IE 492 Graduation Project

Final Report

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Effective Capacity Planning and Allocation

ABSTRACT

This report presents the stages of an IE 492 Graduation Project that was conducted in coordination with Nova Plumbing Solutions which operates in the sanitaryware sector. The company had difficulties in satisfying the orders on time. Upon establishing the root of the problem as the lack of medium-long term capacity planning, aggregate production planning methodology was implemented. In this regard, a cost minimizing linear programming model was formulated; hence, required parameters were identified. Sales demand for the following year was forecasted for different scenarios using various time series models. Other parameters such as machine capacities, subcontracting costs and inventory holding costs were estimated based on the data received from the company. The LP model was solved and its outputs were analyzed. In this phase, sensitivity analyses on different parameters were conducted. In addition, to benefit from the idle capacity left by the baseline scenario, a profit maximizing optimization model was formulated and solved. Aiming at providing the company with the opportunity of repeating the process at suggested intervals and thus achieving sustainable improvement, a graphical user interface was developed using Python programming language.

Etkili Kapasite Planlaması ve Tahsisatı

ÖZET

Bu rapor, banyo ve mutfak malzemeleri sektöründe faaliyet gösteren Nova Plastik Firmasının siparişlerini vaktinde teslim etmekte yaşadığı probleme yönelik çözüm üretilen IE 492 Bitirme Projesinin aşamalarını ortaya koymaktadır. Problemin kaynağının etkili bir orta-uzun vadeli kapasite planlama eksikliği olduğu tespit edilerek bütünleşik üretim planlama metodolojisi uygulandı. Bu çerçevede, maliyeti en küçükleyen bir doğrusal programlama modeli oluşturularak gereken parametreler tespit edildi. Gelecek yıla ilişkin satış talebi, çeşitli zaman serisi modelleri kullanılarak farklı senaryolarla tahminlendi. Makine kapasiteleri, fason maliyeti ve envanter tutma maliyetini içinde bulunduran diğer parametreler şirketten alınan veriler doğrultusunda hesaplandı. Model çözülerek sonuçlar analiz edildi. Bu safhada, farklı parametreler üzerinde duyarlılık analizleri yürütüldü. İlave olarak, esas alınan senaryoda arta kalan kapasitenin değerlendirilmesi adına kârı en çoklayıcı bir eniyileme modeli kuruldu ve çözüldü. Şirketin süreci önerilen aralıklarla tekrarlayarak sürdürülebilir bir geliştirmeye ulaşması amacıyla, bir grafik kullanıcı arayüzü Python programlama dili kullanılarak geliştirildi.

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1. Introduction

The project was conducted in coordination with Nova Plumbing Solutions, a company that operates in the sanitaryware sector since 1988. In its factory located in Kırklareli - Vize, Nova has more than 200 employees and produces around 750,000 pieces every month [1]. Its products are classified into six main groups and are produced through operations performed in plastic injection and assembly departments.

Recently, the company had difficulties in satisfying the orders on time. Searching for the root of the problem, the Production Planning Department realized that proactive actions —such as producing in prior months when capacity was not fully utilized— could have been taken if they had a strategic level plan in which predictions were taken into consideration. During a visit to the facility, the team came across other issues that can be avoided to some extent by having a production plan with a longer horizon. One of them is the oscillating inventories and another is delays occurring in the arrival of raw materials for which lead times are long and uncertain.

Although there are alternative approaches for solving aggregate production planning problems, the exact solution methodology is formulating and solving a math programming model [2]. For this purpose, some key parameter values needed to be derived. The first step was to forecast monthly future demand using time series models. In order to do so, raw sales data for the last five years were acquired, filtered and then shaped into the desired format. Later, forecasts were made with more than 10 methods and used to build three scenarios: optimistic, realistic, and pessimistic.

After having baselines for demand, the team explored monthly production capacity in terms of machine hours. Machine loads for each product were given. They were weighted by sales data and averaged for product groups. The task that left the team relatively more freedom of creativity was estimating inventory holding costs. Two different approaches were tried: classical approach which is extensively used in literature, and an innovative behavioral economics approach which aims to derive the costs from the decision makers' understanding. Other parameters such as subcontracting cost, OEE for machine types and number of blue-collar personnel were provided by Nova.

