "working capital" as an additional variable that had a direct effect on the inventory management and the EOQ prediction process. The framework of the proposed model that was designed in Chapter Three covered all the input variables from previously developed demand forecasting and EOQ models to build the supervised regression predictive model that was relevant to the context of the FMCGs distributors. The main input variables to the proposed model were the historical demand, historical sales, forecasted demand, current inventory, unit cost and the newly added working capital variable that showed the highest importance to the EOQ prediction process over the other variables.

Research objective 3: To propose a supervised regression predictive model to predict the distributor's EOQ.

A supervised regression ML model has been proposed to predict the weekly EOQ of the FMCGs distributor in Microsoft Azure ML studio. Before deciding the model with the most accurate prediction results, the research compared between two implementation scenarios (explained in Chapter Four); the PPM and the SPM. The SPM addressed the prediction of the product inventory levels, sales and demand in a sequential order first, before forecasting the final EOQ. The proposed SPM supports the process of predicting the sales, inventory, and demand first. This is a relevant aspect for reliably predicting the final EOQ in the distribution context. The proposed approach made use of three BDT predictive models connected in series, in line with the need for modelling three sequential processes for predicting sales, inventory and demand first. It has been introduced to investigate whether predicting sales, inventory, and demand before forecasting the EOQ has the potential to help the distributor improve the forecast quality. As the NNR model showed superior results over the other models, it was chosen for the last prediction phase of the SPM to predict the EOQ based on the predictable variables (sales, demand and inventory) from the previous prediction phases. The SPM was also useful in determining if sequential implementation of the supervised regression predictive models is more effective than using separate supervised regression predictive models in predicting the distributor's EOQ. The SPM was utilised to improve inventory management and the company's ordering system by optimising inventory levels.

The evaluation of the predictive models, PPM and SPM was governed by the RMSE and the R^2 value (as mentioned in Chapter Five). The SPM (developed by BDT and NNR models) was considered the preferable model as it resulted in lower values of RMSE and an R^2 in addition to the results that would be discussed in Table 6.1 and 6.2. The SPM showed the highest R^2 and the lowest RMSE unlike the PPM that had very high values of RMSE but moderate values of R^2. It was observed that the SPM was performing better than the PPM with RMSE (1.134558) and R^2 (0.99969) while predicting the targeted output (EOQ). Conversely, the PPM generated the biggest error with RMSE (27.211456) from the DF algorithm and R^2 (0.82158). The difference between the errors is large which led this research to conclude that the SPM is a better and more optimized multi-step predicting model than the PPM.

Table 6.2 shows the comparison between the EOQ values predicted by the SPM and PPM using the case company real data as a baseline reference for this comparison. Table 6.2 confirmed the same conclusion that came out of Table 5.2, that it could predict EOQ values which were very close to the baseline over the values generated by the different models in the PPM.

Table 6. 2.Comparison between actual EOQ and predicted EOQ

Week	Capital (EGP)	Baseline EOQ (Unit)	Predicted EOQ with PPM				Predicted EOQ with SPM
			LR	DF	BDT	NNR	

5	22890	65.1581	67.57	74.331	71.303	73.0378	65.997
19	4040	11.4666	-1.282	14.809	14.701	22.904	11.077
25	82915	235.9581	269.89	336.791	254.972	237.519	236.139
38	1365	3.83745	-11.267	6.426	3.9710	16.288	5.59
44	59280	166.5249	190.228	240.488	231.661	156.396	167.04
52	13	0.021619	-19.397	0.7693	-0.239	10.101	0.011

Table 6.3 shows the forecasting error percentages of the two models separately considering the same weeks (5, 19, 25, 38, 44, 52) and the working capital values available in the mentioned weeks as those that have been used in the sensitivity analysis scenarios in Chapter Five. The results also confirmed that the SPM was 83% better than the PPM according to the forecasting error percentages listed in Table 6.3 which would make the prediction of the distributors' EOQ, in a non-linear environment, more accurate. The results also implied that the model was reasonable, representative, and could be reliable for further investigation.

Table 6. 3.Forecasting error percentages of the PPM and SPM

Week	Capital (EGP)	PPM				SPM
		LR	DF	BDT	NNR	
5	22890	3.702 %	14.077%	9.431%	12.093%	1.28%
19	4040	111.179%	29.15%	28.21 %	99.748%	3.393%
25	82915	14.38%	42.733%	8.058%	0.6615%	0.076%
38	1365	393.605%	67.46%	3.481%	324.447%	45.66%
44	59280	14.234%	44.41%	39.114%	6.082%	0.309%
52	13	898.235%	3.458.44%	1210.07%	46622.68%	51.2%

When comparing the models, the proposed LR and DF models, under the PPM, were marginally worse than the other models regarding the performance metrics accuracy (mentioned in Chapter Five) and regarding the prediction accuracy mentioned in Table 6.2. Apart from this, the remaining two models, BDT and NNR, have both great potential for good results, as both have results closer to the baseline and that is why they have been used to build the SPM.

The parallel model showed that the performance of the algorithms in a parallel way resulted in a slight improvement on the performance of the results. Therefore, the sequential architecture was selected as the optimum proposed model suitable for fulfilling this research aim. The proposed model was tested with the data of year 2018 due to the small size of the dataset available. The NNR worked better than the rest of the regression algorithms tested according to the previous figures and quantifiable results. The EOQ value predicted the sequential model showed fewer deviations from the actual EOQ values (baseline) in some of the modelled weeks. This improvement was because the features (sales, inventory, and demand) were more accurate and more optimized after being predicted one after the other in the sequential model. On the other side, those features have been used as inputs to the parallel model in a raw form without any optimization process performed on them. That is why some graphs in the parallel model showed a larger deviation.

