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IMPROVING FORECASTING ACCURACY BY APPLYING LINEAR PROGRAMMING

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AUTHORSHIP STATEMENT

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LIST OF ABBREVIATIONS

CVP – Cost-Volume-Profit Analysis

LP – Linear Programming Models

APP – Aggregating Production Planning

MILGP – Mixed-integer Linear Goal Programming

ANN – Artificial Neural Network

ML – Machine Learning

UPC – Universal Product Code

ABC – Activity-Based Costing

ARIMA – Autoregressive Integrated Moving Average

GARCH – Generalized Autoregressive Conditional Heteroscedasticity

OR – Operation Research

PORS – The Princeton Operations Research Society

GDP – Gross Domestic Product

OPEC – Organization of the Petroleum Exporting Countries

OECD –The Organization for Economic Co-operation and Development

WTI – West Texas Intermediate

USA – United States of America

EIA – Energy Information Administration

BA – Business Analytics

INTRODUCTION

For many of the world's most successful firms, business analytics (BA) is an essential component. However, the definition of business analytics can be rather ambiguous, and it is always changing. BA is a set of methods, skills, technology, and applications for analyzing and investigating business performance in order to achieve strategic structuring and decision making in the future. BA assists businesses in determining future trends, and businesses use this knowledge to develop unique new products and ideas that enable them to stay ahead of the competition by attracting a large number of customers. Business analytics is the act of acquiring, analyzing, and deriving useful conclusions from massive amounts of data. In today's volatile market, businesses of all sizes are utilizing analytics tools to make better decisions. Decision making is a critical phase that can make or break a company's aims (Das, S., Singh., P & Puri., G, 2017).

All businesses strive for profitability, and without it, they will fail to survive in the long run. Better decision making leads to better profits, and in-context decision making is the only method to optimize the results. Profit is a useful metric for determining a company's performance, and it is dependent on a variety of factors such as income, cost of goods produced, and purchase price, and other factors that influence a company's profitability (Kenton, 2019). The term ‘profit' refers to the difference between sales and costs. In order for a company to maximize profits, either the sales value or the cost value must increase, with marginal revenue equaling marginal cost. If we discover a way to increase sales value, we can do it by either increasing product selling prices (maximizing margin) or expanding total sales (sales maximization). Profit maximization has the goal of lowering risk and uncertainty in corporate choices and operations. As a result, the firm's primary goal boosts productivity and efficiency and proper organizational frameworks and management practices have a significant effect on firm efficiency, just as they do on profitability (Goddard, J., Tavakoli, M. & Wilson, J. O. S, 2009). Furthermore, profitability has a direct link to firm success, which plays a critical role in the growth of every company (Fernández & Palazuelos, 2018).

A continual improvement over the business process has a beneficial impact on profitability due to a constantly evolving business climate (Kumar & Harms, 2004). Furthermore, integrating business planning, forecasting, and process management increases firm efficiency because it allows for continuous collaboration with rapid market, sector, and company changes (Pal Singh Toor & Dhir, 2011). In the industries, forecasting approaches are an effective tool for maximizing profits in these processes (Schuh, G., Prote, J.-P., Luckert, M., Hünnekes, P., & Schmidhuber, M, 2019). Recognizing requirements, constraints, risks, and complex variables, and then using them to predict profitability, are important elements. Forecasting models should also be trustworthy, actionable, and combined with quantitative and quantitative approaches (Caniato F, Kalchschmidt M & Ronchi S, 2011). For profit maximization, it is critical to make the right decision about objective and subjective approaches (Stekler, 2015). In economics, producers (also known as firms or companies) are involved in the use of inputs (various factors of production) and the production of commodities and services (output). Firms are critical in selecting what to create and how to generate it and the main objectives of firms are (Khan, 2017):

- Profit maximization.
- Sales maximization.
- Increased market share/market dominance.
- Social/environmental concerns.
- Profit satisficing.
- Co-operatives.

The concept of profit maximization is an important goal for businesses in terms of planning, but establishing this number is challenging due to the difficulties of determining the concepts of marginal revenue (MR) and cost (MC). As a result, calculating the equilibrium point is challenging when these points (MR, MC) are ambiguous or difficult to detect. However, even if managers can decide on these issues, there are still other hurdles to overcome before making a decision. Market, business, and corporate limits and circumstances, for example, limit the decision-making area, and these points (MR, MC, and equilibrium point) are ignored when identifying optimum and then profit-maximizing locations but forecasting techniques were created to assist businesses in making decisions.

When a forecasting approach may reduce the gap between forecast and real values, it improves the precision of the industrial planning process (Haraguchi, Cheng & Smeets, 2017). The most important reasons for ineffective forecasting models are market uncertainty and volatility (Rieg, 2010). When the parameters are facilitated in interaction with forecasting methods in planning, particularly in a context of high uncertainty, forecast accuracy indicators can improve planning efficiency. The items include (Fildes et al., 2015):

- Organizational constraints and the flow of information
- Limited resources
- Combining statistical methods with managerial judgment
- Performance evaluation and monitoring

The aim of this research is to improve the accuracy of profit forecasting by incorporating predictions of profit-influencing factors into Cost-Volume-Profit (CVP) Analysis and Linear Programming Models (LP) for profit maximization. In this master's thesis, a supplementary mathematical model for profit maximization is created instead of existing forecasting methods. It is based on a complementary mathematical model that takes into account both factors that affect profit maximization in order to enhance forecasting methods. This model is based on the Cost-Volume-Profit (CVP) and Linear Programming (LP) methodologies, and it has four variables: the amount of goods sold, fixed costs, variable cost per unit, and sales price, as well as all business, sector, and company-level factors that affect variables. They can be associated in this model and then have an effect on profit maximization calculations. CVP (Cost-Volume-Profit) is a tool for determining a business environment that can be used in both manufacturing and service businesses. The master's thesis demonstrates how to improve decision-making and profitability by combining Linear Programming and Cost-Volume-Profit (CVP) methods (Lulaj & Iseni, 2018).

The first chapter provides a summary of the various forecasting tools, approaches, and techniques used in business processes. The second chapter then discusses the various techniques in terms of qualitative and qualitative approaches. The logics that underpin an integrated forecasting model are discussed in the third chapter, and the fourth chapter introduces a mathematical model based on Linear Programming (LP) and Cost-Volume-Benefit (CVP) for profit maximization. Finally, MATLAB tests this model as a study in the gasoline market in the United States of America to demonstrate how this model can be used in practice in the last chapter. Furthermore, the model's implementation is debated in terms of competitive pricing, price discrimination, pricing on a duopoly market, and peak-load pricing.

1 LITERATURE REVIEW

Forecasting models are divided into two groups in academic literature: quantitative (statistical) and qualitative (judgmental) approaches. When a forecasting model blends two methods for making a decision, it becomes more reliable. At the industry level, combining quantitative and qualitative methods will improve forecasting accuracy (Caniato et al., 2011). If a forecasting model in the business process can predict these variables, such as the number of goods sold, fixed costs, variable cost per unit, and sales price, when taking into account market, sector, and company constraints, as well as dynamic factors that have an effect on variables and correlations between parameters in a model using qualitative and quantitative approaches, then it is considered effective. Since all parameters interconnect in one model for prediction, it can improve the accuracy of a model in a business method (Stastny & Lehner, 2018).

Furthermore, for the prediction and computation of profitability in a business operation, variables such as total cost and revenue, as well as factors that have an effect on variables and constraints at the market, sector, and firm level, are considered. Many studies have shown that there is a strong link between cost, revenue, and profitability (Christopher, 2002a, 2002b; Fontaine, 2004). Furthermore, for improved profitability, rising revenue as well as lowering costs in a system must be considered, with a balance of correlation between variables such as cost and revenue. Using strategic management accounting strategies, cost forecasting, revenue, and profit over a business process with financial and non-financial details have a positive effect on a company's performance and competitive advantage (Abdelmoneim Mohamed & Jones, 2014). In modern production planning, aggregating Production Planning (APP) with the goals of reducing costs, optimizing sales, and then maximizing profit is a top priority. Robust Optimization, Simple Linear Programming, Stochastic Programming, Pre-emptive GP, Mixed-integer Linear Goal Programming (MILGP), Mathematical, Robust Optimization/ mixed Integer Nonlinear Programming, Fuzzy Mathematical, Game Theory, and other methods that increase optimization and then profitability in a business process have all been used to boost APP (Cheraghalikhani, A., Khoshalhan, F & Mokhtari, H, 2019). An intended goal is to improve optimization by determining the optimal amounts of profit maximization components using a mathematical model that takes into account variables such as controllable and uncontrollable, financial and non-financial, interior and exterior parameters that have an effect on components in a market, business, and firm level, and alignment between the production system and business process. Predictive analytics plays a big role in determining whether to use quantitative or qualitative approaches to estimate past and future patterns, as well as how to use them (Waller & Fawcett, 2013; Schoenherr & Speier-Pero, 2015). Because of the importance of interconnection between forecasting models and profitability, stochastic programming was used to increase profitability in the form of linear programming models (Suvrajeet Sen, 1999; Birge & Louveaux, 1997; Kall & Mayer, 2005) and robust optimization (Mulvey J.M., R. Vanderbei, S. Zenios, 1995). There are gaps in the literature between managerial decision-making and economic theories focused on linear programming and mathematical models (Dowling, 1992; Dwivedi, 2008) and linear programming for multi-layer, multi-product reverse supply chain cost minimization in industrial sectors (Mahmoudi & Fazlollahtabar, 2014). Dowling (Dowling, 1992) addressed an advocate of linear programming (LP) for using many inequality constraints for optimization, which was then applied in business decision-making to optimize resource allocation (Dwivedi, 2008). Many studies have looked at how to improve resource management in manufacturing industries by using linear programming (Mechleri & Arellano-Garcia, 2018; Li et al., 2006; Maqsood et al. 2004). Decision variables, environmental parameters, and results were the three components of linear programming models as an essential tool in profit optimization, with the first and second components being uncontrollable and the last one being dependent (Dantzig, 1998; Dwivedi, 2008) and another researcher worked on maximization of total income by the use of linear programming for the integration of various departments that are dependent on production system management (Adeyemo, J. & F. Otiero. F, 2009). According to studies, LP is important and successful in the maintenance phase of manufacturing companies, and it is one of the top-ranking techniques of operation research in the case of modeling economic impact (Paris, 2016). The use of LP was used to develop a specific algorithm for optimizing energy recovery resilience (He, Ng & Su, 2017). LP is also used in the optimization of residential energy systems for surveying and planning the optimum investment in this sector (Lauinger, D., Caliandro, P., Van herle, J., & Kuhn, D, 2016) in order to boost long-term profitability of businesses. Before going any further, it's important to understand that total cost and revenue are two pillars of profit that must be calculated as part of a Cost-Volume-Profit (CVP) analysis. Time series forecasting models are used for demand forecasting, which has a direct effect on profitability. Furthermore, since historical data is uncorrelated, previous data is useless for forecasting, and experts are unable to forecast (Firmino, P. R. A., de Mattos Neto, P. S. G., & Ferreira, T. A. E, 2015). Factors that constantly change markets should be considered as a parameter in forecasting models to increase predictability (Thomson, M. E., Pollock, A. C., Önkal, D., & Gönül, M. S, 2019). This production method has a stronger outcome in terms of profitability when the number of goods sold is the same as the production volume based on just-in-time reasoning for removing the cost of inventory, which can be considered in a Cost-Volume-Profit (CVP) analysis (Fullerton & McWatters, 2001). The market positioning of goods on competitive markets is a prominent and controversial topic in terms of pricing, which is another dynamic principle for making a decision. Pricing a product is difficult because it is dependent on product supply and demand, which makes the pricing system more complex (Sen, 2014). Total revenue is measured using the sales price, the number of goods sold, and the total cost, while cost is determined using fixed costs and variable cost per unit compounded by the number of goods sold (or production volume if the "just in time" principle is used).

1.1 Approaches in Forecasting Methods

One of the significant sections of profit maximization is the forecasting of these variables as systematic guesses of future events (Kurzaki, 2012; Fildes, 2008). Many features of forecasting exist, such as the planning process and the relationship between it and future events. A research that looked at the sales behavior of a medium-sized business using two models, namely Artificial Neural Networks (ANN) and the time series forecasting model, found that ANN is more reliable than time series because it takes into account unpredictable circumstances when making decisions. Many businesses have struggled in these complex and competitive markets due to a lack of reliable forecasting. Moreover, reliable forecasting has a close relationship with planning, which reduces the risks of volatility and plans a better combination of different types of labors, balanced work-load, reduction of production fluctuation, optimization of production facilities, better inventory management, better customer service, and better use of capital and resources with facility design. Forecasting demand is one of the most critical criteria that businesses must consider. It is better than forecasting that the output volume will be the same as the market demand, providing the possibility of warehousing cost savings, based on just-in-time theory and optimum production volume. Other costs associated with overproduction would be minimized as well (Aradhye & Kallurkar, 2014). Furthermore, many methods and techniques for estimation of important variables in production processes, such as econometric (Indirect Approach) and non-econometric (Direct Approach) techniques, have been used to estimate the variable at different times (Perera, H. N., Hurley, J., Fahimnia, B., & Reisi, M, 2019).

1.2 Dimensions in Forecasting Models

Forecasting models can be classified into two classes, both of which contain quantitative and qualitative methodologies, as stated before in this section. Aside from the two categories for classifying forecasting strategies, Table 1 lists a number of other (objective and subjective) approaches with a variety of dimensions. When we talk about objective methods, we're talking about global methods, which consider all available time series to estimate model parameters all at once, while local methods only consider specific time series for estimation. To put it another way, global methods jointly survey a forecasting problem, while local methods do so independently. When it comes to probabilistic and point forecasting, probabilistic forecasts offer an estimate for all potential future outcomes of a random variable, while point forecasts only consider one prediction. As a result, in most mathematical disciplines, linear and non-linear forms such as convexity and linearity can be used to approximate forecasting methods. In terms of subjective approaches, a data-driven approach is associated with Machine Learning (ML), which entails developing an algorithm for data connection and correlation. The model-driven approach, on the other hand, focuses on gaining a thorough understanding of a system or method. To differentiate between single and complex approaches, the ensemble and single models are used. Where there are multiple forecasting models, the ensemble method attempts to incorporate the multiple models as single-based approaches for improved forecasting, resulting in less forecasting errors (Rokach, 2010). In terms of the distinction between generative and discriminative approaches, the generative approach focuses on top-down models, while the discriminative approach focuses on bottom-up models, as described in statistics and machine learning. The last dimension, in terms of subjective category and explanatory, precisely explains what is occurring, while interpretable predicts what will occur. Forecasters can use subjective forecasting to predict outcomes based on their own opinions and feelings. Subjective forecasting relies on brainstorming sessions to create ideas and solve problems in a nonjudgmental, peer-pressure-free environment. When time restrictions prevent objective forecasting, these sessions are frequently used. Decision-makers should be suspicious of subjective forecasts since they are vulnerable to biases.