At the end of parameter estimations, the linear programming model was solved. The final stage was analyzing the results obtained and conducting sensitivity analyses. As an extension, the most profitable product mix to be produced using the idle portion of the capacity was investigated by formulating and solving another LP model.

In parallel, a graphical user interface was designed and developed to be handed over to Nova's Production Planning Department. It not only includes majority of the procedures described, but also gives users space to make changes in parameters. At the end, adjustments on the application were made based on feedback given by Nova's production planning manager.

Although the solution is not yet implemented on the shop floor, it is expected to provide decision makers with insight and reasoning. As a result, data-driven decisions can be taken while expanding machine capacity or subcontracting a machine type, hiring or firing employees. Additional decisions that could be supported by this work may include holding inventory for the sake of reducing cost in the broader picture and ordering raw material batches.

Given the validity of the data received, the work on the forecasting section revealed that monthly sales data does not exhibit a seasonal character. Thus, the problem is not likely to be caused by unexpected demand shocks. By following the operation plan that is offered within the frame of this project, minimal inventory levels as a buffer should be satisfactory for the following year. Moreover, it is shown that the company can benefit from the idle portion of the capacity by taking advantage of planning in advance.

The report is organized as follows. Section 2 defines the problem and investigates it extensively. Section 3 focuses on methodology which is further sectionalized as LP model (3.1), forecasting (3.2) and other parameter estimations (3.3). Section 4 is devoted to output analysis which includes the baseline solution (4.1), sensitivity analysis (4.2), discussion and remarks (4.3). Section 5 presents the extended LP model. Section 6 addresses user interface and implementation. Finally, Section 7 wraps up the project with conclusions and discussion.

2. Problem Definition, Requirements and Limitations

In the problem identification phase, two sources of information were consulted on:

i) Verbal discussion with the managers and engineers.

ii) Shop floor observations during factory visit.

The managers of Nova reported that there were periods when the company was not able to satisfy the orders on time. The extent of this issue came to a point where realistic due dates for the orders could not be promised to customers. On the other hand, only three months prior to this chaotic period, the managers had been even considering downsizing. In addition, during the factory visit, it was observed that inventory levels were quite high even though order satisfaction was told to be problematic. These discussions implied that the root cause of the problem might be an unrecognized seasonality in the demand. Another convincing argument in favor of the above problem statement was that the company back then did not have a tool that provides demand analysis and forecasting.

At this stage, it was also conjectured that the company lacks insight regarding its capacity. They could not firmly recognize the extent to which the capacity would be utilized or idle even in a very near future. The primary need of the company is awareness of the capacity and hence handling it in a rational manner.

The agent that is at the center of this problem is the Production Planning Department. It receives order requests from the Sales Department and reports a due date anticipation. It is informed back if the order is confirmed. Production Planning manages operations through assigning work orders to the facility. Raw material requirements are handled via the Purchase Department. Finally, the subcontractor provides additional capacity if needed. Relevant parties and their relationships within the scope of this problem are illustrated in Figure 1.