Research objective 4: To evaluate and validate the proposed model and measure the accuracy of the results on the business.

The evaluation step was about measuring the trained models' performance accuracy. Microsoft Azure ML studio, used in this research, provides MAE, RMSE, RAE, RSE and R^2 as the performance metrics for evaluating the regression models. In this research, the "Evaluate Model" was used as an evaluation tool for the proposed model. The "Evaluate Model" module provided an estimation of accuracy for the trained models. The models being evaluated in this research have been trained by different regression algorithms. In the SPM, the "Evaluate Model" module was used once at the last phase of the model (EOQ prediction phase) because the model was constructed in a sequential way consisted of four phases. Each phase used to predict the variable that would be used as input to the next phase until the last phase was reached (EOQ prediction phase) so that the module would evaluate the targeted value. The SPM was built using only two algorithms; BDT regression and NNR as mentioned before in (Chapter Four). Choosing the BDT and NNR models specifically for building the sequential model also proved to be correct based on the performance metrics results shown in Table 5.1 that showed the high accuracy of these two algorithms over the rest.

The evaluation of the predictive models was governed by the RMSE and the R^2 value. The model with a lower value of RMSE and an R^2 value closer to 1 was considered preferable. Going through the results produced from both models, the SPM showed the highest R^2 and the lowest RMSE unlike the parallel model that had very high values of RMSE but moderate values of R^2. It has been observed that the SPM was performing better than the parallel model with RMSE (1.134558) R^2 (0.99969) while predicting the targeted output (EOQ). Conversely, the parallel model generated the biggest error with RMSE (27.211456) from the DF algorithm and a R^2 (0.82158). The difference between the errors was huge which made this research to consider the sequential model as a better and more optimized multi-step predicting model than the parallel model. The SPM would best fit the research aim of predicting more accurate amounts to be ordered from the FMCGs distributors.

The validation has been carried out in this research by first developing the model in accordance with the collected data then it was validated against the company's empirical statistics, and finally its results were compared to the actual system. This research applied the 10-fold cross validation to test the robustness of the proposed model. During testing of the model for each fold, multiple accuracy statistics were evaluated. A comparison of performance measures between the proposed model (SPM) and the cross validated model was explained in Chapter 5. The result of the k-fold cross validation of the proposed model that reviewed the 10 folds that were created and evaluated. To validate the developed model, a run was conducted for a period of 12 months which was year 2018. It was concluded that there is a consistent performance and close accuracy measures results between the proposed model and the cross-validated model, as shown in Table 5.4. This means that the proposed model proved that it has low variance and high bias which was due to the small size of the dataset. This behaviour might have changed if the proposed model has been provided with a larger dataset.

Following the development and validation of the prediction model, options for improving the distributor's performance were proposed. Based on some projections and assumptions, each scenario addressed a specific shift in working capital. In certain instances, the analysis showed projected bottlenecks at certain phases of the process under specific circumstances, while in others, it suggested viable solutions to expected problems. The scenario analysis results confirmed the direct effect the working capital had on the target output (EOQ) of the model. Scenario A and B were tested using low capital ranges and that explained the low values of the EOQ predicted in these scenarios. The rest of the scenarios had higher capital ranges which had a proportional relationship with the higher values of the predicted EOQ. Another observation was the close values of the original EOQ and the targeted EOQ which confirmed the stability of predictions and the accuracy of the developed model as well. The stability of the predictions was not affected when some of the inputs had null values, as in week 19, 25, 38, 44 and 52. The values remained optimal during most of the testing scenarios but some distance from the original values in other areas. This explains the high error percentage calculated. These results could give distributors insights into when to order and the optimal quantity to order to have optimized levels of inventory.

The preceding discussion demonstrated how the research methods and processes were used to attain the study objectives, and how the research goal was achieved as a result. The research questions and their answers were presented in the next section.

6.3.2 Revisiting the research questions

This chapter looked at how the research goals were met by providing explicit responses to the research questions that prompted the study in the first place. Furthermore, the research's contributions and consequences must be summarised. The goal of the study was to create a sequential supervised regression predictive model that forecasts the FMCG distributor's weekly EOQ in order to improve and optimise the overall accuracy of the forecasting process by enhancing inventory performance. The goal of this research was to find the best forecasting model for the FMCG supply chain at the distribution stage in order to reduce inventory levels and avoid probable stock-outs and leftovers.

This section evaluates and discusses the degree of fulfilment accomplished during this research. Hence the research raised three main research questions:

RQ1: What are the suitable ML regression algorithms for improving the FMCGs distributor EOQ prediction accuracy?

Experiments developed in Microsoft Azure ML Studio could be trained and transformed into a predictive experiment allowing users to build their models (Ericson *et al.*, 2016; Rajpurohit, 2014). This research aim was to identify the best predictive model for the weekly EOQ of the distributor through a comparison of supervised regression models (LR, BDT, DFT and

NNR) both in a parallel and a in a sequential structure. That is why supervised ML algorithms were chosen for developing the predictive model due to their nature of predicting values only. Among the ordinal regression, poisson regression, fast forest quantile regression, linear regression, neural network regression, decision forest regression and boosted decision tree regression, only four algorithms were chosen because of their accuracy and training time measure. The chosen four algorithms (LR, BDT, DFT and NNR) that had been implemented to train the two models, PPM, and SPM, were explained with a brief comparative analysis in Chapter Four. Ghanbari (2019) highlighted the necessity of applying forecasting algorithms for regression problems. That is why these algorithms were chosen so they could deal with the numerical demand data and predict the targeted output (EOQ). The selected regression algorithms, were chosen among other regression algorithms that existed in Azure ML Studio, based on their accuracy and training time (as explained in Chapter Three).