Table 1: Summary of Dimensions for Forecasting Methods.

Category	Dimension
Objective	Global vs. Local Methods Probabilistic vs. Point Forecasts Computational Convexity Linearity & Convexity
Subjective	Data-driven vs. Model-driven Ensemble vs. Single Models Discriminative vs. Generative Statistical Guarantees Explanatory/Interpretable vs. Predictive

Source: Januschowski et al. (2019).

2 A REVIEW OF METHODS FOR FORECASTING OF DEMAND, COST AND SALES PRICE OF A PRODUCT

For forecasting, there are two types of models: qualitative and quantitative models, which are briefly described in this section. When it comes to qualitative models, the models' characteristics are based on human judgment, opinions, and are subjective and nonmathematical, but they do have strengths and weaknesses. These models have the ability to adapt to recent changes in the environment, which is one of their advantages. The following are some examples of qualitative methods:

1. Survey Method
2. Complete Enumeration Method
3. End-user Method of Consumers (user expectation method) Survey
4. Consensus Methods:

4.1 Expert's Opinion Poll,
4.2 Reasoned opinion – Delphi Technique

5. Market Experimental Method:

5.1 Customer Surveys
5.2 Consumer Panels
5.3 Test Marketing
5.4 Scanner Panel Data

Qualitative approaches, on the other hand, can bias the forecast and reduce the accuracy of forecasting models. These models for prediction based on an interview, discussion, and observation include unstructured data and subjective conclusions. In this section, you'll find a list of various quantitative analysis methods (Carrasco & Lucas, 2015). Among the quantitative approaches are:

1. Time Series and Trends
2. Barometric Techniques or Lead-Lag Indicators Method
3. Correlation and Regression and the Method
4. Compound Growth Rate
5. Moving Average Method
6. Simultaneous Equations Method

2.1 Qualitative Methods in Demand Forecasting

The survey method is a direct methodology that is used by a business to forecast potential customer demand by predicting market demand based on a statement of one or more groups for making a decision. Many techniques of the surveying method are explained in this section of the collection of methods (Holdsworth, J. C., Hartill, B. W., Heinemann, A., & Wynne-Jones, J, 2018). In contrast to other types of qualitative research, the complete enumeration method is a comprehensive survey of all members of the entire population, which can be identified as customers, consumers, and other criteria that are used for calculation. However, the method has major problems with data collection and surveying when businesses must quantify a large number of customers, consumers, and goods in markets and industries. Besides that, the system and procedure are time-consuming and inefficient since the forecaster is unable to collect data from all customers for review. Furthermore, correctly collecting data from all representatives of the entire population is impossible. Last but not least, consumer behavior has been evolving all the time, and many times, consumers do not have enough knowledge about their potential actions because they change their behaviors in response to changing market, industry, and/or company conditions (Aultman-Hall, L., LaMondia, J. J., Ullman, H., & Suender, M, 2018). By comparing the sample survey approach to the previous method, researchers consider a few consuming units and the data collection is less expensive. Furthermore, selecting and analyzing a sample is much simpler than analyzing the entire population. Furthermore, this survey allows researchers to make less data errors. The model, on the other hand, is not comprehensive and does not survey the entire population. Predictions are based solely on the opinions of samples, and if the sample is not chosen in such a way as to reflect the entire population, false predictions will result (Cassel & Lyberg, 2001). Consumers use the end-user approach (user expectation method) to survey customer intentions in order to forecast future demand. This model includes a product end-user, but how do companies find end-users for measurement when industry data isn't readily available, which is a complex problem, particularly for consumer goods? Another issue with these forecasting models is the shift between customers and non-users of the product or service, since consumers cannot predict their future actions in competitive markets. Dynamic variables are shaping end-user behaviors in the marketplace, as mentioned previously, but companies have not used these forecasting models (Abdar & Yen, 2018). Consensus methods are a bottom-up survey technique that is known as qualitative methods for forecasting as an alternative tool for forecasting. They start with a small group and expand from there.

Expert opinion polling and the Delphi methodology are two approaches for reaching a consensus. The expert opinion poll methods are based on a selection of expert opinions from people who know a lot about the market, sales representatives, business, and/or organization. Customers are directly connected to the groups, allowing them to consider how they respond to market changes. While the models are more realistic because they understand the market's practical dynamic variables, they have a number of flaws and severe limitations. In reality, the method's reliability is determined by the researchers' abilities and knowledge. Another significant issue is assessors' subjective judgment. Besides this, there are issues with consumers' and markets' confidence in these experts and their evaluations, moving qualitative to quantitative data for decision-making, finding the right marketplace, consumer, and answer in the right time, only considering users and not non-users, and so on (Ivanova, Z., Pichugin, I., & Naimaviciene, J, 2015).

Delphi techniques are a form of systematic forecasting that depends on a group of experts. Experts replied to questioners, who were then summarized by facilitators for clarity of responses. For taking expert input, the procedure is repeated more than twice. The Delphi method is an exploratory method that prioritizes qualitative responses over quantitative ones. In other words, as the process of achieving consensus progresses, the variability of responses decreases. Furthermore, with the repetition of the procedure, the approach aims to find a consensus in an uncertain zone. The method itself has significant performance limitations, such as:

- Selection of right experts
- Creation of appropriate and high-quality questions
- Extraction of the right response from questionnaire
- No comprehensive method
- Relying on experts, no customers, and users
- Unstable market situation
- In this process, no dynamic factors are taken into account, and only expert opinions are taken into account. (Rowe & Wright, 1999).

The market experimental approach conducts experiments with a selection of influential knowledge about the current and potential demand for the commodity in response to changes in market conditions. The approach analyzes the effect of substitution and other parameters on consumer behavior in a particular segment of the population, as well as different income levels and consumer preferences. Consumer survey as a market experimental method includes a survey of potential Furthermore, demand is forecasted based on price changes as well as other factors such as expenditure. Customers may be surveyed using a variety of market analysis methods, such as individual customer surveys, user panels, test marketing, and scanner panel data (Ryals & Wilson, 2005). Customers are interviewed over the internet, on social media, in online gaming forums, and/or in shopping malls, among other methods. For the purpose of forecasting potential sales, researchers are collecting information about their interest in buying the product. In fact, forecasters use the method to learn about the product's attractiveness and unattractiveness, and then use that information to predict future demand (Eigenraam, A. W., Eelen, J., van Lin, A., & Verlegh, P. W. J, 2018).

In consumer panels, which is another form of grouping, prospective consumers are grouped together in one room and then begin to talk about the product after using it. The organization is limited in size, and the corporation provides several incentives in return for participation. Consumer panels are more useful for identifying product characteristics than for forecasting demand (Song, M., Park, E., Yoo, B., & Jeon, S, 2016; Valkila, N., Litja, H., Aalto, L., & Saari, A, 2010).

Test marketing, as a market research tool, is concerned with the introduction of a new product into a specific geographic segmentation. After positioning the product on a particular market, the representatives monitor and evaluate the demand for and exposure of the product once it has been launchedIt is a popular method of sales forecasting for businesses prior to launching a large-scale product. Consumer products, such as sales-wave analysis, simulated test marketing, regulated test marketing, test markets, and industrial goods, such as Alpha testing and Beta testing, all use the test marketing approach for demand forecasting (Carlson, 2013).

The scanner panel data procedure is based on a valuable database of observed consumer purchasing behavior that is captured at checkout by UPC codes and optical scanners. The database contains useful information about products, sizes, prices, and other variables that are useful surveying parameters.

The other aspects of the supply chain are not included in this study because data is only collected from groceries and checkout devices (Castellari, E., Moro, D., Platoni, S., & Sckokai, P, 2018), and these methods have several advantages and drawbacks, which are mentioned in Table 2.

Table 2: Summary of Advantages and Disadvantages of Selected Qualitative Methods.

Methods	Advantages	Disadvantages
Sample Survey	A small number of consuming units is considered, which is less expensive and time-consuming than analyzing all populations.	Prediction is based on a sample of observations; it is not a systematic process, and market variations are not included in the output.
Complete Enumeration Method	It is a systematic study because it considers all samples, in contrast to any sampling approach that only surveys a small portion of the entire population.	It's very expensive because the process requires collecting data from all users for analysis, which is impossible because there's a lot of data to collect.
End-user Method of Consumers (user expectation method) Survey	It's an effective way to focus on consumers and end-users.	The model's goal is to find end-users of a product, but finding them can be difficult, so it simply makes a decision based on its performance. Customers are also modifying their attitudes as a result of the factors that influence their intentions.
Consensus Methods (Expert's opinion poll, reasoned opinion – Delphi technique.)	The models are based on a selection of expert opinions from people who know enough about the business to be able to survey it. The benefit of these surveys is that they take into account the opinions of experts with sufficient knowledge and experience of business and industry dynamics.	The method's reliability is determined by the researchers' abilities. If experts are poor in this region, the output and decision-making based on their opinions will be a problem for forecasting.
Market Experimental Method (Customer surveys, consumer panels, test marketing, and scanner panel data)	The model's benefit is that it collects key information about a product's current and potential demand, taking into consideration current market conditions when forecasting. It can also be paired with other forecasting methods.	The business situation is complex and constantly evolving. In this approach, there is a high risk of human error, and participants will influence the current situation. The development of an implausible scenario based on a tainted and incorrect judgment.

Source: Own work.

2.2 Quantitative Methods in Demand Forecasting

These models are focused on mathematical equations and numerical data, with a more objective approach. The model can deal with a lot of data and knowledge, as well as structured data, statistical analysis, and objective conclusions, but the lack of quantitative models is a flaw. In general, there are a variety of quantitative models that can predict performance based on historical data, and these models are mentioned in Table 3. (Rutberg& Bouikidis, 2018).

As a quantitative model, time series and trends are based on the compilation of a sequence of observations (numerical data) at frequent and informal intervals over time. One of the method's assumptions is that the past will repeat itself in the future, necessitating a set of data for forecasting, but the method has both advantages and disadvantages for forecasting. In terms of advantage, it does not require any assumption on underlying activity (economic knowledge) for forecasting, and in terms of disadvantage, it is a methodology better suited to short-term forecasts than long-term forecasts. Finally, secular trends, seasonal variation, cyclical variation, and irregular variation are all included in the process. There are many different types of trends that can appear on a time-series graph, including the straight line, exponential line, and quadratic line (Lim, 2018). When it comes to barometric techniques, also known as the Lead-Lag indicators system, the method forecasts future demand using historical data from the product and economic indicators. The product's future trends are clarified by economic indicators, and demand is forecasted based on movement in the index of economic indicators. Many indicators are included, including leading, coincidental, and lagging indicators (Jugović A, Hess S, Poletan Jugović T, 2012).

Another approach is correlation and regression, which examines the statistical relationship between two variables or groups of data. Correlation slopes are negative or positive, and a straight line is used to estimate correlations between variables between one dependent variable and one or more independent variables. The second approach uses statistical analysis to demonstrate the effect of adjusting independent variables on a dependent variable. Regression analysis methods include linear regression, ordinary least squares, logistic regression, lasso regression, elastic net regression, and others (Hribar, R., Potočnik, P., Šilc, J., & Papa, G ,2019).

A mathematical formula with the name of the compound growth rate can also be used for demand forecasting over a specific timeframe. The formula calculates the value at the end of the measurement using a constant growth rate and the sum of value at the start of a given period. Actually, the approach has a wide range of applications that can be discussed, including communicating average investment fund returns and comparing investment advisor results. Forecasting future values of a data series is another popular application of this approach. Last but not least, it can examine trends in a variety of business metrics such as revenue, market share, costs, and efficiency over time (Jagerson, 2018), but it does so using a constant growth rate. Another technique for demand forecasting is the moving average method, which is used for technical analysis with the help of historical data when there is a pattern.

Simple moving average and exponential moving average are two common moving average strategies. Simple moving average accounts for a simple average of all given numbers and gives more weight to recent numbers in turn. If there are two unknown variables in one equation that cannot be solved by a single solution, the simultaneous equation approach can be used to solve the problem using two equations. There are many types of methods for solving equations, including reduction, substitution, and using a straight-line graph (Yang & Lee, 2018).

Table 3: Summary of Advantages and Disadvantages of Selected Quantitative Methods.

Methods	Advantages	Disadvantages
Time Series and Trends	For forecasting, the technique makes a decision based on a series of numerical data over a period of time and does not require economic expertise.	For forecasting, a set of data is needed, and if one is not usable, the model will be useless. Furthermore, the method is suitable for the short-term but not for the long-term.
Correlation and Regression and the Method	Forecasting future results, or making projections and forecasts, is one of the most popular applications for these techniques. Another advantage of these forecasting methods that can evaluate the outcomes and correct errors is that they can improve business performance by supporting business decisions.	On the other hand, there are several flaws in the methods, such as poor data, human error, and incorrect queries, and regression is vulnerable to outliers because they can have a significant impact on the regression.
Compound Growth Rate	The compound growth rate is an effective tool for evaluating the performance of various portfolios, as well as a stock's performance in relation to other stocks in a market forecast.	Since there is a constant rate in this technique, the fact can often vary from the expectation since volatility will alter the trends of a rational assumption. Furthermore, historical data and trends are not always

		accurate forecasting sources, which the model relies on.
Moving Average Method	The model can be used to calculate both linear and non-linear trends for any sequence. Besides that, this approach provides a smoothed graph, which is a significant benefit.	The approach is not applicable for a limited period of time, despite the fact that trend values are not available for certain periods.
Simultaneous Equations Method (Using a straight line graph, solution by elimination, solution by substitution)	When there are two unknown variables in a single equation and no single solution can solve the problem, the model comes in handy. The approach could be used, for example, where there are supply and demand calculations in a commodity market.	When data has aggregated quantities, the consistency of the simultaneous equation approach is called into question.

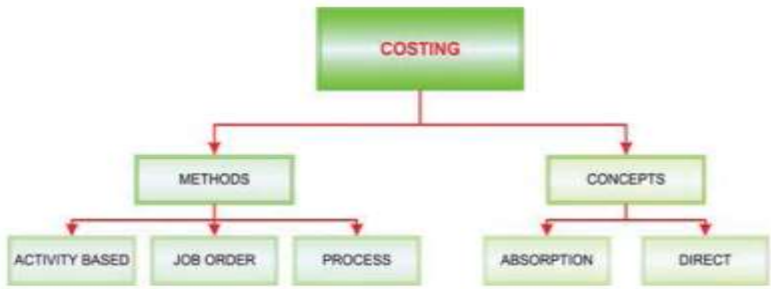
Source: Own work.