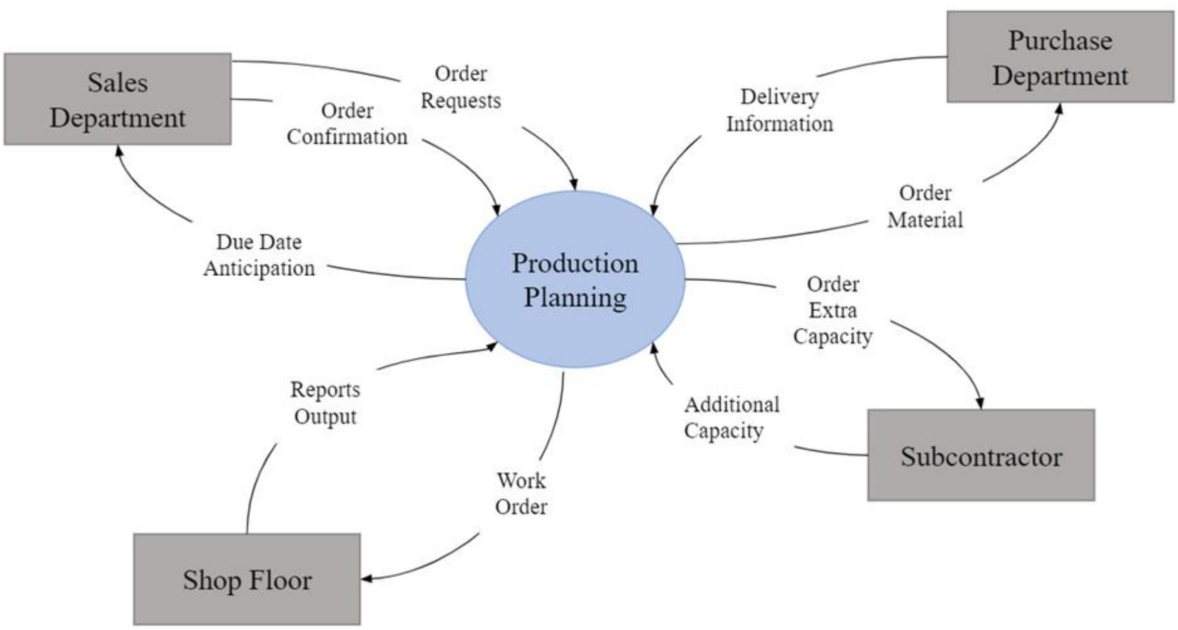


Figure 1: Context Diagram of the Problem

This project is expected to increase the performance of the system in terms of a few criteria:

- Profit: The core LP formulation aimed at minimizing the sum of some cost items.
- Order lead time: When the capacity bottlenecks are foreseen, long and uncertain order lead times are expected to be prevented.
- Inventory levels: Optimal inventory levels are expected to be attained with the aid of a mathematical modeling approach.

A potential source of limitation to this project was the recently opened Uzbekistan plant of the company. The focus of this project was solely on Vize plant, so possible capacity contribution or absorption due to the Uzbekistan plant were neglected. However, by altering the data received and eliminating the customers that are going to be served by the Uzbekistan plant, operations of the plants were isolated and the overlap was minimized.

3. Methodology

To address this problem, the methodology of sales and operation planning, also known as aggregate production planning in the Industrial Engineering domain, was followed. The reason for this choice was that the problem was stemming not from operational matters but from the lack of high-level monitoring. According to Chopra and Meindl, such a planning approach deals with the capacity decisions and presents volumes as well as the mixture for future production [3]. The role of aggregate production planning in the overall planning framework can be seen in Figure 2.

The steps that were taken in this project to come up with such a plan consisted mostly of formulating and solving a linear programming model which was followed by the analysis of outputs. Of course, the LP model required estimation of some parameters. In terms of estimation effort, the tasks were separated as:

1) Forecasting the future demand for the planning horizon

2) Estimation of other parameters

Other than demand, it was not possible to exactly know what parameters would be needed before formulating the LP model. Another reason for the above distinction was that at this level of planning, predictive performance has acute significance; hence, forecasting plays an essential role [2].