The PPM was developed based on the four previously mentioned regression models in a parallel design and then the output predicted by each algorithm was evaluated. To decide which of the four algorithms and in which sequence the structure of the model would be, 19 organized predictive experiments, were conducted in Azure ML Studio. Each of the four algorithms was trained separately in a predictive model, once with each of the sales, inventory, and the demand inputs. The DF algorithm showed the most noticeable difference between the actual and the predicted EOQ and this difference slightly decreased until it almost disappeared in the NN algorithm graph. The EOQ predicted by the NN algorithm showed remarkable consistency with the actual EOQ followed by the BDT algorithm. Moving to the SPM, it was built in a sequential way opposite to the PPM. The SPM consisted of three sub models that predicted three of the model main inputs first (sales, inventory, and demand) before predicting the main target (EOQ). Only two algorithms were used in the implementation of the SPM which were the BDT and the NNR. The results of the three sub models showed that the BDT was the algorithm with the most accurate performance metrics for predicting the sales, inventory, and demand and the NNR was the was the most accurate for predicting the EOQ.

RQ2: How can the developed supervised regression predictive model fulfil some of the ML success criteria?

The predictive supervised regression model was able to fulfil the main ML success criteria throughout the different phases that ranged from the model building till the model deployment. The ML success criteria were mentioned in Chapter Three with a short definition for each one of them (see Table 4.1). It was advised by (Studer, 2021) to define a minimum acceptable level of performance which is good enough to support the business goals and the KPIs for the developed predictive supervised regression model. Each one of the ML success criteria (mentioned in Table 4.1) was discussed in the research. The first ML success criterion is the performance. This research used some specific performance metrics for evaluating regression algorithms. Performance metrics are used in ML regression trials to compare the trained model predictions with the actual (observed) data from the testing data set (e.g., Botchkarev, 2018a; Makridakis, Spiliotis and Assimakopoulos, 2018). The outcomes of these comparisons can have a direct impact on the decision-making process for which types of supervised regression models to choose. Azure ML Studio has a designated module – Evaluate Model – to perform comparisons. The performance metrics that were used to evaluate the developed model were MAE, RMSE, RAE, RSE and R^2 (explained briefly in Chapter Four, Section 4.4.1). These metrics were used to compare between the performance prediction between the PPM and SPM, (see Table 5.2), which helped in choosing the SPM as a more optimized and accurate model to fit this research aim.

The robustness is the second ML success criterion discussed in this research. This research applied the 10-fold cross validation to test the robustness of the proposed model. A 10-fold cross validation gives better results in the parameter search by making better use of the training data because a prediction is made once for each instance, as opposed to only the test instances in expanding window cross validation (Tryman, 2019). The "Cross-Validate Model" module in Azure ML Studio accepts a labelled dataset as well as an untrained NNR model to train the proposed model with. The "Cross-Validate Model" module generates a set of performance metrics and scored results for all of the data after all folds have been generated and analysed. The "Cross-Validate Model" module also provides expected outcomes and probabilities for the dataset, allowing you to assess the correctness of the predictions. The NNR model was used to cross validate the proposed model on the pre-processed dataset. The “Cross-Validate Model” module is computationally more intensive than the modules (Split Data, Train Model, Score Model and Evaluate Model) and can replace them when developing a model. One main advantage of the “Cross-Validate Model” module is that it minimizes the risk of the model overfitting, in addition to scoring the entire dataset instead of scoring only the remaining percentage of the test data (Azure ML, 2019). The results viewed from Table 5.4 showed the k-fold cross validation of the proposed model that reviewed the 10 folds which were created and evaluated. The results showed evaluation metrics for each of the folds (MAE, RMSE, RAE, RSE, R^2) with results that were getting closer and closer together, and this confirmed that the sample used was appropriate and reliable. The standard deviation resulting from the 10-folds was going down throughout the folds which also proved that the sample is less likely to be overfitted. When the cross validated model results were compared to those of the proposed supervised regression predictive ML model, the results were very close, and they had low RMSE values and high R^2 values. This proved that the model has high robustness performance because it did not deteriorate too much when it was trained and tested by the cross-validation method. This also showed that the chosen algorithms (BDT and NNR) that built the proposed model showed stability, as the training error was close to the testing error.

The third ML success criterion is the scalability, and this research discussed whether the developed model was scalable or not. Organizations gain from cloud computing because it provides business flexibility, cost savings, automatic hardware and software upgrades, agility, and scalability (Xue and Xin, 2016). The scalability of cloud services aids in the resolution of problems and increases client satisfaction. Smaller businesses, in particular, benefit from cloud computing since they may scale up their resources as needed (Michael et al.,2010). The proposed predictive supervised regression model built in Azure ML Studio is scalable due to its nature of being a cloud-based ML model. It supports datasets of up to 10 GB of dense numerical data for common use cases. The built predictive model with its features is suitable with users of small businesses because it is scalable with a limit, unlike other ML models that are scalable with compute targets (unlimited size of datasets).