2.3 Cost Forecasting

Cost can refer to the amount of money, time, and labor that is needed to spend on products or services, and cost in business, retail, and accounting is the sum of money spent on producing something or acquiring something during the business process (Bertoni & Bertoni, 2018). Over the course of a business operation, costs are broken down into fixed and variable costs, direct and indirect costs, long-term and short-term costs, and so on fixed costs do not fluctuate with changes in production; in fact, even if the business has no output, it must pay this expense. Fixed costs include, for example, the procurement of supplies, executive salaries, the leasing of a manufacturing site extension, and these specific costs. Variable cost, on the other hand, is affected by the level of output and is most closely linked to material costs; additionally, both are variable in the long run as output rises (Novák & Popesko, 2014).

Direct costs in a production system, such as material costs and labor costs, are traceable, while indirect costs, such as energy, are untraceable or less traceable. Account analysis, engineering method, high-low approach, and linear regression analysis are only a few of the many approaches for estimating overall costs. Total costs in these methods are directly proportional to the amount of output, but accounting costs, which classify all costs as either fixed or variable, is a simple method to compute total costs based on the input costs of each production step as well as fixed costs (Larry & Christopher, 2017). The engineering approach, as previously discussed, is another method for total cost estimation, and it is the proper method for estimating direct material costs. It is also a method for estimating the total cost of a product when the product has not yet been manufactured and there is no data from the previous processes (Xu et al., 2012). Another approach to estimating total cost based on high and low levels of output is the high-low approach, which determines total cost by taking into account high and low levels of production and calculates total cost using a cost volume formula (Kenton, 2019 Regression analysis is a system of mathematical equations for estimating the best fit line between a set of data points, which is another realistic tool for estimation. Another technique that is similar is the scatter graph method, which takes into consideration more than just the highest and lowest levels of activity. A horizontal x-axis and a vertical y-axis with a representation of production operation and a cost in turns make up the process (Kenton, 2018). Companies can estimate costs using a variety of methods and techniques, including parametric cost estimates, neural networks and expert, function costing, feature costing, and group estimation, all of which are categorized differently in Figure 1.

Figure 1: Different Concepts and Methods in Costing.



Source: Walther & Skousen (2009).

Process costing (Wood, 2015), which assigns costs to production units, is one method for mass production of a homogeneous commodity. But in the other hand, an approach known as job-order costing assigns all costs in one particular product for calculation, and this method is suitable for estimating production costs when units of production differ significantly from one another (Bertoni & Bertoni, 2018). It is possible for a manufacturing company to use both processes in its operations. In addition to the previous two strategies, activity-based costing (ABC) defines and organizes operations within a company before assigning costs to each one.

In general, costing terms are divided into two categories: absorption and direct. In terms of absorption, all production costs, including direct materials, direct labor, variable manufacturing costs, and fixed manufacturing costs, have been allocated to the unit's manufactured or finished product. Variable production costs, on the other hand, are only considered in the context of the direct measurement principle. Furthermore, since it only considers variable costs, the direct costing principle is useful in the short term (Walther & Skousen, 2009). A good business has a strong tie to forecast costs when it comes to cost estimations and forecasting techniques, and this capacity is critical for increasing profitability in the process. In supplement to this topic, the standard of forecasting depends on the company size, sector, equipment, financial system, etc. Besides that, effective cost forecasting is advantageous in terms of production trends, pricing, competitive strategy, potential expenditure, and optimized input and output values (Hatamleh, M. T., Hiyassat, M., Sweis, G. J., & Sweis, R. J, 2018), which is divided into two data analysis techniques.

2.3.1 Qualitative Techniques in Cost Forecasting

When it comes to cost estimation and forecasting techniques, qualitative techniques are the first, with several sub-techniques that are applicable to mainly exploratory analysis, such as expert opinions on potential production costs. Analogous cost estimation for a comparison of two items, such as systems and goods, is one of the sub-techniques. The target product's cost is calculated by comparing it to a comparable product, based on the premise that the costs of similar goods are similar. The back-propagation neural network model is a data processing approach that aims to simplify a complex network structure. Each complex network, according to the method, is made up of basic processing that can be abstracted in a straightforward manner for better forecasting. Back-propagation is a common and simple process that is made up of three layers of neurons: input, multi-layer, and output. The gradient of the error function is determined in relation to the weights of the neural network. As a consequence, the approach is used in forecasting approaches involving the simplification of a complex network and the study of data transformation within a simple process. The input data is represented by the first layer, which is referred to as the input layer, and this approach works by approximating the non-linear relationship between the input and output by assigning weight values in a multi-layer system (Hecht-Nielsen, 1992).

Intuitive approaches, which include case-based techniques and decision support techniques, are other sub-techniques of qualitative techniques. In the case of the first, an approach focused on an exploration of parallels between old and new problems and on previous experience for solving previous problems is attempting to solve a new problem that can be used for cost forecasting based on previous experience. For cost measurement, techniques such as nearest-neighbor indexing, inductive indexing, and intuitive knowledge-based indexing are used in addition to the methodology. The method of making the best choice between two or more alternatives is addressed by decision support techniques.

Since a decision-maker must forecast the successful parameters and then make a future decision, combining decision-making approaches with forecasting models is necessary. When a model combines forecasting approaches with decision-making strategies, the outcomes are more reliable (Machina, 2005; Hamel, 2018; Moon, 2015; Uyar & Kuzey, 2016; Pradhan, 2010; Schoute, 2009; Kim, 2004; Meigs, 1998).

2.3.2 Quantitative Techniques in Cost Forecasting

Another cornerstone of cost estimation techniques, as mentioned in the previous section, is quantitative techniques, which are divided into two sub-techniques: parametric and analytical techniques. The first technique, called metrics, is based on equations for cost estimation. Historical evidence for cost calculation, such as multiple regression analysis, is one of the existing parametric cost estimation approaches (Gunduz, M., Ugur, L. O., & Ozturk, E, 2011).

Another model, which is dependent on safety stock, predicts production costs based on used stocks and historical production trends. They specifically add an additional 20% to estimate a rising rate of cost. As a result, a manufacturing firm establishes a specific rate of growth based on the previous estimate, and then estimates the cost based on potential unforeseen expenditures (Creighton, 2014; Sthl, 2012).

The parametric technique is a structured estimating method that uses a series of mathematical equations to estimate variables based on past events. There are several alternatives to one analytical technique, such as activity-based cost estimation, operation-based cost estimation, feature-based cost estimation, and the breaks down approach. For estimation, the activity-based method breaks down a product's related costs to the smallest activity level. In other words, the method estimates the cost of a product by breaking down production costs based on activities; if it breaks down based on the operation process, it is called an operation-based approach**.** Furthermore, the cost of output or commodity is broken down by the type of operating process.

Furthermore, it is called featured based on cost estimate whether it is broken down based on product or development features. Besides that, cost forecasting can be done in a variety of ways, including top-down and bottom-up methods. In terms of the top to down approach, it forecasts costs using historical data, but when more accurate information about the product, demand, and project is available, a bottom-up approach is used to forecast costs (Hueber, 2016).

Last but not least, the analogical approach is a tool for cost estimation that relies on historical data. As previously discussed, the regression analysis model is a statistical equation that depicts a relationship between one independent and one dependent variable. It is one of the most widely used and simplest techniques in market research. The method has many key benefits for researchers for usage. For example, the method demonstrates a significant relationship between independent and dependent variables, as well as the relative strength of the relationship and also the effects of independent variables on dependent variables, which researchers can use in market analysis for use in various statistical models for forecasting (Chen, X., Li, H., Liang, H., & Lin, H, 2019).

2.4 Price Forecasting

There are many similarities between market, cost, and demand forecasting methods and approaches; additionally, many techniques have several applications in pricing, cost systems, and demand forecasting. Cost-based pricing as a production cost-based is one of the best and easiest methods for pricing. Full cost and direct cost are two types of calculation methods, but full cost covers fixed costs, variable costs, and a percent markup, while direct cost only includes variable costs and a percent markup.

Companies maximize their output until marginal revenue intersects marginal expense, at which point profit maximization is pursued, and then charge a price based on this forecast. A markup is also the difference between a product's cost and its selling price. The method is one of the easiest methods for price forecasting since it does not require complex calculations and only requires a small amount of data (Zhang & Huang, 2014).

Time series, data mining, and simulation are three types of market forecasting methods that can be used to forecast the price. There are three sub-techniques within the time series category: linear regression, stochastic, and non-heuristic The artificial natural network, which is analogous to neurons in the brain and has three layers for forecasting, was discussed in notes from previous forecasting models. T the approach is used to forecast prices by analyzing the relationship between input and output variables (Tealab, 2018). Another time series strategy that is applicable to stochastic characters for short-term planning is the use of time series. Jumped diffusion (Hess, 2017) and geometric Brownian motion are the models used in this group. In reality, in option pricing, jump-diffusion uses last historical movement prices for forecasting future prices, as well as a combination of a jump and a diffusion mechanism. (Prakasa, 2016).

Regarding the third technique, autoregressive integrated moving average (ARIMA) is a common time series forecasting tool used in the gas and oil industries for price forecasting. As a practical technique, many countries such as Norway and Spain have used it and obtained reasonable results. The model has three parameters: x, y, and z, with x denoting an autoregressive model, y denoting the degree of difference, and z denoting a moving-average model. Positive integers are used in the parameters, as well as seasonal and non-seasonal versions (Ohyver & Pudjihastuti, 2018).

Another technique in this group is generalized autoregressive conditional heteroscedasticity (GARCH), which is used when the variance or volatility of a sequence changes over time (Hafner & Herwartz, 2001). In terms of data mining, which is a subcategory of price forecasting methods, the method has applications in travel, electricity, stock, home, and commodity price forecasting as a process of transforming a large amount of data into effective and usable knowledge for use in operating systems, for instance, production lines, product development in marketing, data dredging for investigations into low-quality research papers with weak hypotheses, and artificial intelligence. It's also a tool for finding patterns in a vast amount of data and then using those patterns to create an information system (Yang, 2019).

Fuzzy logic is a data mining method that has been used in a variety of projects and industries. The techniques, in reality, are the polar opposite of true or false logic (binary system (1 or 0) and attempt to operate on the basis of degrees of truth. Another description of the technique is the manipulation of ambiguous knowledge about degrees of fact. According to the process, there are millions of numbers between 0 and 1 that can be used to describe unknown data (Al-Mousa & Faza, 2019). Another mining methodology is concerned with the estimation of nonlinear variables that are difficult to predict. Climate change, weather, the stock market, and the IT mechanism all use chaos theory to forecast complex variables. The stock market is a good example of a chaotic market. When the value of a stock begins to fluctuate, the number of people interested in selling or purchasing the stock increases, causing the stock market's value to rise and fall. Initial state, a series of equations, mathematical models and simulations that are described functions of the system, and final condition are the three parts of the model. This is a chaotic system if the outcome is entirely different from another result; otherwise, it is a non-chaotic system (Klioutchnikov, 2017).

Game theory as an analogical method for estimation (Kreye, M., Goh, Y.M., Newnes, L.B, 2009) is an interconnection technique between companies for making a decision, as stated in the last category. As a result, one organization makes a strategic decision based on the strategy of another, and the approach helps businesses make strategic decisions. Game theory can also be applied to economics, industry, finance, and politics. In terms of the method's application in pricing strategy, game theory players make decisions on various strategies based on their outcomes. Pure strategy is used when players try to maximize profit and outcomes, but mixed tactics are used when they want to take the best possible result. As a result, Nash equilibrium refers to the point at which neither player will change their pricing strategies (Sepahi Chavoshlou, A., Arshadi Khamseh, A., & Naderi, B, 2018). Taking all from chapter two into account, all of the techniques listed will assist in defining tolerances for variables and constraints such as the amount of products produced (as production volumes), fixed costs, variable cost per item, and sales price, and then this model is presented as a complement to all of the methods and techniques that have been described. Figure 2 summarizes all approaches, procedures, and strategies for easy reference.

Figure 2: Summary of Methods, Approaches and Techniques for Definition Tolerance of Variables, and Constraints.

These methods may be used to define a **price tolerance** for this supplementary mathematical model.	Cost-Based Pricing, Time Series, Data Mining, Simulation, Linear Regression, Stochastic and Non-Heuristic, Artificial Natural Network, Stochastic Characters, Jump Diffusion, ARIMA, Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Data Mining, Fuzzy Logic, Chaos Theory, Game theory, etc.
For this supplementary mathematical model, these methods may describe **demand tolerance.**	Complete Enumeration Method, Sample Survey Method, End-user Method of Consumers (User Expectation Method) Survey, Consensus Methods, Experts Opinion Poll, Reasoned Opinion – Delphi Technique, Market Experimental Method, Customer Surveys, Consumer Panels, Test Marketing, and Scanner Panel Data, Barometric Techniques or Lead-Lag Indicators Method, Correlation and Regression and the method, Compound Growth Rate, Moving Average Method, Simultaneous Equations Method, etc.
For this supplementary mathematical model, these methods may describe **cost tolerance.**	Account Analysis, Engineering Method, High-low Approach, Linear Regression Analysis, Scatter Graph Method, Parametric Cost Estimates, Neural Networks and Expert, Function Costing, Group Estimation, Process Costing, Activity-based Costing (ABC), Primarily Exploratory Research, Opinions of Experts, Analogous Cost Estimation, Back-propagation Neural Network Model, Three Neurons Layer, Case-based Techniques and Decision Support Techniques Nearest-neighbor Indexing, Inductive Indexing, Intuitive knowledge-based Indexing, Decision Support Techniques, Parametric and Analytical Techniques, Model Logic Method, Activity-based Cost Estimation, Operation Based Approach, Feature-based Cost Estimation, Top to Down Approach, A Bottom-up Approach, etc.

Source: Own work.