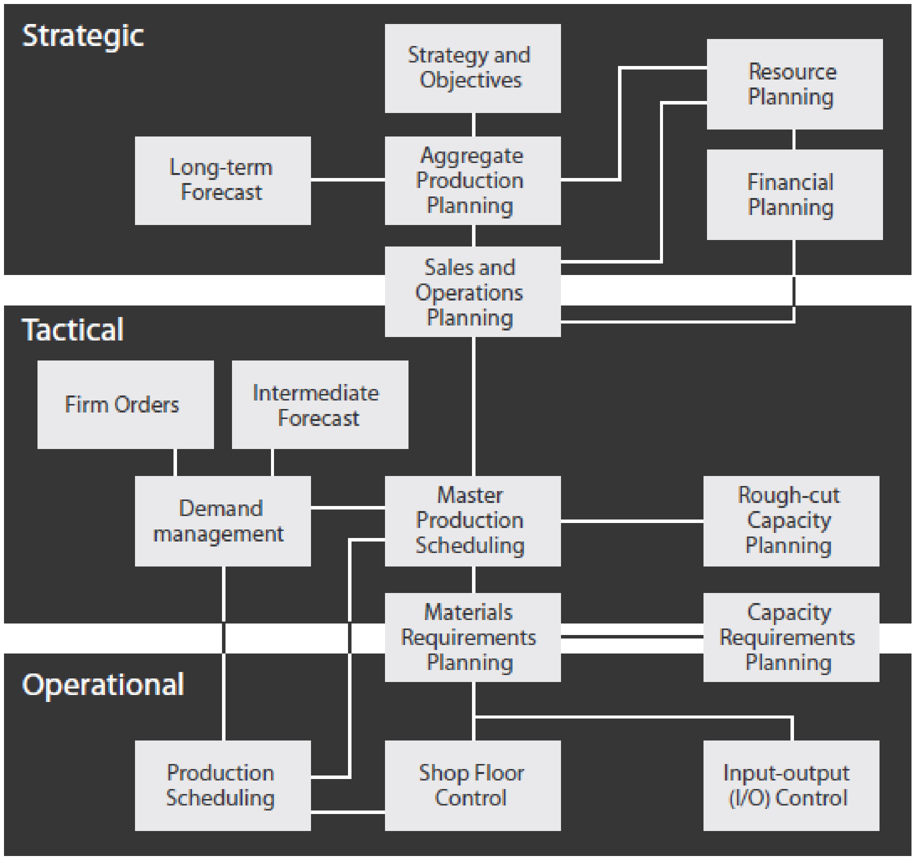


Figure 2: An Example Case of Planning and Control Framework for Heineken Netherlands. Reprinted from *Production and Operations Analysis* (p. 134), by Steven Nahmias and Tava Lennon Olsen, 2015, Copyright 2015 by Steven Nahmias and Tava Lennon Olsen [2]

Aggregate production plans generally cover 3 to 18 months into the future [3]. For the scope of this project, a planning horizon of 12 months was regarded as a reasonable choice. Thorough analyses were conducted for this time period. For the sake of sustainability and flexibility, a capacity planning tool was decided to be delivered to the company. Steps that were taken through the course of the project is summarized in Figure 3.