The last ML success criterion is the model complexity. Model complexity in machine learning relates to the number of features or words in a predictive model, as well as whether the model is linear, nonlinear, or other. It can also refer to the computational or algorithmic learning complexity. Overly complicated models are more difficult to interpret, are more prone to overfit, and are more computationally expensive (Castrounis, 2021). The supervised regression predictive model presented in this thesis was not considered as a complex model according to its framework and it size. Taking about the framework, this research used supervised regression algorithms to develop both the PPM and the SPM. The models were easily comparable to each other because they have the same frameworks and the same performance metrics. The framework of the proposed model was not complex as it depended on the same type of regression algorithms. Even the SPM used a combination of BDT and NNR which are still under the umbrella of supervised regression models. Concerning the model size, it was of moderate size with nine parameters defined as input parameters in the dataset. The structure of the model viewed in Figure 4.8 showed the sequential way of building the model which was smooth and did not show any complex structure. The dataset used in this research contained 260 weekly records of units sold over five years from 2014 to 2018 and it contained 9 columns that presented the input attributes of the dataset which were: week, year, demand, sales, forecast, inventory, unit cost, capital, and EOQ. The dataset used was a small dataset with clear attributes that were easily understandable and showed no complexity at all.

Any supervised regression algorithm's purpose is to achieve low bias and low variance in order to get good prediction performance. According to Dhabarde (2019), if the model is too simplistic and contains few parameters, it will have a high bias and low variance. On the other hand, if the model contains a large number of parameters, the variance and bias will be considerable. Therefore, this research approached the importance of the developed model bias and variance to understand its behaviour through applying 10-fold cross validation (as illustrated in Figure 5.8). It was concluded that there is a consistent performance and similar accuracy measures results between the proposed model and the cross-validated model (as shown in Table 5.4). This means that the proposed model proved that it has low variance and high bias which was due to the small size of the dataset. This behaviour might have changed if the proposed model has been provided with a larger dataset.

RQ3: How can the developed supervised regression predictive model improve some of the key performance indicators (KPI) by predictions?

Many aspects of supply chain management, including the usage of KPIs, are being affected by machine learning. When it comes to improving a supply chain process or achieving overall efficiencies, ML combined with performance indicators can be a strong combo. When applying the models to improve a supply chain process, the KPIs define the expected outcomes (Maria and Saenz, 2021). Paying attention to KPIs that affect the distributors' performance could be a significant opportunity to improve competitiveness and profitability. Predictive KPIs can aid management in making decisions and taking actions that avoid or improve unfavourable outcomes. Every distributor requires information and tools to successfully monitor and manage its processes, and KPIs assist managers and owners in making appropriate decisions and measuring the impact of those actions.

An evaluation of the predictions made by the supervised regression predictive model was made to estimate their relevance. This process is explained later in this Section using Table 6.4 that includes predictions of the chosen KPIs related to the distributor and its inventory management process. The columns showed the KPI value from the case company compared with the KPIs values predicted by the developed predictive model in this research.

Table 6. 4. Comparison between the company's KPI (baseline) and Predicted KPIs

Weeks	Working Capital	Baseline ATP	Predicted ATP	Baseline OCF	Predicted OCF	Baseline ITR	Predicted ITR	Baseline OFR	Predicted OFR
5	22890	5.10405	5.9426617	25148.94	25443.1288	853.0375%	812.5473%	93.361%	92.354%
19	4040	5.6166	6.005754	6435.452	6298.34756	197.4768%	201.72%	75.743%	76.985%
25	82915	39.22905	39.410476	70410.43	70474.1612	931.7073%	927.7973%	83.64%	83.576%
38	1365	2.3625	4.1150578	6559.485	7176.05242	137.1561%	128.8680%	75.088%	70.148%
44	59280	48.975	49.490627	46113.77	46297.253	420.4297%	416.9439%	72.46%	72.252%
52	13	19.55408	19.542993	642.9002	638.904597	8.7877%	8.7901%	8.414%	8.418%

The data the included in the previous table had the same working capital values and weeks that have been considered in the sensitivity analysis section in Chapter Five. Each week reviewed the capital available in that specific week with the calculated (baseline) KPI and the predicted KPI by the developed supervised regression predictive model. From the results listed in Table 6.4, the ATP was improved by 83% over the baseline which would decrease the occurrence of overstocking products at the distributor, while at the same time allowing for on-time replenishment of any low products. The results also showed that the OCF was improved by 66% over the baseline during the weeks that had high working capital. This should always encourage the distributor to compare the OCF to the total working capital available to identify financial issues at a very early stage and before the distributor run into financial trouble in ordering products while having no cash to pay for them. The predictive ITR and OFR KPIs showed only 33% improvement over the baseline and that means that the model did not contribute to an improvement to this KPI, and the distributor could still depend on the baseline ITR to measure the efficiency of the overall inventory performance and the OFR to track how many orders had been efficiently fulfilled.

6.3.3 Interview findings

To be able to develop a ML predictive model, there was a need to understand QEBAA's purpose of implementing ML into their inventory management systems. From the findings of the interviews, it was revealed that the inventory management and prediction strategies encountered by the Egyptian FMCGs distribution company (QEBAA) investigated in this research. In this thesis semi-structured interviews have been held to get more profound insights into QEBAA as a company and their prerequisites in the model. The information from interviews have been very valuable not only in the sense of gathering knowledge for where they have problems in their supply chain, but also in order to be able to integrate with employees to find underlying reasons for why problems may occur.

Data from reviews of company documents (i.e., sales, pricing, and inventory documents) to support the findings from the interviews. The following three themes emerged from my analysis of the data gathered: understanding sales trends, inventory management with demand and EOQ prediction, and seasonality. According to the interviewee, there is potential to improve the demand forecasting method. The interviewee believes that the most important possible improvements enabled by AI relate to cost savings derived from reduced manual work and more accurate forecasts.

Although the interviewee believes that significant improvements can be made due to flaws in the current forecasting methods, accuracy is not measured today since it is not prioritised by the management. AI is not used for any activity within QEBAA related to the supply chain. The interviewee believes that the use of AI within demand forecasting could provide benefits to the company by enabling the handling of big data sets. This could then be used to optimize order quantity and shorten the project lead time. The use of AI within demand forecasting could also provide real-time forecasts which should be more accurate than six months since a lot can change within such a long period.