3 AN INTEGRATED FORECASTING MODEL

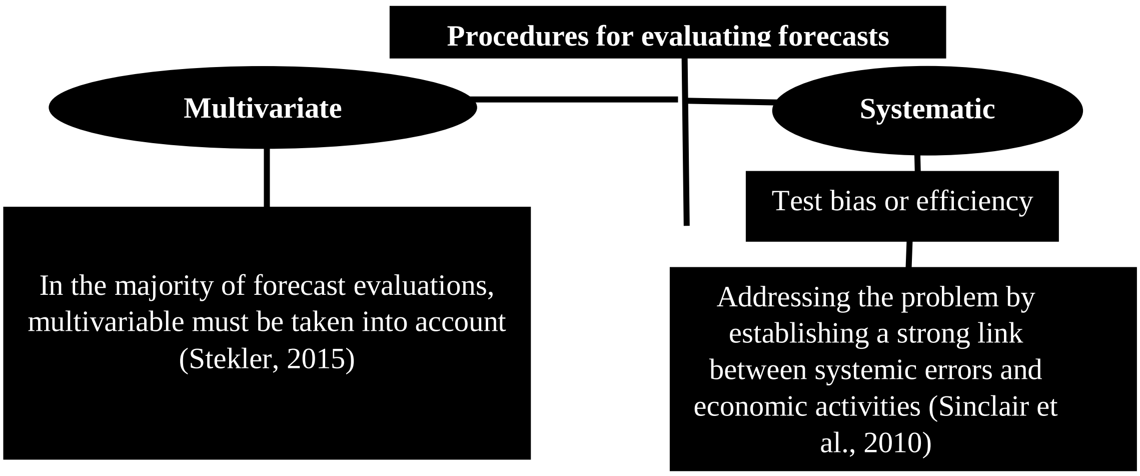
With regard to the first component of the profit formula, cost estimation models should be accurate because markets are competitive, and methods must interconnect with other methods for calculation rather than relying solely on past patterns for decision making. Furthermore, they are unable to evaluate multiple products at the same time and do not account for the fact that markets can be affected by complex factors. In addition, the models do not use dynamic market, industry, or company variables to estimate costs over time and then maximize them (Salmi, A., David, P., Blanco, E., & summers, J. D, 2016; Niazi, 2006).

Researchers need exact and dynamic demand forecasting for prediction of the number of goods sold (as production volumes) based on parameters that have a direct and indirect effect on demand and the production volume when it comes to demand forecasting for prediction of production volume, which is the second component of the profit formula. Besides that, a single model and methodology is not a comprehensive tool for measurement; rather, all elements, such as the number of goods sold, fixed costs, variable cost per unit, and sales price, must be combined for profit maximization prediction (Hyoduk Shin & Tunca, 2010; Armstrong, 2002; Armstrong; 2006). Pricing is a prominent and controversial topic for the market positioning of products into competitive markets, since it is the final factor and another dynamic concept for making a decision. Pricing a product is difficult because it is dependent on product supply and demand, which complicates the purchase price in a pricing system (Soumya Sen, 2014).

These models have a lot of errors and weaknesses when it comes to forecasting the future, and they've worked out the characteristics of forecasts (Günay, 2018). According to researchers, forecasting models are often incorrect, and accuracy decreases as the forecasting period lengthens. The first is that aggregate forecasts are more accurate, forecast models are not realistic when there is no data, and even the availability of a single number is not practical. For the estimation of the mean value and standard deviation, data must have a sequence of numbers. When it comes to the reasons for the existence of the characteristics, they are often linked to forecasters and other times to dynamic factors that alter business, industry, and company parameters. Human factors can affect the outcome of models by causing errors in decision-making (Shahriari, M., Dessy, Aliandrina., Yan, F, 2005). Even a minor adjustment can lead to a significant improvement in the outcome (Nenova & May, 2016). Looking at these errors, one of the reasons as a parameter that causes the performance of the models to shift is the self-interest of experts, managers, and forecasters due to their preferences, which is briefly discussed in this section (Moore & Loewenstein, 2004). As a result, self-interest in a specific market will lead to these specific errors in decision-making, since a market with a market and a product with a product are not the same, and models do not make decisions solely based on individual preferences. Many decision-makers find decision-making challenging and complicated because they lack the necessary knowledge expertise to make decisions when there is no suitable and usable data and a broad data set (Björklund, 2013). In addition, psychological bias can reduce the quality of decision-making and forecasts (Ramnath, S., Rock, S., & Shane, P, 2008), and the quality is also reduced with a repeatable and extensive decision-making process. In addition, combining human judgment with a statistical forecasting model may give a system added value. Because of human factors in decision-making and forecasting, the things in Figure 3 are particularly susceptible to psychological bias and self-interest (Baecke, P., De Baets, S., & Vanderheyden, K, 2017).

A mixture of decision-making and forecasting models is used to increase the accuracy of forecasting models as well as the ability to make informed decisions (Spithourakis, G. P., Petropoulos, F., Nikolopoulos, K., & Assimakopoulos, V, 2015). Furthermore, several researchers have performed a variety of studies in order to promote forecasting models and ultimately make informed decisions. Since a single model can have limitations and errors, Barrow and Kourentzes attempted to demonstrate how combining multiple forecasts can reduce the errors and limitations of a single model while still increasing forecast accuracy (Barrow & Kourentzes, 2016). One of the most critical factors in reducing forecasting errors is a better understanding of the forecasting mechanism, which needs more focus (Stekler, 2015). In order to modify the problem, Lahiri and Sheng used the forecast method in the Bayesian decision-making system (Lahiri & Sheng, 2008). Another problem with the forecasting model is the process for assessing predictions, which has two foundations (see Figure 3) (Stekler, 2015).

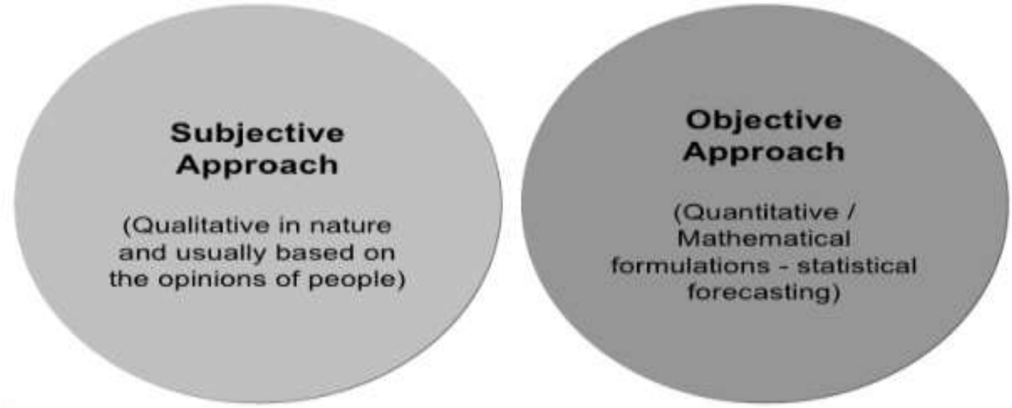
Figure 3: Procedures of Evaluation in the Forecasting Models.



Source: Own work.

Further to that, since forecasting models are linked to events that will occur in the future, reorganizing forecasting models to include ex-ante approaches is another beneficial problem for accuracy. These enhancements aim to move the models closer to real-time forecasting when taking into account complex variables (Fildes & Stekler, 2002). Figure 4 illustrates the two methods to make decisions about people's opinions (qualitative) and formulation – predictive forecasting (quantitative). To put it another way, the objective approach is concerned with Global vs. Point Methods, Probabilistic vs. Point Forecasts, Computational Convexity, and Linearity & Convexity, while the subjective approach is concerned with Ensemble vs. Single Models, Driven vs. Model-driven, Discriminative vs. Generative, Statistical Guarantees, and Explanatory/Interpretable vs. Predictive vs. Predict (Januschowski. T, Gasthaus. J, Wang. Y et al., 2019; Fildes, Robert and Petropoulos, Fotios, 2015).

Figure 4: Approaches in the Forecasting Models.



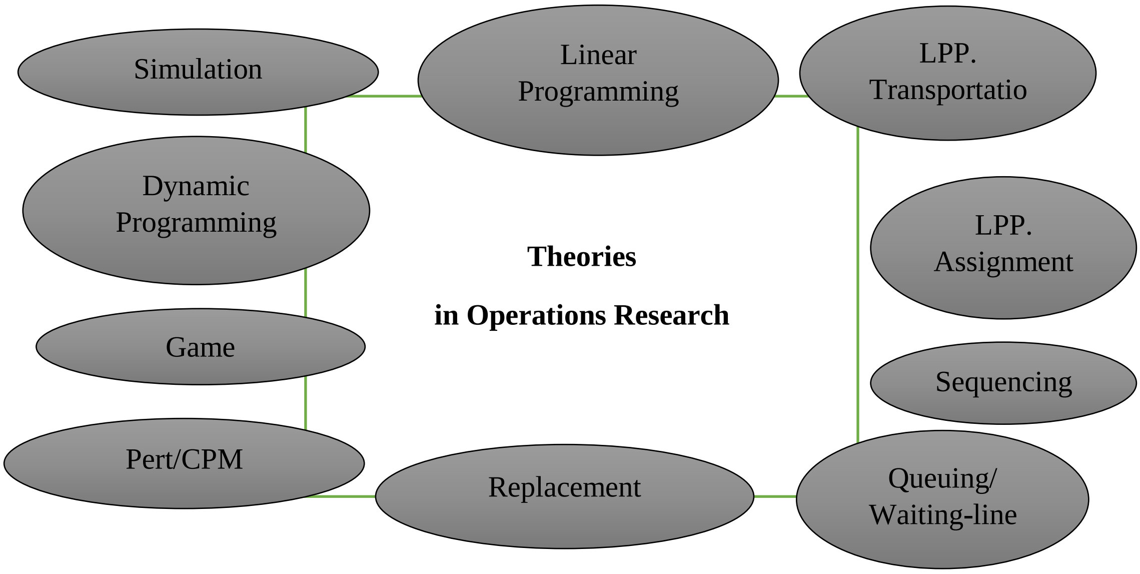
Source: Own work.

A forecasting model may be timely, but the right one must be accurate, as well as meaningful and simple to use for forecasters. In addition, for the estimation of variables and profit maximization, a supplementary mathematical model must be used. All aspects of forecasting must be considered, including market, industry, and company dynamic indicators, quantitative and qualitative methods, subjective and objective approaches, and so on, and both of the approaches described in figure 4 can be used in this model, which is the aim of this study to make a decision. It is derived from one of the operation research methods for developing this supplementary mathematical model, and operation research methods also have powerful tools for enhancing the precision of decision-making in forecasting models that can incorporate these aspects of the model (Fildes, Robert and Petropoulos, Fotios, 2015).

4 OPERATION RESEARCH METHODS

Operation Research (OR) methods are quantitative and numerical decision-making methods that use a mathematical and analytical model to quantify more accurate and precise performance for large and small, private and public organizations. Moreover, the model carefully forecasts outcomes when taking into account complex variables and constraints. The model of operation research can be linked to optimization, game theory, economics, simulation, network analysis, quality and productivity of operations management, pricing, supply chain management, revenue management, and so on, as shown in Figure 5. There are many methods of operation research that have applications in industries.

Figure 5: Operation Research Techniques.



Source: Operations Research Proceedings 2019, (2020).

Operation research examines existing operations in order to improve performance, particularly in terms of making successful decisions in the data processing process and monitoring decisions for optimization in various industries under unique conditions. In addition, the models can be used in a variety of areas, including agricultural planning, organized military administration, governmental organization, mission scheduling, delivery of products and services, emergency and rescue operations, engineering systems design, commercial and industrial processes, environmental management, financial planning, allocation and distribution in projects, inventory control, resource allocation, facilities planning, manufacturing of products, military operations, production process control, risk analysis, sequencing of tasks and functions, telecommunications, and traffic control and has also application different departments supply-chain system, enterprise resource planning, total quality management, just-in-time production and inventory management, and materials requirements planning (Thies, 2019). One of the applications of the methods in manufacturing companies is the deployment of a proper workforce in the production site in order to achieve an optimized output and proper machine allocation in the production lines. The model may also design a manufacturing system in terms of plant size, warehouse location, and other facilities. Other applications include procurement cost minimization, product mix selection, investment decision-making, and a variety of others (Glock, C. H., Grosse, E. H., Jaber, M. Y., & Smunt, T. L, 2018). In order to formulate problems in a case, planners must consider elements such as the environment, objectives, and decision-maker. Then, as shown in Figure 6, a problem is formulated based on action and reaction, which must be generated when taking into account the real environment, constraints, and objectives. The following step involves deriving the solution and testing the model. Finally, the model should be managed and monitored on a regular basis before an optimal solution is found. Linear programming is one of the most widely used techniques in operations research.

Figure 6: Processes of Creation of a Model.

Source: Tomaskova H, Weber G. (2020).

4.1 Linear Programming (LP)

In this study, linear programming (LP) is used, which is a mathematical method for calculating the value of obtainable variables under a given condition. LP was invented by Leonid Kantorovich in 1937 during World War II as a mathematical tool for predicting and preparing for the optimal outcomes. LP is a mathematical method for determining the best feasible outcome or solution from a set of characteristics or needs represented as linear connections. LP is used in the manufacturing industry to analyze supply chain activities. Their goal is to maximize efficiency while keeping operating costs to a minimal. The factory can restructure their storage architecture, modify their personnel, and decrease bottlenecks based on the linear programming model's recommendations.

In manufacturing organizations, LP is one of the most basic methods for optimizing and solving a complex problem. The model aims to find the best options for industrial companies by taking into consideration various constraints. In organized retail, linear programming is also utilized to optimize shelf space. Because the quantity of products on the market has grown by leaps and bounds, it's critical to know what the customer wants. The products in the store are deliberately placed to accommodate the purchasing habits of the customers. The goal is to make it simple for customers to find and purchase the proper products. This is limited by factors such as shelf space, product variety, and so on. Delivery Routes can also benefit from optimization. This is a variation on the well-known traveling salesperson issue. For several salesman traveling to multiple places, the service business employs optimization to identify the optimal path. The delivery routes are determined using clustering and a greedy algorithm, with the goal of reducing operation costs and time. Machine Learning makes use of optimizations as well. Supervised Learning is based on the linear programming fundamentals. From labeled input data, a system is trained to fit a mathematical model of a function that can predict values from unknown test data.