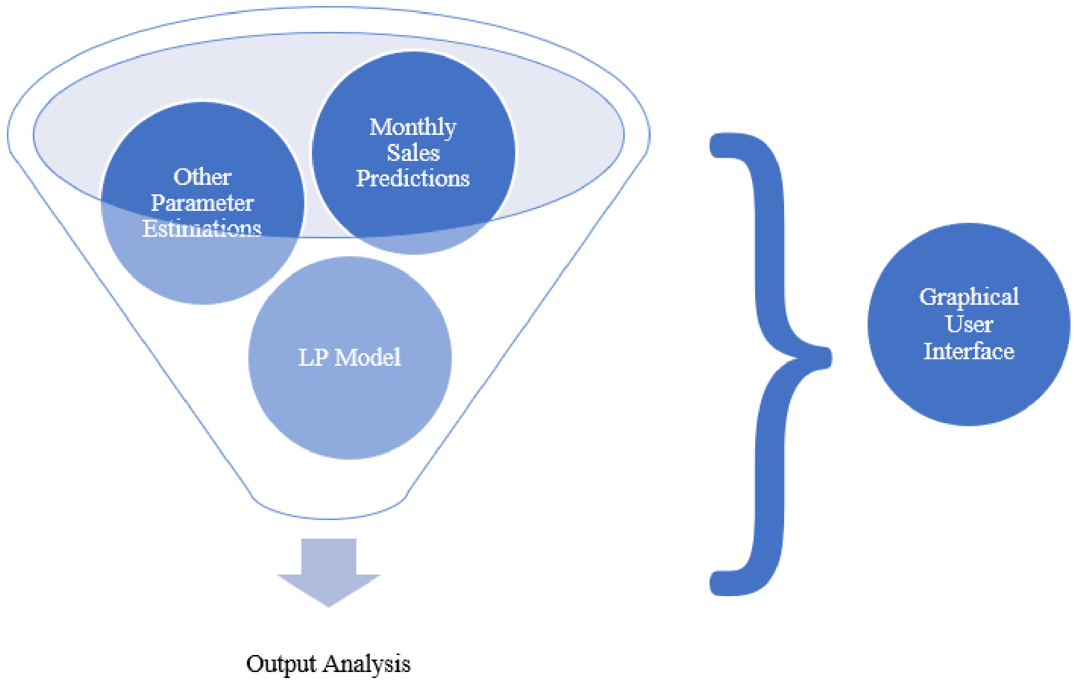


Figure 3: An Overview of the Methodology

3.1. Linear Programming Model

In the broad sense, the objective of the aggregate production plan in this case is to minimize some cost while satisfying the demand within the feasibility of capacity. Previous solution approaches in the literature can be classified into two: (1) approximate graphical solutions, (2) exact LP formulations [2]. There were obvious reasons to go for the LP formulation in this project. First of all, product variety is large enough to make it impossible to be modeled as a single generic product. Also, the capacity has different components namely plastic injection machines with varying pressure tonnage as well as human resources.

After making a decision in favor of LP, the model started to be conceptualized. Since the team had a rough idea about how such a formulation would look like, this phase included mostly the assumptions and simplifications.

Assumptions and Simplifications

- End products of the factory were aggregated as the following six generic groups: siphons, shower and bathtub siphons, toilet seats, reservoirs, cistern mechanisms, built-in reservoirs.

- Plastic injection machines were aggregated as the following six generic groups based on pressure tonnage: 90 T, 120 T, 160 T, 200 T, 320 T, 500 T.
- In each month, demand of each product type must be satisfied. No shortage/backordering is allowed.
- Monthly adjustments in capacity is not allowed. Hiring-firing option was discarded by management. Machine purchase possibilities were left to the output analysis section.
- The model would be pure continuous linear programming, which means decision variables such as production and inventory levels could take fractional values. In the aggregate level of planning with high volumes, such simplification was decided to be reasonable.
- Production cost was assumed to be stable through the planning horizon. Therefore, it is discarded from the objective function since producing in different months would bring the same cost and all demand must be satisfied.
- Starting inventory levels were assumed to be zero believing that it would not cause considerable difference while drawing inferences.

In addition, the team was informed that the company has the possibility of subcontracting extra machine hours if needed. Hourly rates are constant for the planning horizon and available. Considering the above discussion regarding assumptions together with the problem requirements, the model given in Table 1 was formulated.

The objective function consists of three cost components. The first one stands for inventory holding cost. The second term is for the overall labor cost. Besides regular (R_t) and overtime (O_t) labor hours, a decision variable named extra labor hours (E_t) was included to prevent the model from being infeasible due to labor capacity. Its cost parameter was assigned a very high value so that it would be relevant only if the labor capacity reached its full. Constraint names are given in the right and are self-explanatory.

The model was then translated into the computer environment using Coliop Mathematical Programming Language (CMPL). Before actually being able to solve the model, its parameters needed to be determined, which is the subject of the following sections 3.2. and 3.3.