The interviewee claims that the forecasts' accuracy is insufficient, and that the forecasts often need to be adjusted manually based on experts' judgements. The poor accuracy also contributes to high inventory levels and therefore the company experiences a need to improve their forecasting process. There is an interest, by the company, in technology and how it may improve the process. One potential improvement the company sees is reduced inventory levels. However, according to the interviewee, the company does not have sufficient knowledge about AI to implement it. The company would either need a supplier that could help with the implementation or an information system with integrated AI services, and hence mentions availability of competent and mature AI suppliers, that can help with implementation for a reasonable price, as a prerequisite. To implement AI technologies, decision makers for supply chain improvements at the company would need more information about the different systems available to assess related benefits and ensure return on investment.

Currently, the interviewee sees potential in implementing AI techniques and believes that AI can lead to improved forecast accuracy. According to the interviewee, due to the company's high profitability, there is no incentive to improve internal processes, which is a prerequisite to implement AI. The company's focus is to sell as much as possible, and, therefore, the internal priorities are, instead, focused on sales and product development. Furthermore, the interviewee does not see the lack of technical competences required for AI as a barrier. There is no competence in the company today, but thanks to their high profitability, the company can hire consultants and bring in expertise if needed. The interviewee believes that management should pay attention regarding the potential of improving supply chain performance is necessary, because this issue has been addressed lately. Also, financial capital is required, and the team needs to be keen and competent for the implementation to be successful. The interviewee cannot estimate the impact of AI in demand forecasting but believes it has potential. The potential from improved forecasting accuracy lies mainly in decreased inventory levels which ties a lot of capital and freeing the workforce from certain tasks that AI can perform.

6.4 Discussion of the key findings

1-The proposed supervised regression predictive model provided an effective tool to analyze, assess and improve the performance of the distributors' EOQ prediction accuracy.

Following a thorough examination and analysis of the published literature, it was discovered that supervised regression techniques are critical for businesses to respond fast to changes in client needs and implement changes as quickly as possible to fulfil them. Previous research has found that studying advanced forecasting methods for optimal order determination helps with safety stock management, productivity, inventory cost reduction, and income generation.

However, the literature revealed that the existing modelling approaches for EOQ determination cannot fully deal with vague data, uncertainty, and no inputs as they depended on determining EOQ through existing formulas and numerical methods only. The prioritization and choice of relevant input parameters were highlighted in the literature as an important aspect that can contribute to developing more flexible EOQ models. The proposed supervised regression predictive model focused on identifying an optimum combination of supervised regression models which will produce least error measures along with predicting the weekly EOQ to be ordered by the distributor based on newly added EOQ variables, which will reduce the inventory levels and eventually will decrease inventory costs. Experiments have been carried in Azure ML Studio to measure and evaluate the prediction results of each of the supervised regression models (LR, DF, BDT and NNR). The NNR model's results were superior to the other models and the surprising result was that the BDT model's result was close to those of the NNR model. The comparison conducted between different supervised ML algorithms led to choosing the BDT and NNR as the best and optimum combination of supervised regression models to be used for developing the predictive model. The sequential prediction approach that the predictive model used in this research provided the distributor with the flexibility to predict the EOQ without having exact values of the variables: sales, inventory, and demand. This enabled the distributor to optimize their inventory levels and provided more insights into their decision making when dealing with uncertain environments.

2- The working capital parameter added as an input to the ML predictive model showed a positive impact on the EOQ prediction results enhancing the distributor's overall inventory levels.

The review highlighted that more awareness should be directed towards the factors that affected the EOQ determination rather than other variables found in the normal EOQ formula. Developing a ML predictive model should be tailored to align with the distributor's strategic objectives. The developed model included the variables that existed in developed models in the literature and proposed adding a new variable "working capital" to assess its effect on the EOQ predictions. A feature importance analysis has been performed on the main variables that affected the EOQ prediction (sales, demand, inventory, unit cost, working capital) throughout the multi-prediction phases of the proposed model (see Table 5.4). During the sales prediction phase, the "demand" feature was the variable with the highest importance. During the three phases of prediction in the developed model, the working capital showed a high score among the other variables, and it specifically showed the highest score during the EOQ prediction phase which made it the most influencing feature/variable among the rest of the features in the EOQ prediction phase. The previous findings confirmed what was mentioned before in Section 5.1.1.3. When the developed model was tested, three major points through the year were found to have a high percentage of error because during these weeks, the working capital was very low at the time. This explains the contribution the developed model in this thesis has by highlighting and measuring the effect of including the working capital as a new input variable and how that affected the ordering decisions of the distributor to order the right quantity of products to keep their inventory levels optimized.

3- Conducting a case study of an Egyptian FMCGs distribution company demonstrated the applicability of the research procedure in the distribution sector and empirically validated the research proposition.

Although previous research has confirmed the positive effects of demand and EOQ forecasting via ML on SCM performance, the existing literature has differing opinions, and empirical studies for the development and validation of the determination/prediction of EOQ within companies have yielded different results than those presented in this study. A holistic view as well as in-depth information about the examined phenomenon can be recognised because the case study research method uses multiple data, sources based on both quantitative and qualitative approaches. The steps of the case study were detailed in Chapter Three to demonstrate the research framework's applicability in a real-world setting. The case company's EOQ prediction results were assessed and analysed to discover EOQ performance drivers that needed to be improved (demand, sales, inventory levels and unit cost). Based on the feature importance analysis, the key areas for improving prediction performance were traced and their related performance metrics established. The results showed that using the suggested ML predictive model implementation improved prediction performance.