Linear programming has the following basic components:

- Decision variables
- Objective function
- Constraints
- Data

Decision variables, objective function, constraints, and data are all part of the LP. The outcome will be determined by the decision variables. They are the last solution. Any problem must first be solved by identifying the decision variables. The decision variables in the preceding example are the total number of units for A and B, which are denoted by X and Y, respectively. Objective function represents how each decision variable influences the cost, or, more simply, the value that must be optimized. Constraints refer to the restrictions or limitations placed on the decision variables. They frequently set a limit on the decision variables' value. The availability of resources is limited in the preceding situation. Furthermore, the decision variables in all linear programs should always be non-negative. This means that decision variables should have values that are larger than or equal to 0. The steps involved in formulating a Linear Programming issue:

- Identify the decision variables
- Write the objective function
- Mention the constraints
- Explicitly state the non-negativity restriction

Advantages of Linear Programming includes: Decision-makers who use this strategy are more objective in their decisions. Another benefit is resource maximum. This strategy aids in the maximization of natural resources that are restricted. This strategy can be used by managers to allocate restricted resources. In terms of the third, the technique has the ability to tackle complicated problems that managers face in everyday life. In terms of the model's use in this study, this model has three independent variables that are also decision variables: the number of goods sold, the cost, and the sales price. Decision variables influence performance, and the model makes decisions based on the variables. Furthermore, these decision variables must first be described in order for LP to find a solution. Profit is a dependent variable that is attempted to be maximized using linear programming as an objective function in the model, which is one of the more applicable tools of operation analysis. Another aspect of this model is the constraints, which specify the parameters that must be met in order to calculate exact performance (Kersting, K., Mladenov, M., & Tokmakov, P, 2017). Other advantages of the model are multiple constraints, simplicity, and multipurpose (Solaja et al., 2019).

4.2 Making a Mathematical Model by Linear Programming

By combining a decision-making model and Cost-Volume-Profit (CVP) analysis with consideration of dynamic variables, constraints, and other factors previously listed for improving the quality and accuracy of a forecasting model, this research develops a model to reduce many failures of past forecasting models.

The first phase of the model is applicable to the combination of linear programming as an operation research model with Cost-Volume-Profit (CVP) analysis, as defined in this chapter. Figure 7 provides a graphical representation of the method of creating this model. For making a decision, the constraints of this model can use all approaches, techniques, and methods that have been listed and not mentioned in this report.

Constraints determine the dimension of making a decision, while dynamic factors that affect variables multiply as a growth rate to variables. This model aims to maximize profit by estimating four variables as part of a long-term output, including the number of goods produced, fixed costs, variable cost per unit, and sales price with a value greater than zero. Furthermore, output volume is equal to the demand and the number of goods sold. Eventually, growth rates between variables are not zero, and new variables are the last variables in the previous period plus additional amounts applied to the next period. This section defines the mathematical model's variables, such as the sales price of each unit, the level of output in a given time period, variable cost per unit, average fixed costs, and fixed costs that can be adjusted over time in the short or long term and have an impact on the forecasting model's outcome.

P = Sales price of each unit

Q = Level of output in a given time period (the number of goods sold in a given time period)

AVC = Variable cost per unit

AFC = Fixed costs per unit

FC = Fixed costs

Many constant parameters are included in this mathematical model, and these parameters affect the variables of the mathematical model in the next time period. These constant parameters cannot be modified by adjusting the model's variables over a given time period, and they are constant in this model and markets because indicators determine these parameters, and a business cannot alter the market's indicators but can change its own internal variables.

This section includes a list of constants parameters, such as

a = Market indicators

R_a: Rate of growth in output over the next time period

R_β: Growth rate of each unit's sales price over the next time period

R_e: Variable cost per unit growth rate in the next time period

R_u: Rate of increase in average fixed costs over the next time period

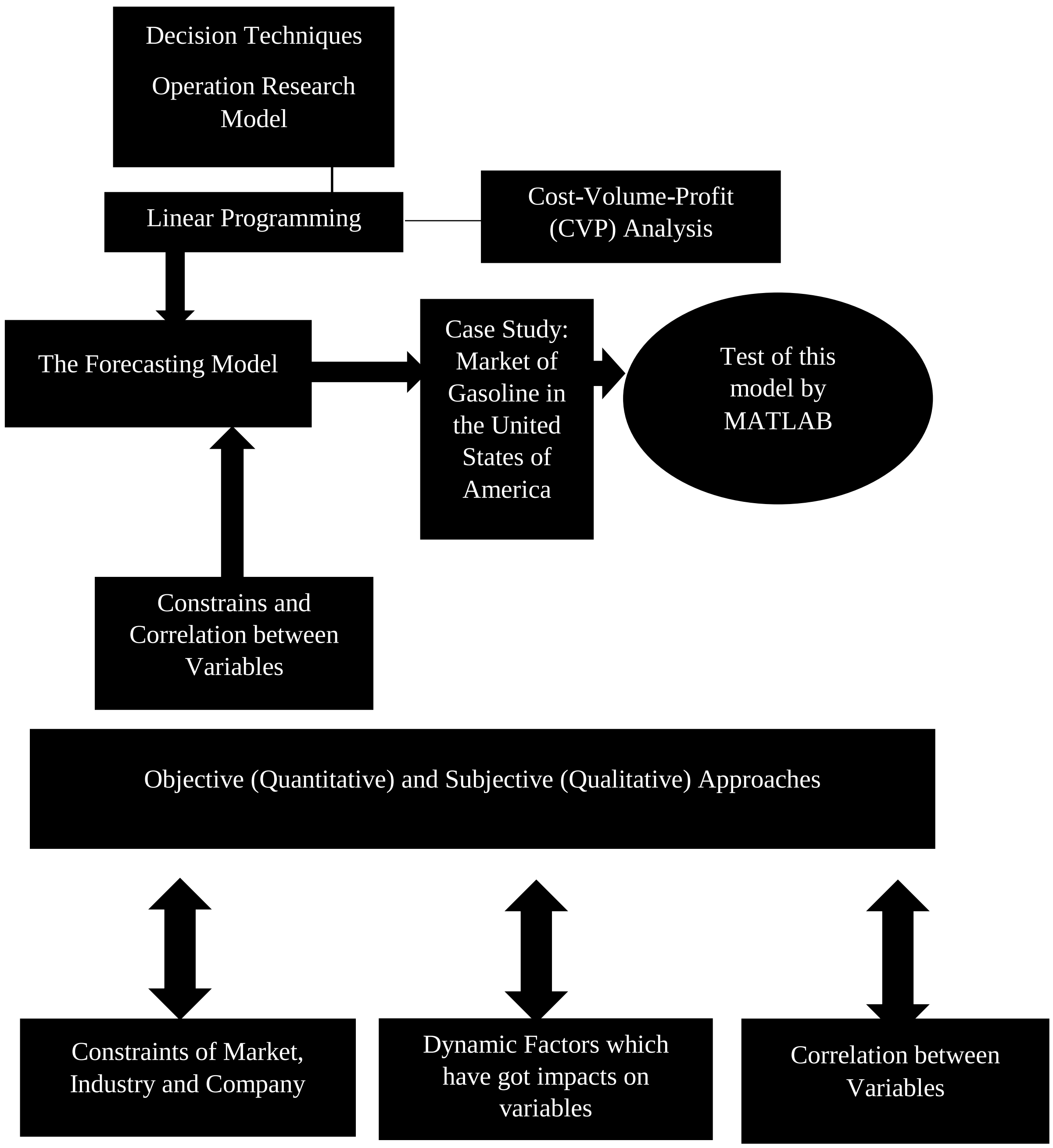
Q_n = Next level of output in a given time period (number of goods sold)

Q_o = Previous level of output in a given time period (number of goods sold)

ΔQ = The growth rate of level of output (Increased or Decreased)

n: The number of growth rates that cause variables to increase or decrease in the next time period.

Figure 7: Graphical Description of this Mathematical Model.



Source: Own work.

5 CREATING AN INTEGRATED FORECASTING MODEL BY COMBINATION OF LINEAR PROGRAMMING AND COST-VOLUME-PROFIT (CVP) ANALYSIS

This mathematical model for decision-making requires the incorporation of linear programming (LP) and Cost-Volume-Profit (CVP) Analysis. The CVP specifies the parameters of the decision-making model, while the LP organizes the mathematical model. The model is developed by combining these two models to define the variables that allow profit to be maximized in a business while taking into account market constraints and indicators.

5.1 Cost-Volume-Profit (CVP) Analysis

With a combination of total revenue and expense, the model determines profitability at various levels of output.

The Cost-Volume-Profit (CVP) analysis is shown in equation 1.

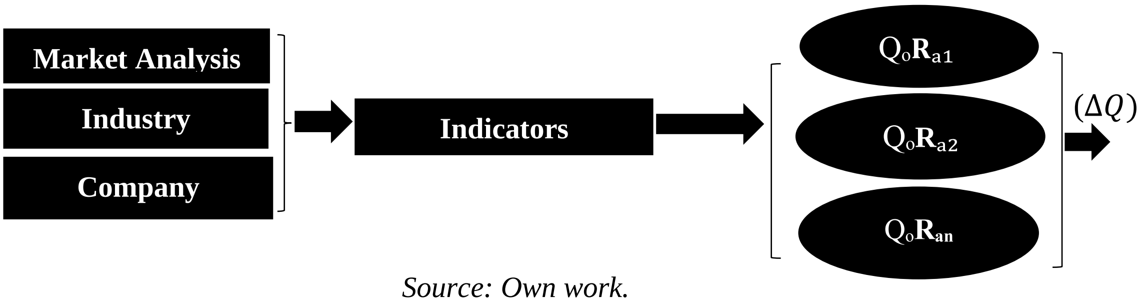
$$\text{Profit} = \text{Total Revenue} - \text{Total Cost} \quad (1)$$

$$\text{Profit} = QP - QAVC - FC \quad (2)$$

Total revenue is calculated by multiplying the sales price of each unit by the level of output in a given time period (number of goods sold). Total cost, on the other hand, includes fixed costs that do not change with output level and variable cost per unit, which is a variable that varies with output level. In addition, variable cost per unit multiplied by the amount of output for a given time period yields variable cost, which is then added to fixed costs to yield total cost. Finally, profit is determined by deducting total costs from total revenue (equation 2). Since growth rates have an impact on these parameters, Q is a variable that businesses must forecast. These growth rates are determined by market, industry, and company complex variables that must be derived from indicators such as Figure 8. Equation 3 indicates that the next level of output in a given time period is determined from the previous level of output in a given time period plus ΔQ, which fluctuates due to growth rates in the next given time period due to the changing of the dynamic factors. As a regression form, Q_o is an intercept, and ΔQ are factors that affect the variable.

$$Q_n = Q_o + \Delta Q \quad (3)$$

Figure 8: The Number of Goods Sold Variable (Level of Output in a Given Time Period) is Influenced by these Dynamic Factors (ΔQ).



Source: Own work.

As growth rates that have an effect on the level of output in a given time period (number of goods sold) begin to fluctuate, they have a direct impact on this variable (level of output in a given time period) that must be taken into account in forecasting. Equation 4 shows how the level of output in a given time period changes due to a variety of dynamic factors that affect the growth rate of the first to the last factor (n). According to just in time theory, the amount of goods sold equals the level of production in a given time period.

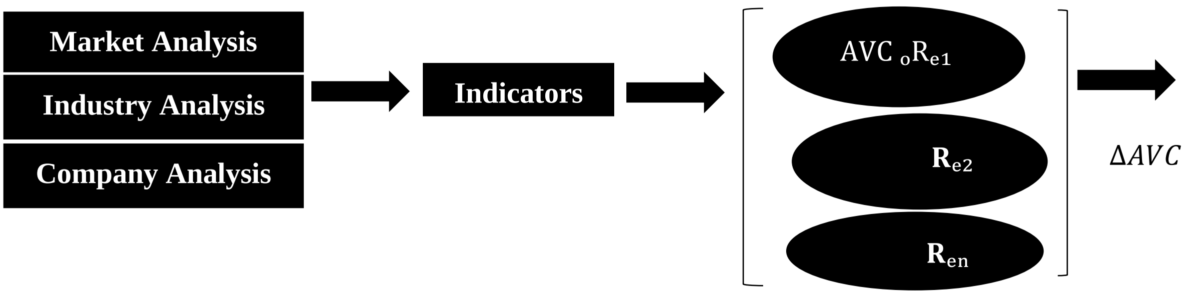
$$\Delta Q = Q_o R_{a1} + Q_o R_{a2} + \ldots + Q_o R_{an} \tag{4}$$

In the Cost-Volume-Profit (CVP) analysis, equations (3) and (4) are used instead of ΔQ. Equation 5 is derived from a study of different growth rates that result in a change in output over time.

$$\begin{cases} \text{Profit} = PQ - QAVC - FC \\ \text{Profit} = P(Q_o + \Delta Q) - AVC(Q_o + \Delta Q) - FC \\ \text{Profit} = P(Q_o + (Q_o R_{a1} + Q_o R_{a2} + \ldots + Q_o R_{an})) - AVC(Q_o + (Q_o R_{a1} + Q_o R_{a2} + \ldots + Q_o R_{an})) - FC \end{cases} \tag{5}$$

Dynamic factors' growth rates influence and adjust variable cost per unit, and Figure 9 depicts a breakdown of the dynamic factors of production cost based on three components: sector, business, and company. R_e is the growth rate of variable cost per unit in the next given time period multiplied by factors ranging from 1 to n.

Figure 9: *The Costs are Influenced by these Dynamic Factors (ΔAVC).*



Source: Own work.