Table 1: Linear Programming Model

Indexes
i: *Aggregated product groups* j: *Aggregated machine groups* t: *Time index* $\{0, \dots, 12\}$
Parameters
c_i: *Inventory holding cost of product i* d_{it}: *Forecasted demand for product i in period t* m_{ij}: *Standard hours spent on machine j to produce one unit of i* H_j: *Total hours available on machine group j in a month (OEE adjusted)* s_j: *Cost of subcontracting an extra hour of machine j* k_i: *Standard labor hours spent for one unit of i* r: *Cost of using one regular hour of labor* o: *Cost of using one overtime hour of labor* e: *Cost of needing one extra hour of labor (To prevent infeasibility in a model without hiring)* REG: *Maximum regular labor hours available in a month* OT: *Maximum overtime labor hours available in a month*
Decision Variables
X_{it}: *Production amount of product i in period t* I_{it}: *Amount of inventory for product i carried from period t to* $t+1$ S_{jt}: *Subcontracted hours of machine j in period t* R_t: *Regular labor hours used in period t* O_t: *Overtime labor hours used in period t* E_t: *Extra labor hours needed in period t*
Model
$Minimize \quad \sum_i \sum_t c_i I_{it} + \sum_t (rR_t + oO_t + eE_t) + \sum_j \sum_t s_j S_{jt}$ $s.t.$ $X_{it} + I_{i,t-1} - d_{it} = I_{it} \quad \forall i, \forall t \quad (Balance\ equation)$ $\sum_i k_i X_{it} \le R_t + O_t + E_t \quad \forall t \quad (Labor\ hour\ requirement)$ $0 \le R_t \le REG, \ 0 \le O_t \le OT \quad \forall t \quad (Regular\ and\ OT\ labor\ hour\ limit)$ $\sum_i m_{ij} X_{it} \le H_j + S_{jt} \quad \forall j, \forall t \quad (Machine\ hour\ requirement)$ $X_{it} \ge 0,\ I_{it} \ge 0,\ S_{jt} \ge 0,\ R_t \ge 0,\ O_t \ge 0, E_t \ge 0 \quad (Nonnegativity)$

3.2. Forecasting

Forecasting task can be divided into two subtasks as:

i. Identifying and implementing forecasting methods
ii. Describing evaluation measures and techniques to compare performances of selected forecasting methods.

3.2.i. Forecasting Methods

In the forecasting phase of this project, only time series data were used and no external regressor was included. It was assumed that time series methods were sufficient to forecast demand accurately. Many potential characteristics of data were investigated through stationary, trended, seasonal and even non-linear models. Forecasting methods that were used in the project can be classified into two in terms of complexity.

a. Simple Forecasting Methods

As Hyndman mentions in his book, some simple forecasting methods are extremely easy to implement and surprisingly effective [4]. These methods are: mean, naïve, drift and seasonal naïve methods. Short explanations of these methods along with their formulations are provided in Table 2.

Table 2: Simple Forecasting Methods

Method	Explanation	Formula
Mean	It uses the average of all historical data in the train set. It is a solid and simple benchmarking method.	$\hat{y}_{T+h\|T} = \bar{y} = (y_1 + \cdots + y_T)/T$
Naïve	It predicts the future demand as the last observed data point. It works well when the data is random and does not follow any pattern.	$\hat{y}_{T+h\|T} = y_T$
Drift	It is an extended version of the naïve method. It takes the average change in train data into consideration.	$\hat{y}_{T+h\|T} = y_T + h(\frac{y_T - y_1}{T-1})$
Seasonal Naïve	It uses the last season's observed data to forecast the next season. It is a solid benchmark for strongly seasonal data.	$\hat{y}_{T+h\|T} = y_{T+h-m(k+1)}$

These methods were used as benchmarks. It is important to have benchmarks in forecasting projects, to draw a conclusion on performance of other complex methods. If any other complex method does not perform better than these simple methods, it is not worth using [4].

b. More Complex Forecasting Methods

1) Exponential Smoothing

Simple exponential smoothing is used as another method. It works well when there is no clear trend and seasonality [4].Given that sales data for some product groups do not follow any clear trend, it is worth using this method. Smoothing parameter alpha, according to which the last observation affects the forecast, was determined by computer by maximizing the log-likelihood [5].

2) Double Exponential Smoothing

Double exponential smoothing method is an extended version of the simple exponential smoothing. It additionally includes a smoothing parameter for the trend component [4]. Similar to simple exponential smoothing, the values for smoothing parameters were not predefined but they were determined by computer.

3) Holt-Winters

Holt-Winters method is an extension of Holt's method which includes seasonality. Trend and seasonality elements in Holt-Winters models are defined either as additive or as multiplicative. Additive models are used when the variations are almost constant throughout the series, whereas multiplicative versions fit better when variations change with the level of the series [4]. This method is more complex compared to basic seasonal methods such as seasonal naïve, because it uses a smoothing parameter for the seasonal component [4]. Two versions of Holt-Winters were implemented in this project:

a. Holt-Winters Additive Trend Multiplicative Seasonality
b. Holt-Winters Additive Trend Additive Seasonality

Parameter estimations were done automatically.