4- The chosen distributors' KPIs provided an effective way to evaluate, monitor and control the distributor's prediction performance.

The proposed KPIs helped in evaluating and monitoring the distributor's performance by establishing links between performance measures which facilitate analysis of the distributor performance from different perspectives. They worked like a decision support system that allowed the distributor to identify inventory related processes that need improvement and helped them to focus on the EOQ prediction problematic areas allowing them to decide the necessary corrective actions and identify the right purchasing decisions to take.

6.5 Chapter summary

This chapter discussed the thesis' overall contribution. It began with a description of the issues selected for study as a result of the literature review, and then outlined the research framework and methodology used throughout the study, connecting the research's key objectives to its conclusions. Its contributions to philosophy and industrial practise were also examined in the chapter. The next chapter will outline the existing work's limits as well as a set of recommendations for future academic work as well as future industrial advances and policies.

Chapter Seven

Conclusions and Recommendations

7.1 Chapter overview

The previous chapter focused on the overall thesis's findings by connecting the study objectives, questions, and gaps to the primary findings. This chapter begins with a summary of the thesis, summarising what was covered in each chapter. The research's key contribution to theory and industrial practise is then highlighted. Finally, the chapter finishes with a list of the study's limitations, as well as some recommendations for further research.

7.2 Summary of the research

The research background and overall framework, including the research goal, objectives, and research questions, as well as the technique used throughout the study, were introduced in Chapter One. In Chapter Two, the main requirements for a supervised regression predictive model to achieve the aim of the research, which was to develop a ML predictive model to predict the weekly EOQ of the FMCGs distributors, were explored. The chapter reviewed the literature available on the inventory management of the FMCGs distributors, the ML applications in the supply chain, and the EOQ models developed in the supply chain context, generally focusing on the FMCGs distributors EOQ prediction particularly.

The research approach was discussed in Chapter Three. It presented the research's scope as well as its framework process. The various research strategies were discussed, with the case study strategy serving as the primary strategy used in this research. It introduced the CRISP-ML(Q) methodology that this research used, and it identified the interviewing and the internal documents as the main data collection techniques adopted. Based on the requirements discussed in Chapter Two, it was concluded that supervised regression ML algorithms were the most suitable to address the prediction of the weekly EOQ of the distributors through a ML predictive model developed in Microsoft Azure ML Studio.

In Chapter Four, a detailed explanation of the two developed supervised regression predictive models, PPM, and SPM which were trained to forecast the EOQ of the FMCGs distributor. The two predictive supervised regression models were implemented using regression algorithms; LR, BDT, DF and NNR. The initial experiments discussed in this chapter showed that the combination of BDT and NNR algorithms showed the best results other than any other combinations of the stated algorithms. Then Chapter Five presented the evaluation, validation, and deployment processes for the two scenarios of the proposed supervised regression predictive model. The SPM proved more successful and accurate than the PPM, making it to the chosen scenario of the predictive ML model to be ready for validation and deployment. A "10-fold cross validation" technique was used to validate the model and results revealed that the model had low variance and high bias due to the small size of the dataset. Then the ML predictive model was deployed showing how to access the API through Microsoft Azure ML cloud service so that users can enter the requested input and get the desired output.

Chapter Six recapped the research gaps and discussed how these gaps were closed throughout the thesis. It also highlighted the answers to the research questions and how the research objectives have been achieved. The research revealed some interesting results surrounding the link between the working capital and the EOQ while could be further investigated to enhance the purchasing decisions of the FMCGs distributor to achieve better inventory performance. With the final model introduced in Chapter Four, trained with data collected with the modules also introduced in Chapter Five, the main aim of the thesis was achieved, verifying all requirements. Finally, Chapter Seven outlines the general conclusions of the research followed by a set of recommendations for future research and future industrial developments. Finally, it lists the research limitations and suggestions for future work.

7.2.1 Research conclusions

In this research, a supervised regression model for determining EOQ and its realisation by distributor was proposed, which was based on merging supervised regression techniques. The developed model was utilised to handle the specific problem of estimating the EOQ of the distributors' FMCGs, which was the research's main contribution. In comparison to other techniques, the suggested ML predictive EOQ model has numerous key advantages. First, in comparison to prior models, the benefits are more complex and incorporate working capital concerns as a new parameter that influences the choice on EOQ prediction. Second, the model was built in a sequential predictive manner, allowing the input parameters to be predicted before the EOQ prediction was used to optimise the model. The model's third virtue is that it is adaptable; it can be modified and used to compute the EOQ of various types of commodities with minor changes and input parameter specificities. To anticipate weekly EOQ, the example company was advised to use the ML predictive EOQ model to its inventory control model. The proposed model has been tailored to the needs of the case company's business, but it may be used by any organisation that manages the flow of commodities with minor adjustments.

The constructed machine learning predictive model was shown to be accurate, responsive, and dependable. A final step was made to bring the research to a close. This step involved presenting and discussing the model, its validation, and the suggested scenarios with the case company in order to obtain their feedback and assessment, as well as to develop a set of recommendations based on their valuable feedback and constructive comments, either for future research or for industrial developments. A visit to the company was made in this regard, and the study's concept was presented to them. They praised the efforts made throughout the research, particularly the building and development of the prediction model, which provided important information for their purchasing decisions. They provided data from 2014 to 2018 to verify and validate the machine learning forecasting model. Following a lengthy debate, several practitioner comments were created, from which several recommendations will be described in the sections below. An internal corporate official report was created at the end of the tour to validate the visit and outline the main outcomes. The report was not translated since the company does not produce translated reports. To summarise much of the chapter content, the next section will highlight the research contribution to knowledge and industry practise, followed by recommendations for further academic study and future industrial advances.