In equations 6 and 7, the previous variable cost per unit and the next variable cost per unit are determined from the first to the last factor (n), which is affected by the dynamic factors' growth rates.

$$AVC_n = AVC_o + \Delta AVC \tag{6}$$

$$\Delta AVC = AVC_o R_{e1} + AVC_o R_{e2} + \ldots + AVC_o R_{en} \tag{7}$$

The growth rates that affect the variable cost per unit are factored into Equation 8.

$$\text{Profit} = P\,(Q_o + (Q_oR_{a1} + Q_oR_{a2} + \ldots + Q_oR_{an})) - (AVC\ _oR + AVC\ _oR_{e1} + AVC\ _oR_{e2} + \ldots + AVC\ _oR_{en})\,(Q_o + (Q_oR_{a1} + Q_oR_{a2} + \ldots + Q_oR_{an})) - FC \tag{8}$$

The model is improved by including price and dynamic price variables in equations 8 and 9, followed by equations 9 and 10. The new price is calculated using the previous price plus price growth rates. R_β denotes the growth rates of each unit's purchase price over the next time period, which are influenced by dynamic factors.

$$P_n = P_o + \Delta P \tag{9}$$

$$\Delta P = P_oR_{\beta 1} + P_oR_{\beta 2} + \ldots + P_oR_{\beta n} \tag{10}$$

Equation 11 is obtained by combining equations 8 and 10.

$$\text{Profit} = (P_o + P_oR_{\beta 1} + P_oR_{\beta 2} + \ldots + P_oR_{\beta n})\,(Q_o + (Q_oR_{a1} + Q_oR_{a2} + \ldots + Q_oR_{an})) - (AVC\ _o + AVC\ _oR_{e1} + AVC\ _oR_{e2} + \ldots + AVC\ _oR_{en})\,(Q_o + (Q_oR_{a1} + Q_oR_{a2} + \ldots + Q_oR_{an})) - FC \tag{11}$$

Since forecasting models are developed based on short and long-term planning, the model is created as long-term planning for a production system, since fixed costs are constant in the short term but variable in the long term. Since the fixed cost is constant, equation 11 is considered for the short term, while equation 12 is for the long term and is written by entering the correlation between growth rates and the fixed cost per unit. Ru is the correlation vector, and its components relate to the long-term effects of growth rates on the fixed cost per unit.

$$\text{Profit} = [P_o(1+\textstyle\sum_1^n R_{\beta n})(Q_o(1 \pm \sum_1^n R_{an}))] - [AVC_o(1 + \sum_1^n R_{en})(Q_o + \sum_1^n R_{an})] - [AFC_o\,(1+\sum_1^n R_{un})(Q_o + \sum_1^n R_{an})] \tag{12}$$

In terms of linear programming (LP), it is a mathematical model for maximizing or minimizing objectives when taking constraints into account. To make a decision, the models should be paired with linear programming. There are several variables in the equation, and the correlation coefficients are intertwined. Furthermore, the model has a goal, which is to maximize profit by converting all numbers into constraints tolerances. In this profit maximization model, Z is an objective that is shown in equation 13.

$$\text{Profit: Max } Z = [P_o(1+\textstyle\sum_1^n R_{\beta n})(Q_o(1 \pm \sum_1^n R_{an}))] - [AVC_o(1 + \sum_1^n R_{en})(Q_o + \sum_1^n R_{an})] - [AFC_o\,(1+\sum_1^n R_{un})(Q_o + \sum_1^n R_{an})] \tag{13}$$

5.2 The Final Model

This section addresses the issue of incorporating constraints into mathematical modeling because constraints determine the data tolerance for making a decision; in other words, variables make decisions within the given tolerances. The following model is a final and systematic equation that uses qualitative and quantitative methods to understand both growth rates, constraints, and the association between variables, as well as profit maximization.

$$\text{Profit: Max } Z = [P_o(1+\sum_1^n R_{\beta n})(Q_o(1\pm \sum_1^n R_{an}))]-[AVC_o(1+\sum_1^n R_{en})(Q_o+\sum_1^n R_{an})]-[AFC_o\,(1+\sum_1^n R_{un})(Q_o+\sum_1^n R_{an})]$$

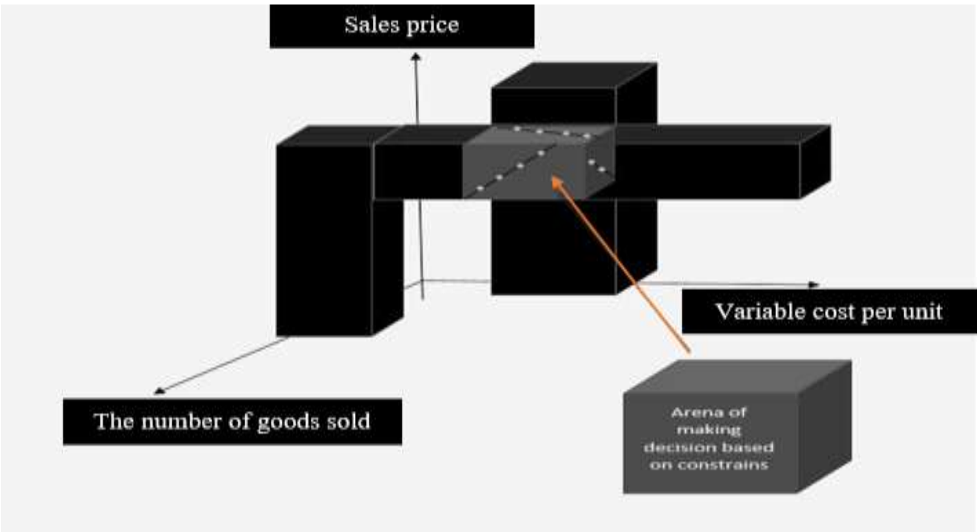
S.t:

Company constrains	Factors of firm-level that limit variables, and tolerance of them (P_o, Q_o, AVC_o and AFC_o) $P_o > 0$ $Q_o > 0$ $AVC_o > 0$ $AFC_o > 0$
Industry constrains	Factors of industry-level that limit variables, and tolerance of them (P_o, Q_o, AVC_o and FC_o) $P_o > 0$ $Q_o > 0$ $AVC_o > 0$ $AFC_o > 0$
Market constrains	Factors of market-level that limit variables, and tolerance of them (P_o, Q_o, AVC_o and FC_o) $P_o > 0$ $Q_o > 0$ $AVC_o > 0$ $AFC_o > 0$
Correlation between variables by using qualitative and quantitative approaches	P_o, Q_o, AVC_o and AFC_o

(14)

Figure 10 shows how the model makes a decision in the given domain based on constraints and variable correlation. For making a decision, constraints restrict the number of goods sold, fixed costs, variable cost per unit, and sales price.

Figure 10: Area of Making a Decision.



Source: Own work.

This model can be used in a variety of industries to determine the best point for profit maximization by businesses. To evaluate the model, it is applied to the gasoline market in the United States. With the exception of the factors discussed in this case study as an assumption, all factors in that market remain constant for the next specified period of time. The price of fuel in this market is one of the variables in this model. The industrial production, distribution, refining, and marketing of petroleum products are the key pillars of the gasoline industry in the United States for classification and study. Since the United States, China, Japan, and India are the world's top petroleum consumers (Sönnichsen, 2020), the gasoline industry is a significant market in this region. Retail gasoline prices are influenced by a number of factors, the most important of which are crude oil prices and the level of gasoline supply in relation to demand. When looking at the data, the retail price of gasoline has four major components, which are specified in this section (US Energy Information Administration – EIA, 2020).

- The cost of crude oil
- Refining costs and profits
- Distribution and marketing costs and profits
- Taxes

The cost of crude oil is one of the most significant components of the retail price of gasoline, and it fluctuates continuously over time across various regions of the United States due to a variety of factors that influence and alter the retail price.

This segment discusses seven main factors that have a significant effect on the cost of crude oil and then the retail price of gasoline.

1. Supply by Non-OPEC
4 Supply by OPEC
5 Balance between demand and supply
6 Spot Prices
7 Financial Markets
8 Demand by Non-OECD
9 Demand by OECD

These seven main factors have a number of components that cause them to fluctuate cost of crude oil, as shown in Table 4 (US Energy Information Administration – EIA, 2020).

Table 4: The Factors which Influence the Cost of Crude Oil.

Supply by Non-OPEC	Production & WTI crude prices Changes in production capacity & GDP, price of WTI crude Projected supply, annual average OPEC and Non-opec supply disruption
Supply by OPEC	Changes in Saudi production & WTI crude prices Spare production capacity & WTI crude prices
Balance between Demand and Supply	OECD inventories & WTI futures spread
Spot Prices	World crude oil prices U.S. retail gasoline price, refiner acquisition cost of crude oil Crude price reaction to events

Financial Markets	Average daily open interest in crude oil futures Futures positions by producers, merchants, processors, & end users Futures positions by money managers Correlations between daily prices changes of crude & other commodities Commodity index assets under management & Dow Jones UBS price index Composition of the Dow Jones UBS commodity index Correlations between daily returns on crude oil & financial investments
Demand by Non-OECD	Consumption & GDP World oil consumption, world GDP & WTI crude oil prices Projected non-OECD production, annual average
Demand by OECD	Crude oil consumption & WTI crude oil price World oil consumption, world GDP & WTI crude oil prices

Source: U.S. Energy Information Administration - EIA - Independent Statistics and Analysis, 2020.

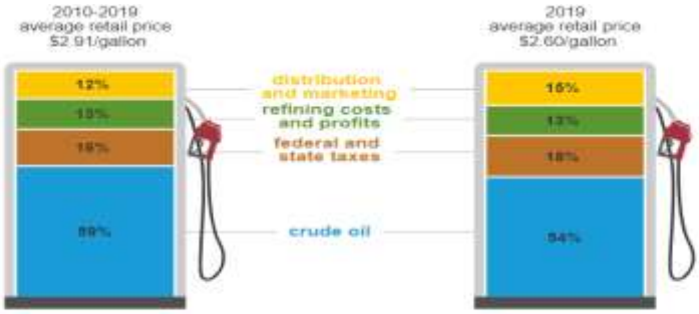
The refining costs and profits are another factor that influences the retail price of gasoline. The characteristics of gasoline vary depending on the season and area, as well as the type of refining and crude oil used, technology, other ingredients such as fuel ethanol, and formulation. In 2020, the sum of overall state and federal taxes is 29.86 cents per gallon and 18.3 cents per gallon, respectively, when looking at the effect of taxes on the price of fuel. Distribution, marketing, retail dealer prices, a local condition such as fueling position and the owner's marketing plan, state and local taxes, wages and salaries, benefits, vehicles, lease or rent payments, and insurance are all factors that influence the price of retail gasoline. When these factors have an effect on the cost of producing fuel, the retail price of gasoline increases proportionally. Based on appendix 2 components of annual gasoline price changes include Brent crude oil price, wholesale margin over crude, and retail margin over wholesale. Taking all into account, annual gasoline price changes with complex factors that affect the price of gasoline are expected to be about 0,09 from 2020 to 2021, according to the forecast in appendix 2.

$$0.09 = \Delta P = P_o R_{\beta 1} + P_o R_{\beta 2} + \ldots + P_o R_{\beta n} \quad (15)$$

$$P_n = P_o + (0{,}09)P_o \quad (16)$$

Figure 11 shows the shift in average retail price between 2010 and 2019 as a result of adjusting these parameters.

Figure 11: The Price of Per Gallon of Retail Gasoline



Source: U.S. Energy Information Administration, (2020).

Because of seasonal declines and the growth rate of COVID-19 events, consumption dropped to 8,1 million b/d in the fourth quarter of 2020, but EIA forecasts consumption to rise to an average of 8,9 million b/d in the second half of 2021. According to the following estimate, gasoline consumption will rise at a rate of about 0,09 b/d in the next given time period (U.S. Energy Information Administration – EIA, 2021).The growth rate of gasoline consumption is

$$\frac{(8{,}9-8{,}1)}{8{,}1} = 0{,}09 \quad (17)$$

According to the EIA, Brent crude oil spot prices will rise to an average of $53/b per barrel in 2021, up from an average of $42/b per barrel in 2020, and crude oil will account for 46% of the price of retail gasoline in this study's Figure 12 and appendix 1. Finally, based on the calculations below, the variable cost will increase by 0,11 in the next given time period (U.S. Energy Information Administration – EIA, January 2021).

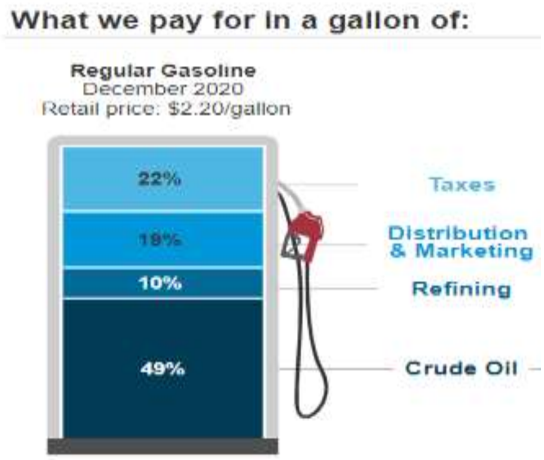
$$\frac{(53-42)}{42} = 0{,}26 \quad (18)$$

$$(0{,}26)(0{,}46) = 0{,}11 \quad (19)$$

Assume that the growth rate of average fixed costs per gallon of gasoline, which only includes fixed costs, is 0.26 for the next specified time period (Frequently Asked Questions (faqs)-US Energy Information Administration – EIA, 13 February 2021; State-Motor-Fuel-Notes-Summary, 2021).

$$\frac{(37{,}85-29{,}86)}{29{,}86} = 0{,}26 \qquad (20)$$

Figure 12: Variable and Fixed Costs of Gasoline.



Source: U.S. Energy Information Administration, (2021).

Finally, coefficients are added to equation 21 to affect the variables in both positive and negative ways.

$$\text{Profit: Max } Z = [(P_o(1+0{,}09))(Q_o(1+0{,}09))]-[AVC_o(1+0{,}11)(Q_o(1+0{,}09)] - [AFC_o(1+0{,}26)(Q_o(1+0{,}09)] \qquad (21)$$

In terms of the model's constraints, the model makes a decision based on the company's, market's, and industry's established limitations and constraints. Simply put, constraints restrict the model's tolerance for variables when making a decision. The retail gasoline price, in particular, could fluctuate between 1.07 and 4 dollars per gallon, with an estimate of 2.4 dollars per gallon in 2021 based on the tables in appendix 3. Furthermore, according to Appendix 4, daily gasoline intake ranges between 20000 and 60000 gallons.

Following the regression analysis in Excel, a table in appendix 5 displays data on retail fuel sales and prices over the last three decades, and the outcome of the analysis in relation to appendix 6 is shown in equation 22.

$$Q = (69859{,}97753)–(12932{,}9)P \tag{22}$$

In terms of other model correlations, according to figure 12, 59 percent of gasoline is related to the price of crude oil and refining, all of which are variable costs. These two costs are considered in the category of average variable costs in the measurement and the model, based on an assumption in this case and only for checking the model, and then 46 percent of gasoline also concerns taxation, promotion, and distribution. In addition, equations 23 and 24 show a relationship between average variable costs and retail prices, as well as average fixed costs.

$$\text{AVC} = 0{,}78 \text{ sales price} \tag{23}$$

$$\text{AFC} = 0{,}22 \text{ sales price} \tag{24}$$

Equation 25 is the model for research when all factors are considered.

$$\left[\begin{array}{l} \text{Profit: Max } Z = [(1,1881)P_oQ_o]-[(1,2)AVC_oQ_o] - [(1.3)AFC_oQ_o] \\ \text{S.t} \\ 2 \text{ dollars per gallon} \leq \text{sales price} \leq 4 \text{ dollars per gallon} \\ 20000 \text{ gallons per day} \leq level\ of\ output\ \leq 60000 \text{ gallons per day} \\ \text{AVC} = 0{,}78 \text{ Price} \\ \text{AFC} = 0{,}22 \text{ Price} \end{array}\right.$$

$$\text{Level of output} = Q = (69859{,}97753) – (12932{,}9) \text{ Price} \tag{25}$$

MATLAB is one of the most useful programs for analyzing these specific samples. To put it simply, it is a mathematical computing software used by engineers and scientists to evaluate complex mathematical models. For technical computing, MATLAB is a high-performance language. It combines computing, visualization, and programming in a user-friendly environment in which problems and answers are expressed in mathematical notation.In this case, MATLAB is used to write linear programming to obtain the same result. The model's codes are depicted in a figure in Appendix 7, and they are written with constraints and complex factors in mind. The result is determined by MATLAB after writing the model's codes, and it is shown in Figure 13. For profit maximization, the effects of this model include optimal levels of sales price, number of goods sold, average variable cost, and average fixed cost.