4) ARIMA

ARIMA models are used in time series analysis because of their strength in including autocorrelations of data points. It includes differencing, autoregression and moving average. An Auto ARIMA function was used in the project. It chooses the best model parameters by searching for the minimum AIC value [4].

5) SARIMA

Seasonal ARIMA model is an extended version of ARIMA model which has two parts: seasonal and non-seasonal. SARIMA is used to include seasonal characteristics of the data [4]. Again, parameter estimations were done automatically.

6) Long Short-Term Memory

Including an artificial neural network architecture to the forecasting arsenal was intended. To do so, a comprehensive literature review was carried out. Two alternatives were considered as candidates: feedforward neural networks (FNNs) and recurrent neural networks (RNNs).

RNNs can be defined as “a natural generalization of feed forward neural networks to sequences” through use of networks and loops [6]. In such neural network architectures, a dynamic feedback system is maintained by feeding the network back with its outputs [7]. Zhang discusses that this dynamic feedback system contributes to a richer characteristic for RNNs over FNNs, especially when dealing with dynamic nonlinear patterns [7]. Although it is not concluded that RNNs are more successful than FNNs in forecasting tasks, their popularity in literature has been growing [7] [8].

Continuing with RNNs was decided on. In that stage, search for an appropriate RNN architecture started. Although RNNs are one of the most commonly used types of neural networks, most RNNs are still susceptible to some issues including: (1) vanishing or (2) exploding gradient when fitting the model or (3) failing to learn Long-Term Dependencies [6] [7] [9]. Solution to these problems are provided by a method called Long Short Term Memory (LSTM) which was proposed by Hochreiter and Schmidhuber in 1997 [6] [9]. The method was implemented after some hands-on experience with Keras library in Python under the guidance of Brownlee’s book [10].

3.2.ii. Evaluation Measures and Techniques

To compare the forecasting methods fairly, ultimate attention was paid on selecting right evaluation measures and techniques. Weighted mean absolute percentage error was chosen as the main metric. Mean absolute percentage error and mean squared error were used as supplementary. Two evaluation techniques were investigated.

- Fixed Origin Evaluation

Forecasting origin is the last data point of the train set, meaning that it separates train and test data [11]. If the practitioner chooses to perform evaluation using a single forecasting origin, it is called "fixed origin evaluation" [11]. Since performance on only one test period is evaluated, it is not robust to outliers or level shifts that might be contained in the test set [11] [12].

- Rolling Origin Evaluation

Rolling origin evaluation involves having multiple forecasting origins and evaluating performance using multiple forecasts corresponding to these origins [11] [12]. Since it gives the opportunity to make more observations, it provides a better assessment of data and is more robust to outliers and level shifts [11] [12]. One problematic aspect of rolling origin evaluation can be defined as working with models that are generated by different sizes of train sets. It is worth keeping in mind that forecasting quality of different methods can change according to data size [13].

Instead of choosing one of these alternatives, the team decided to use two techniques jointly. It was conjectured that this was an intelligent way to be protected against weaknesses that are discussed above. Performances of forecasting methods were inspected using aforementioned measures and techniques. The best performing forecasting method was selected based on overall success.

After determination of forecasting methods and evaluation techniques, the implementation phase started. Two programming languages, Python and R, were employed. An example plot for Plastic Flush Tanks is given in Figure 4.

Shortly after experimenting with forecasting methods, it was observed that LSTM did not perform competitively. Although there were instances where it was diagnosed as the best performing method, due to stochasticity in the initialization phase of the network, no stability was ensured. Combined with the fact that it brings a heavy computational burden, it was decided to be excluded from the list.