7.3 Research contribution

This study contributes to knowledge and industrial practise in light of the framework outlined above. The next sections will go through these contributions.

7.3.1 Contribution to knowledge

This study proposed a sequential ML predictive model for FMCGs distributors to predict a weekly EOQ for the products they should order from the supplier. This supervised regression predictive model contributes to optimizing the prediction results in the entire EOQ forecasting process through analysing the sequential prediction of some inputs to the model at different stages of the forecasting process. There were some generalizations in the results which supported the flexibility of the developed predictive model structure. The model had potential to be recalibrated to support decision making in other industries and companies. Therefore, the model would assist FMCGs distributors, planners, and operators in making judgments about the strategic/tactical and operational planning issues highlighted in the literature review.

Although considerable advances have been made in the forecasting sector for several FMCGs, many potential approaches have yet to be evaluated. In this context, using machine learning algorithms to forecast EOQ in the distribution industry could be a promising study topic. Dey and Ghose (2019) advocated for a robust system for predicting proper order amount, which is critical in this case. If a model is accurate for a current system, that does not guarantee that it will be accurate for the same system in the future. As a result, incorporating data dynamics into the forecasting methodologies used by distributors can improve forecast accuracy (Ghalehkhondabi et al., 2020). Most of the forecasting models for different industries like retail, transportation, wholesale distribution and manufacturing industries focus on demand forecasting and not the EOQ forecasting (Bouganim and Olsson, 2019; Priyadarshi et al., 2019; Granda et al., 2019; Kilimci et al., 2019; Pezente, 2018; Gdowksa and Mikulik, 2016; Sustrova, 2016; Slimani et al., 2015; Kochak and Sharma, 2015). Concerning the existing EOQ models reviewed in the literature, most of them focused on determining the EOQ either through mathematical approaches, modifying existing formulas or calculation techniques (Senthilnathan, 2019; and Nestorenko et al., 2020). Dey and Ghose (2019) argue that ANN is the only solution under the domain of AI which can solve the issue of predicting right order quantity. None of the previously mentioned models have considered developing a model that would predict the EOQ through ML, and the models that were developed to calculate the EOQ, depended on annual demand data. The only developed EOQ model mentioned in the literature that combined ML and NN was for determining a reordering point and not the EOQ (Inprasit and Tanachutiwat,2018). The other research by Dey and Ghose (2019) conclude that ANN is the only solution for predicting the EOQ. This led the research to identify the second contribution to knowledge in being able to develop a ML predictive model that predicts the weekly EOQ of the FMCGs distributor based on the historical data fed into the model.

This research confirmed its third contribution by being able to develop a sequential predictive ML model that combined the BDT and NNR algorithm to be able to predict the weekly EOQ of the FMCGs distributor. To the best of my knowledge, this is the first attempt to consolidate three predictive models in a sequential implementation, each one of them is predicting a variable that would be used as input to forecast the optimal quantity to be ordered by the FMCGs distributors, as the studies carried out before (Ghanbari et al., 2019; Priyadarshi et al., 2019; Goli et al., 2019; Liu and Fricke, 2018; Pezente, 2018) were just comparing the results of different algorithms implemented as single methods but not incorporated in one framework. The accuracy of the performance metrics and the predicted values of the EOQ of the sequential model proved to be better than applying the NNR alone in the parallel model as mentioned before in Table 5.2 and Table 6.1. This research was able to propose a model that would be capable of handling certain and uncertain demand data and use it to predict the weekly EOQ.

This research addressed the “working capital” variable as one of the essential inputs to the developed predictive model. None of the previously mentioned EOQ models have considered the working capital as an indicator that would influence the prediction of the EOQ by they included the working capital as an important driver in managing the inventory levels. The previously mentioned models have focused mainly on the price, reordering time (Nestorenko et al., 2020); demand and unit price (Birbil et al., 2014); divided payments (Taleizadeh, 2014); lot size (Jaggi and Mittal, 2011); constant price and lead time (Elyasi et al., 2014). The research had its fourth contribution by showing the importance and influence the working capital had on the prediction of the EOQ (as listed in Table 5.5) that showed its logging the highest score, which made it the most influencing feature among the rest of the features. This should give people who would develop models that predict EOQ to consider having the working capital as one of the main inputs to their models.

7.3.2 Contribution to industrial practice

The study contributes to industrial practise by allowing FMCGs distributors to use the created predictive model as a tool to make strategic and operational purchasing decisions. The predictive model allowed for the testing of many scenarios, such as scenarios with potential solutions to the problems. Distribution managers would be able to make managerial decisions based on scenario testing to improve performance in areas that concern them. An empirical contribution of this research would be considered from a point of view that a real case (problem) was chosen and a real company (QEBAA company) with its real data. To the best of my knowledge, this is the first time in FMCGs distribution industry in Egypt that this kind of ML prediction method of EOQ has been proposed and applied. Different businesses in different nations could further validate and verify the model’s usefulness, given its potential for generalizability.

Another industrial contribution was provided by the research that dealt with the possibility of missing information in the input dataset of the model. To determine or calculate the EOQ of a specific item, all previous research depended on the existence of all the variables in their equations to get the right EOQ. However, this research suffered from lack of data (there was access to only sales records of over a five-year period), a new method, in the model building phase, of predicting variables in a sequential way was introduced. This method enabled the model not only to predict the EOQ but also to be able to predict the sales, demand, and inventory variables in case they were missing from the dataset. This method increased the accuracy of the EOQ prediction when compared with other models. This means that users who would use this model would get accurate EOQ results in addition to three other separate outputs (sales, demand, and inventory) whether they are valid in the dataset or they are missing.