Figure 13: The Result of this Model (Case Study).

```
Local minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the default value of the optimality tolerance,
and constraints are satisfied to within the default value of the constraint tolerance.



ans =

[ 3.855, 20000.0, 3.007, 0.8482]


ans =

-3209.0
```

Source: Own work.

Based on the results of this MATLAB sample, the sales price per gallon of fuel, the level of output in the next given time period, the average variable cost, and the average fixed cost must be 3.855, 20000, 3.007, and 0.84 dollars in turns in the next period until the company reaches profit maximization with a total of 3209 dollars per day. When a linear programming result is minimized, it can be reversed, and the maximization can be used instead. To put it another way, these profit and variable quantities are the optimal amounts at which the gasoline company should expect to optimize profit when taking into account demand, business, and company constraints, as well as dynamic factors and their effects on variables. The output of the mathematical model is shown in Table 5 for consideration.

Table 5: The Output of the Mathematical Model.

Optimum Retail Price	Optimum level of Output	Optimum Average Variable Cost	Optimum Average Fixed Cost
3.855	20000	3.007	0.84

Source: Own work.

5.3 Analysis of the Model

Although profit maximization is a well-known goal of a business, several thinkers have questioned its validity. They have objected to the profit maximization goal for the following reasons. Profit maximizing has been criticized for a number of flaws, some of which are listed here. The term "profit" is a bit of a misnomer. It's because people with various mindsets have different perspectives on profit. Profits can be defined as net profit, gross profit, profit before taxes, profit per share, or profit rate, for example. In terms of profitability, there is no clearly defined profit maximization rule. Besides, The larger the profit, the better the proposal," says the profit maximization formula. In essence, it is focusing on the raw gains without taking into account the timing of those profits. "A dollar today is not equal to a dollar a year later," states another major finance concept. As a result, the temporal value of money is entirely disregarded.

Another disadvantage of profit maximization as a goal is that it ignores intangible rewards like quality, image, technological breakthroughs, and so on. The importance of intangible assets in generating value for a company should not be overlooked and the firm's profit maximization goal is more important in the near run. This goal will not allow a company to survive in the long run. If profit maximization is the fundamental goal of all businesses, they may engage in unethical practices in order to maximize profits.

According to the Profit Maximization Rule, if a company wants to maximize profits, it should choose an output level where Marginal Cost (MC) equals Marginal Revenue (MR) and the Marginal Cost curve is rising. To put it another way, it needs to produce at a level where MC equals MR. However, in the actual world, determining your Marginal Revenue and Marginal Cost of the most recent things sold is difficult. For example, knowing the price elasticity of demand for their goods – which influences the MR – is challenging for businesses. The use of the profit maximization rule is also influenced by how other businesses react. Demand may be inelastic if you raise your pricing and other businesses follow suit. However, demand will be elastic if you are the only company to raise the price. Furthermore, the impact of price changes on demand is difficult to separate. Apart from price, a variety of other factors can influence demand. On the other hand, this intelligent model can evaluate profit maximization while taking into account all internal and external elements when making decisions, improving decision accuracy while reducing the limitations and drawbacks of the profit maximization concept in businesses.

When a business considers profit maximization concept, the maximized sales revenue combined with the highest level of production and/or price, as well as cost minimization, results in a profit maximization model based on conventional models. The situation of markets and businesses, on the other hand, is extremely complex, and the presented model attempts to fill in the gaps by taking into account all possible scenarios and connecting them with variables. You will see the flaws in the previous theories and then see how the mandatory mathematical model will change the profit-maximization principle.

$$\begin{cases} \text{Profit: Max } Z = [(1,1881)P_oQ_o]-[(1,2)AVC_oQ_o] - [(1.3)AFC_oQ_o] \\ \text{S.t} \\ 2 \text{ dollars per gallon} \leq \text{sales price} \leq 4 \text{ dollars per gallon} \\ 20000 \text{ gallons per day} \leq level\ of\ output \leq 60000 \text{ gallons per day} \\ AVC = 0{,}78 \text{ Price} \\ AFC = 0{,}22 \text{ Price} \\ \text{Level of output} = Q = (69859{,}97753) - (12932{,}9) \text{ Price} \end{cases} \tag{26}$$

In terms of production, a business should consider the maximized amount of output if it wants to optimize its sales revenue. If the business is going to increase the sales revenue based on the below formula, the price is calculated 0.76 dollars, but 0.76 is outside of the deemed tolerance based on the model's situation.

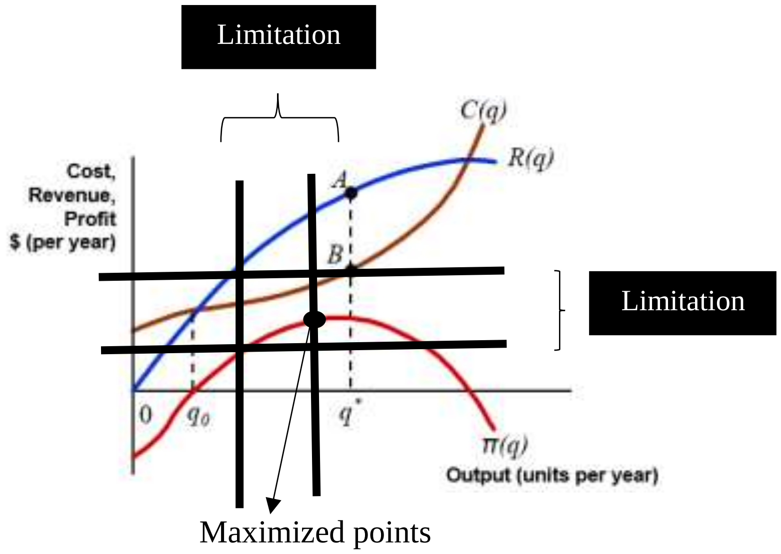
$$\begin{cases} \text{Level of output} = Q = (69859{,}97753) - (12932{,}9) \text{ Price} \\ 60000 = 69859.97 - (12932.9) \text{ Price} \\ \text{Price} = 0.76 \\ \text{Tolerance of price} = 2 \text{ dollars per gallon} \leq \text{sales price} \leq 4 \text{ dollars per gallon} \end{cases} \tag{27}$$

Given the current market environment, the retail fuel price ranges between 2 and 4, making the price range considered for optimizing sales revenue difficult to account for since a business cannot account for 0.76 as a price based on the defined tolerance. In terms of price, if the maximized price of 4 dollars per gallon is used for profit-maximization calculations, the amount of production calculated below is about 18000 gallons per day, which is impossible because it is less than the given tolerance of 20000.

$$\begin{cases} \text{Level of output} = Q = (69859{,}97753) - (12932{,}9) \text{ Price} \\ Q = (69859{,}97753) - (12932{,}9)\ (4) \\ \text{Level of output} = 18000 \text{ gallons per day} \\ \text{Tolerance of the level of output} = 20000 \text{ gallons per day} \leq \\ level\ of\ output \leq 60000 \text{ gallons per day.} \end{cases} \tag{28}$$

There are several drawbacks for finding the equilibrium point if the company only considers a normal formula for calculating profit based on standard models, as shown in Figure 14. Restrictions and connections between variables with variables restrict the company's ability to find the equilibrium point, but the available models' decision-making area is often limited by limitations, but the current model intelligently considers these mistakes and makes decisions while taking these obstacles and circumstances into account.

Figure 14: The Area of Making a Decision by Traditional and Presented Model.



Source: Own work.

With respect to costs minimization and based on the calculations below, assuming cost minimization, variable and fixed costs, and the price of gasoline should tend to zero.

$$\text{AVC}= 0{,}78 \text{ Price} \tag{29}$$

$$\text{AFC} = 0{,}22 \text{ Price} \tag{30}$$

As a consequence, the reduced costs cannot be considered without taking other variables, equations, and constraints into account, which the presented model does.

The model is intelligent and makes decisions based on orders and equations that a company can specify based on the company's, business, and industry's situation, and the orders can be an equation or a parameter tolerance. Variables can be combined with limitations and the growth rate of the variables in the next time period to make a decision. Furthermore, grow-rates can be linked to variables since these parameters cause the variables to shift in the next time period. This decision has no self-interest because an intelligent model makes a decision in the next time period, and it therefore resists self-interest in the internal organization.

When the variables do not have a fixed number and there are many tolerances for them, the model will calculate an amount for the variables, which is a path map for many businesses' decision-making.

The model solves the problem of traditional profit maximization being restricted models like the

1. Finding an equilibrium point, marginal cost, and revenue is a difficult issue for a business, and managers' decision-making is hampered by the principles of predicted points.

2. When managers have another target in mind for making decisions, the model will assist them in combining those goals with profit maximization to arrive at the best outcome.

5.4 Analysis of Accuracy of the Model

The difference between observed and forecasted values should be used to determine predictive accuracy. The projected values, on the other hand, can refer to a variety of factors. As a result, the prediction accuracy that results might apply to a variety of concepts. In this section, the proposed model will be compared to two other available models, including the Neoclassical Model (Profit Maximizing Model) and Baumol's Single-Period Model (Sales-Maximising Model). The model demonstrates that the available model cannot calculate the maximum point in this situation, but the presented model can do so based on the defined parameters and when linear programming has an output based on defined equations and correlations, and no based on self-interests.

5.4.1 Comparison of this Model with Neoclassical Model (Profit Maximizing Model)

If a corporation wishes to maximize profit, it should select an output level where Marginal Cost (MC) equals Marginal Revenue (MR) and the Marginal Cost curve is rising, according to the Profit Maximization Rule. To put it another way, it needs to generate at a level where MC equals MR. Because total revenue and total cost are both represented as functions of quantity, the derivative of the total profit equation with respect to quantity can be used to determine what quantity of output will maximize profits.

The profit maximization equation is shaped with the derivative of the profit equation respect to quantity if the level of output equation ($Q = (69859{,}97753) - (12932{,}9).\ P_o$), AFC = 0,22 Price and AVC= 0,78 Price are utilized in the main equation, and then the equation 31 is created.

$$Q = (69859{,}97753) - (12932{,}9).P \longrightarrow P_o = -(0.000077).Q + 5.4017$$

$$\text{Profit maximization} = [(1,1881)P_o]-[(1{,}2)\ 0{,}78\ P_o] - [(1.3)\ 0{,}22\ P_o] \quad (31)$$

The result of the Neoclassical Model, where MC and MR are equal, is Q = 70892.8, which the market and industry are not capable of producing in this amount, so the company cannot reach and calculates to this point based on constraints, but the presented model makes a more accurate decision based on different concepts.

5.4.2 Baumol's Single-Period (Sales-Maximising Model)

The next important business theory is sales maximization. If a company wishes to increase sales, it must choose the highest production amount. Based on the most recent data, 60000 gallons per day must be chosen to obtain the highest level of output. If this amount of output is taken into account, the price must be 0.76 based on this equation ($Q = (69859{,}97753) - (12932{,}9).\ P_o$), which is outside of the market and industry's price tolerance range of 2 to 4 euros, preventing the company from attaining its aim. However, the presented model, which took into account all criteria, resolved the issues that businesses will confront if they fail to meet their objectives.

6 EXTENSION OF THIS MODEL

It can be used in business decisions, game theory, benefit maximization with respect to outputs and inputs, Baumol's single-period sales-maximization model, price discrimination, the two-part tariff in terms of pricing, bundling, tying, buy or make on the market, maximum willingness to pay and consumer surplus, competitive advantage and value creation, strategic positioning, VRIO analysis, production function, cost function, and other supply chain and production system issues, for example. Examining a variety of approaches in which this mathematical model can be applied.

6.1 Application of the Model in Dynamic-pricing

Dynamic pricing refers to a pricing strategy that changes commodity prices on a regular basis based on demand and supply, as well as market conditions. The game theory model, which was defined in the paragraph on price forecasting, is a model that can be used in dynamic pricing.

$$\text{Profit: Max } Z = [(P_o + \sum_{1}^{n} W_{\beta n}.R_{\beta n}).(Q_o + \sum_{1}^{n} W_{an}.R_{an})] - [AVC_o + \sum_{1}^{n} W_{en}.R_{en}].$$
$$[Q_o + \sum_{1}^{n} W_{an}.R_{an}] - [(AFC_o + \sum_{1}^{n} W_{un}R_{un}).(Q_o + \sum_{1}^{n} W_{an}.R_{an})]$$

S.t

Pc is price of our competitor

Correlation between P_o and Pc

If Pc is … the model defines P_o with consideration of all other factors (32)

6.2 Application of the Model in Price Discrimination

Price discrimination occurs when a business charges different prices for the same good or service to different consumers. The price that the company sets is the highest price that a consumer can pay for it.

$$\text{Profit : Max } Z = [(P_o + \sum_{1}^{n} W_{\beta n}.R_{\beta n}).(Q_o + \sum_{1}^{n} W_{an}.R_{an})] - [AVC_o + \sum_{1}^{n} W_{en}.R_{en}].$$
$$[Q_o + \sum_{1}^{n} W_{an}.R_{an}] - [(AFC_o + \sum_{1}^{n} W_{un}R_{un}).(Q_o + \sum_{1}^{n} W_{an}.R_{an})]$$

S.t

The first block:

P_{o1} = price for the first block

Q_{o1} = number of goods sold for the first block

The second block:

P_{o2} = price for the second block

Q_{o2} = number of goods sold for the second block

The third block:

P_{o3} = price for the third block

Q_{o3} = number of goods sold for the third block

(33)

$$\text{Profit: Max } Z = \left(P_{o1} + \sum_{1}^{n} W_{\beta n}.R_{\beta n}\right).\left(Q_{o1} + \sum_{1}^{n} W_{an}.R_{an}\right) + \left(P_{o2} + \sum_{1}^{n} W_{\beta n}.R_{\beta n}\right).\left(Q_{o2} + \sum_{1}^{n} W_{an}.R_{an}\right) + \left(P_{o3} + \sum_{1}^{n} W_{\beta n}.R_{\beta n}\right).\left(Q_{o3} + \sum_{1}^{n} W_{an}\right)$$

Correlation between variables with consideration of qualitative and quantitative approaches

P_o, Q_o, AVC_o and AFC_o

(34)

6.3 Application of this Model in Pricing on a Duopoly Market

Where firms 1 and 2 sell the same commodity, firm 1 must choose the best pricing strategy in contrast to firm 2's pricing strategies. The model determines profit maximization in firm 1 when taking into account the commodity price in firm 2.