7.4 Limitations of the study

Despite the fact that the research adds to existing information and industrial practise, it has a few limitations that might be described as follows:

First, this research depended on a relatively small-sized dataset. This limited the ability of the supervised regression predictive model, in a way, of not recognizing some patterns because the ability of the algorithms used to recognize patterns is proportional to the dataset size used. As the dataset was considered a small one, the results of the model showed less accurate EOQ predictive results in specific weeks. If there was a wider range provided for some of the main parameters in the model, the behaviour of the model would have changed in certain weeks with some specific ranges of working capital and would have provided more realistic EOQ predictive values.

Second, due to the nature of the data collected during the first stage of the research, which was primarily operational data, the input parameters of the developed supervised regression predictive model did not take into account the time factor, as it was only concerned with the operational aspect of the forecasting process rather than the time issue. The variables that were used in the predictive model were limited to the data that was available. Additional features, such as lead time factors, that could affect EOQ were not incorporated into the model due to the data not being available. This can provide information for improving the study by using the generated supervised regression predictive model to determine the shortest time or best values for any other variable previously added in the predictive model.

Finally, the findings of the study are unique and specifically presented in the context of the case study company. This study was based on a case study of a specific Egyptian FMCGs distributor. As a result, the parameters of the generated EOQ prediction models were customised based on the case study data. Although generalising the predictive model was not examined in this study, it is conceivable to apply the predictive model to other scenarios. The curve exhibits a considerable variation from the actual at the early segment because the model was trained and tested against three years' historical demand or sales data and the factors considered are based on the recent market scenario that reveal the recent demand trend. If more data were included, the early period deviations would be negligible, and the move from greater to fewer, as well as inconsequential, deviations would be more clearly visible.

7.5 Suggestions for future work

From the results and conclusions extracted in this thesis, a few implications arose for future research in this area. The following research lines may help to further improve the existing knowledge and the methodology proposed for EOQ prediction process:

- The research did not go into generalising the predictive model due to time constraints. In this regard, it is strongly suggested that this model be used to additional Egyptian cases with minor modifications to the model based on the case and the data acquired. The case company works with other FMCGs manufacturers, and it was advised that the study's built predictive model be deployed, and more situations investigated. In accordance with the acquired data and investigation done and revealed in Chapter Three, the predictive model's field of application can also be expanded to additional Egyptian FMCG wholesalers.

- Because the study only looked at operational concerns and ignored the time aspect, future research can include the time factor in the ML prediction model's parameters. The study can also benefit from using ML prediction optimization as a more advanced technique, which is the process of determining the best values for particular decision variables for a model whose performance is evaluated using the output of a simulation model of the system.

- The Egyptian FMCGs market has several weaknesses and risks, mentioned and explained in Chapter 2. One of the major weaknesses is the fluctuation in exchange rates, which will immediately impact the purchasing price of the product and accordingly will affect the prediction of the EOQ at the end. It is suggested that the input parameters to the model should be adjusted to include a new parameter called the “exchange rate” to be included in the prediction of the EOQ in order to have more accurate results putting in consideration all the market changes.

- The suggested model can be modified in the case of business and new market trends by integrating a larger number of input variables, completing a full economic quantification of costs (ordering costs, inventory holding costs), and covering other logistics activities in SCM (Abdulshahed & Badi, 2018; Yazdani et al., 2017). With the input model parameters adjusted to specificity for the given order, the proposed model can be used to determine the quantity of order for various sorts of commodities.

- The focus of this study covered only one range of the FMCGs products (detergents), and the model addressed the operation of the inventory management related to the FMCGs distributors only. Further research can adjust the model to consider the other distribution operations that were not covered in this research, like transportation and logistics, customer service and packaging and materials. The predictive model developed does not handle disruptions to different ranges of products, although this update can be easily introduced in the Azure ML Studio. Thus, prospective researchers are invited to adapt the model to represent different product ranges taking into consideration the issue of adding the lead time factor.

7.6 Chapter summary

This chapter presented the study's overall findings, followed by a series of recommendations for future research and industrial advances based on the findings of the visit to the case company to discuss the research's concept.

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APPENDIX I

Interview Sample Questions

- **About the company:**

-What is/are the objective(s) of the company?
-Who are the main competitors for the company?
-Who are your customers?
-What is the main business of the company?
-Are you satisfied with the performance level of the company?
-What are the main performance indicators for the company?
-How do you measure the company's performance?
-What issues do you think may affect this performance?

- **Inventory Operation Process:**

-What is the situation of your company's inventory?
-How long do inventories stay in the warehouse in average?
-When do you know you should place new order? And how much do you know to order?
-Did you set the forecast for most items to help you to determine the new order?
-Did you set the safety stock for each item?

- **Forecasts and EOQ determination:**

-How would your company calculate the EOQ?
-How do your forecast tools work?
-How much do you trust your forecast tools?
-How much do you use the historical data in your forecast and from where do you receive it?
-Do you measure the forecast error yourself? Do you adjust the forecasts?
-Should there be more guidelines related to the forecast process?
-How would you appraise your company's current forecasting? how accurate is it?

- **Current applications within demand and EOQ forecasting:**

-When does the company start to use information system to involve into daily operation?
-What functions you are using of your information system?
-How mature do you perceive your company is with AI?
-Where do you believe the greatest potential AI lies within your company and/or industry?
-Which advantages do you believe AI can bring to demand forecasting?
-If AI is not used within EOQ prediction, why?
-How does your company compare to your competitors with AI in SC?
-What prerequisites do you think are necessary to apply AI?
-What difficulties do you perceive with implementing AI in EOQ prediction?