P_o1 = Price of product in firm 1

P_o2 = Price of product in firm 2

$$\text{Profit: Max } Z = \left[\left(P_o1 + \sum_{1}^{n} W_{\beta n}.R_{\beta n}\right).\left(Q_o + \sum_{1}^{n} W_{an}.R_{an}\right)\right] - \left[AVC_o + \sum_{1}^{n} W_{en}.R_{en}\right].\left[Q_o + \sum_{1}^{n} W_{an}.R_{an}\right] - \left[\left(AFC_o + \sum_{1}^{n} W_{un}R_{un}\right).\left(Q_o + \sum_{1}^{n} W_{an}.R_{an}\right)\right]$$

S.t

Relationship between commodity prices in firm 1 (P_o1) and firm 2 (P_o2). For example, if firm 2 chooses the high price (P_o2), the model should take Po1 into account.

Tolerance $8\$ \leq P_o1 \leq 10\$$

If firm 2 chooses the low price (P_o2), the model should take P_o1 into account in this tolerance $5\$ \leq P_o1 \leq 7\$$ and make a decision based on these values.

(35)

6.4 Application of this Model in Peak-load Pricing

Peak-load pricing takes into account when a company charges higher rates during peak periods and when demand rises dramatically during that time.

P_{o1} = Regular price

P_{o2} = Prices during peak periods

Profit: $\text{Max } Z = [[(P_{o1} + \sum_{1}^{n} W_{\beta n}.R_{\beta n}).\ (Q_{o1} + \sum_{1}^{n} W_{an}.R_{an})] - [AVC_{o1} + \sum_{1}^{n} W_{en}.R_{en}].\ [Q_{o1} + \sum_{1}^{n} W_{an}.R_{an}] - [(AFC_{o1} + \sum_{1}^{n} W_{un}R_{un}).(Q_{o1} + \sum_{1}^{n} W_{an}.R_{an})]] + [[(P_{o2} + \sum_{1}^{n} W_{\beta n}.R_{\beta n}).\ (Q_{o2} + \sum_{1}^{n} W_{an}.R_{an})] - [AVC_{o2} + \sum_{1}^{n} W_{en}.R_{en}].\ [Q_{o2} + \sum_{1}^{n} W_{an}.R_{an}] - [(AFC_{o2} + \sum_{1}^{n} W_{un}R_{un}).(Q_{o2} + \sum_{1}^{n} W_{an}.R_{an})]]$

S.t

$P_1 \leq P_{o1} \leq P_2$

P_{o2} = Maximized P = P_2 (36)

CONCLUSION

Various external forces have an impact on an organization's decision-making process. Some are uncontrollable by the company since they are external. Others are generally under control because they are within the firm. In this volatile globalized economy, these factors fluctuate with time, hence forecasting and decision-making models should be enhanced as much as possible. Although profit maximization is a clear managerial goal, it does not always indicate that short-term profit increases will result in long-term sustainable profits. A decline in product quality that lowers production costs, for example, will result in a quick boost in profit, but it will also tarnish a company's reputation and give the competition an advantage. Lowering a company's staff training or R&D expenditure will reduce operating costs while simultaneously increasing short-term profitability. The competition, on the other hand, may not follow suit and instead offer a far superior product or service. The corporation that decides to cut its budget to pursue a short-term profit gain could lose a considerable amount of market share in the long run. Profit maximization concept is a significant aim for businesses in terms of planning, but they face significant challenges in determining this amount due to the difficulty of determining the concepts of marginal revenue (MR) and cost (MC). As a result, when these points (MR, MC) are ambiguous or difficult to locate, calculating the equilibrium point is a difficult task. If managers can decide these points, however, there are other obstacles to overcome before making a decision. For example, market, business, and company constraints and circumstances restrict the decision-making region, and these points (MR, MC, and equilibrium point) are not taken into consideration when determining the optimum points and then profit-maximizing points. Besides that, managers and decision-makers have various priorities, such as maximization of sales revenue and cost minimization, which makes it difficult for managers to consider all theories and options when making decisions. When there isn't a consistent number for the variables, the available models are prone to making several errors when attempting to produce a suitable result. The aim of this study was to develop a supplementary mathematical model that would determine the optimal price, variable costs, fixed costs, and production volume for profit maximization while taking into account various constraints, correlations between variables, and growth rates, and also with external dynamic factors and equations that take into consideration growth rates of variables that are related to dynamic factors, as well as constraints and correlations between variables, in order to estimate the optimal points of sales price, number of goods sold, average variable cost, and fixed cost for profit maximization. All external and internal factors can be considered as equitation in this mathematical model's portion of constraints, which is dependent on variables such as risks, competitors, product quality, and R7D in the real world and market. In reality, the model is a supplementary mathematical model that employs other tools, techniques, and approaches to improve forecasting model accuracy and address model limitations. In other words, by combining Linear Programming with Cost-Volume-Profit (CVP) methodologies, this model explains how to improve decision-making and profitability. Furthermore, organizations must be able to relate all elements to profit maximization model variables in order to make a decision. The model was tested using MATLAB software after it was created and based on a case study. The gasoline industry in the United States of America is examined for measurements, and an attempt is made to demonstrate the model's use. The optimum selling price, the optimum level of output, the optimum average variable cost, the optimum average fixed cost, and profit are 3.855 dollars, 20000 gallons a day, 3.007 dollars, 0.84 dollars, and 3209 dollars in turns, according to the MATLAB output. After obtaining a result using the presented model, the model's capability was briefly addressed in the section of model analysis in relation to available theory for determining the optimum point. The models can then be generalized to other sections, such as pricing systems, cost systems, profit maximization, market share maximization, and other business theories and methods that were briefly discussed in the model extension section.

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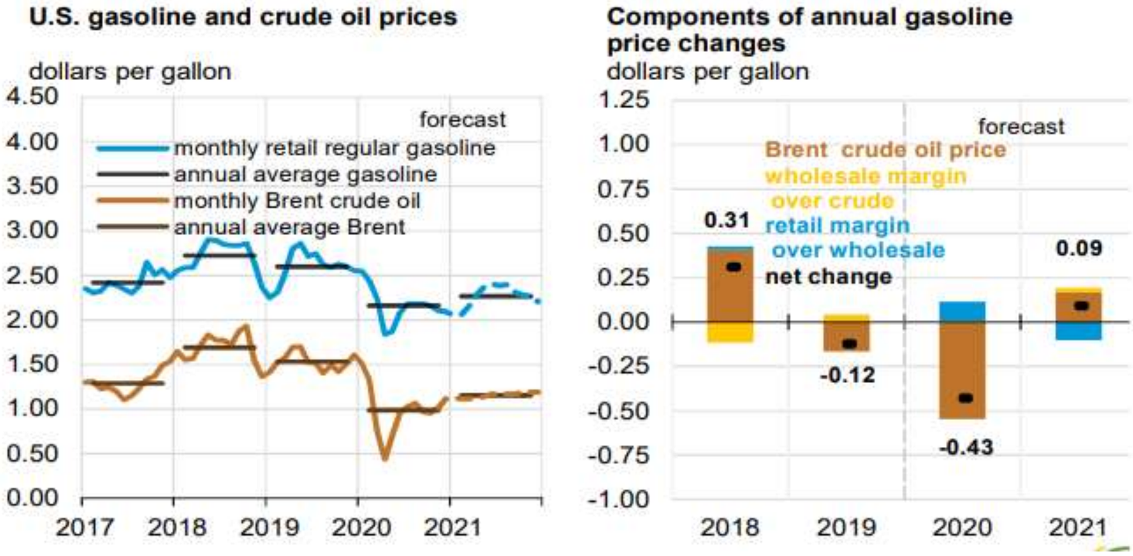
APPENDICES

Appendix 1: Summary in the Slovenian language.

Namen raziskave je izboljšati točnost napovedovanja dobička z vključevanjem predvidevanj analize vpliva obsega proizvodnje na dobiček (angl. Cost-Volume-Profit, CVP) in modela linearnega programiranja za maksimizacijo dobička. V magistrski nalogi je razvit dodaten matematični model za maksimizacijo dobička namesto obstoječih metod napovedovanja. Temelji na komplementarnem matematičnem modelu, ki upošteva oba dejavnika, ki vplivata na maksimizacijo dobička, da bi tako izboljšali metode napovedovanja. Ta model temelji na metodologiji vpliva obsega proizvodnje na dobiček (angl. CVP) in metodologiji linearnega programiranja ter vključuje štiri spremenljivke (količina prodanega blaga, fiksni stroški, variabilni stroški na enoto in prodajna cena), poleg tega pa tudi vse dejavnike bodisi podjetja, njegovega sektorja ali poslovanja nasploh, ki vplivajo na te spremenljivke. Lahko so povezani s tem modelom in nato vplivajo na kalkulacije maksimizacije dobička. Vpliv obsega proizvodnje na dobiček (angl. CVP) je orodje za določanje poslovnega okolja, ki je lahko uporabno tako v proizvodni kot storitveni dejavnosti.

Appendix 2: Components and Annual Gasoline and Crude Oil Prices between 2017 and 2021 in the United States of America.



Source: U.S. Energy Information Administration (2021).

Appendix 3: The Retail Gasoline Price in the United States of America.

Year		Data 1: U.S. All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon)
1994		1.078
1995		1.158
1996		1.245
1997		1.244
1998		1.072
1999		1.176
2000		1.523
2001		1.46
2002		1.386
2003		1.603
2004		1.895
2005		2.314
2006		2.618
2007		2.843
2008		3.299
2009		2.406
2010		2.835
2011		3.576
2012		3.68
2013		3.575
2014		3.437
2015		2.52
2016		2.25
2017		2.528

Source: U.S. Energy Information Administration (2020).

Appendix 4: Information about Gasoline Consumption between 1994 and 2017 in the United States of America.

A	B
Back to Contents	Data 1: U.S. Total Gasoline Retail Sales by Refiners (Thousand Gallons per Day)
Sourcekey	A103600001
Date	U.S. Total Gasoline Retail Sales by Refiners (Thousand Gallons per Day)
1994	55033.2
1995	55922.5
1996	57536
1997	61123.4
1998	63330.3
1999	61956
2000	60896.9
2001	62013.4
2002	63638.4
2003	63830.5
2004	58388.6
2005	58977.4
2006	59977.8
2007	57653.5
2008	55108.1
2009	49797.6
2010	44697
2011	39002.1
2012	29725.8
2013	24722.5
2014	21633.6
2015	25454.1
2016	25604.5
2017	24498.1

Source: The World Bank and U.S. Energy Information Administration (2020).

Appendix 5: The Total Retail Sales and Price by Refiners between 1991 and 2019 in the United State of America.

AH27

	A	B	L	M
1	U.S. Total Gasoline Retail Sales by Refiners		U.S. Total Gasoline Retail Sales by Refiners	
2	https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMA_EPM0_PTG_NUS_DPG&f=A		https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=a103500001&f=a	
3	22:03:23 GMT+0100 (Central European Standard Time)		21:53:56 GMT+0100 (Central European Standard Time)	
4	Source: U.S. Energy Information Administration		Source: U.S. Energy Information Administration	
5	Year	U.S. Total Gasoline Retail Sales by Refiners Dollars per Gallon	Year	U.S. Total Gasoline Retail Sales by Refiners Thousand Gallons per Day
6	2019	2.245	2019	24239
7	2018	2.303	2018	24267
8	2017	1.976	2017	24498
9	2016	1.73	2016	25605
10	2015	2.003	2015	25454
11	2014	2.855	2014	21634
12	2013	3.049	2013	24723
13	2012	3.154	2012	29726
14	2011	3.05	2011	39002
15	2010	2.301	2010	44697
16	2009	1.888	2009	49798
17	2008	2.775	2008	55108
18	2007	2.345	2007	57654
19	2006	2.128	2006	59978
20	2005	1.829	2005	58977
21	2004	1.435	2004	58389
22	2003	1.156	2003	63831
23	2002	0.947	2002	63638
24	2001	1.032	2001	62013
25	2000	1.106	2000	60897
26	1999	0.781	1999	61956
27	1998	0.673	1998	63330
28	1997	0.839	1997	61123
29	1996	0.847	1996	57536
30	1995	0.765	1995	55923
31	1994	0.738	1994	55033
32	1993	0.759	1993	57219
33	1992	0.787	1992	59128
34	1991	0.797	1991	61181

Source: U.S. Energy Information Administration (2020).

Appendix 6: The Result of the Regression of Gasoline Retail Sales and price between 1994 and 2017 in the United States of America.

	A	B	C	D	E	F	G	H	I	J
1	SUMMARY OUTPUT									
2										
3	*Regression Statistics*									
4	Multiple F	0.728194								
5	R Square	0.530266								
6	Adjusted I	0.516845								
7	Standard E	10149.29								
8	Observati	37								
9										
10	ANOVA									
11		*df*	*SS*	*MS*	*F*	*gnificance F*				
12	Regressio	1	4.07E+09	4.07E+09	39.51025	3.25E-07				
13	Residual	35	3.61E+09	1.03E+08						
14	Total	36	7.68E+09							
15										
16		*Coefficient*	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*	
17	Intercept	69859.98	3467.926	20.1446	7.77E-21	62819.71	76900.24	62819.71	76900.24	
18	X Variable	-12932.9	2057.499	-6.28572	3.25E-07	-17109.8	-8755.91	-17109.8	-8755.91	
19										

Source: Own work

Appendix 7: The Codes of this Mathematical Model in the MATLAB for the Calculation of the Result (Case Study).

```
Aeq=[0.78 0 -1 0;0.22 0 0 -1;12932.9 1 0 0];
beq=[0;0;69859.97753];

lb=[2;20000;0;0];
ub=[4;60000;inf;inf];

A=[];
b=[];

x0=[0 0 0 0];

[x_opt,f_opt,flag]=fmincon(@GF,x0,A,b,Aeq,beq,lb,ub);
f_opt=-f_opt;


vpa(x_opt,4)
vpa(f_opt,4)
function y=GF(x)
y=1.1881*x(1)*x(2)-1.2099*x(3)*x(2)-1.3*x(4)*x(2);
y=-y;



end
```

Source: Own work