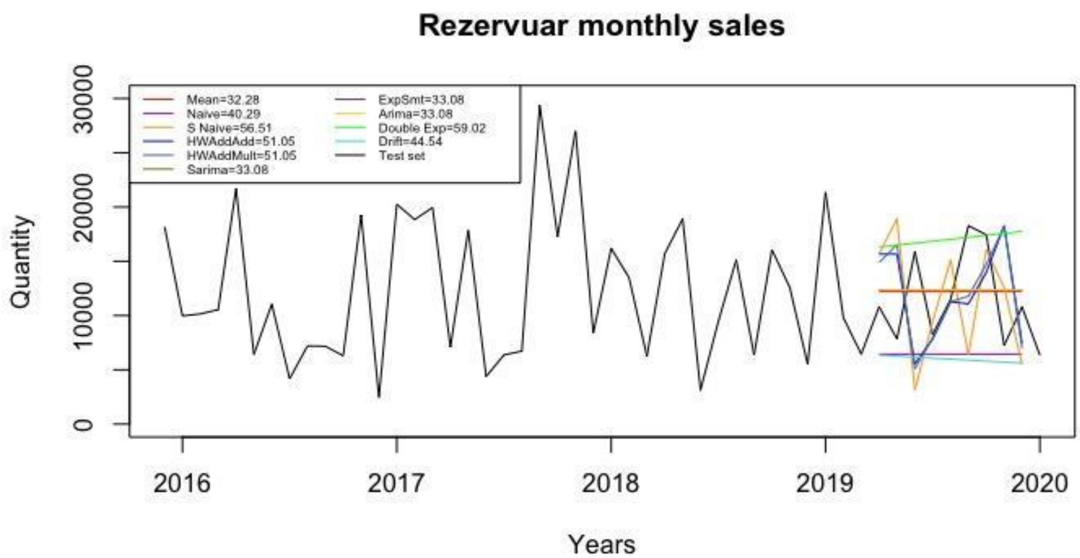


Figure 4: Forecasting Methods Evaluated Using WMAPE and Fixed Origin Evaluation

Observing the time series plots of product types, the team suspected a trend change occurring in the early 2018. Thus, predictions were generated one more time after eliminating different trended data. One shortcoming of this decision was that data left was not sufficient to test forecasting methods with seasonality, hence they were excluded. An example plot for Built-in Reservoirs is given in Figure 5.

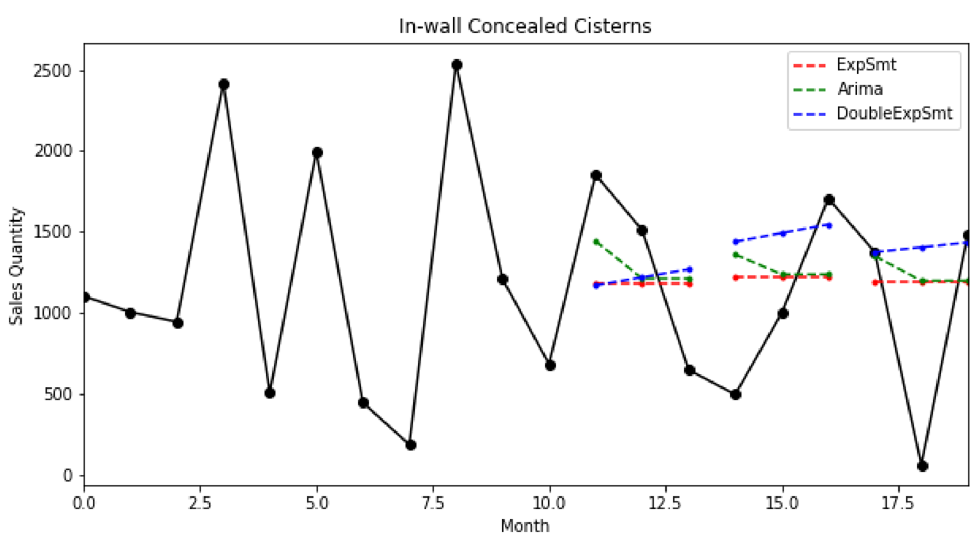


Figure 5: Predictions Generated with Rolling Origins After Data Elimination

Yet, forecasting performances were still not satisfactory. The team decided to seek for alternative ways to improve forecasting quality. Altering the time resolution and making quarterly forecasts seemed to be a reasonable option. Aggregation increases forecast accuracy thanks to reduced variance, and this phenomenon is also called risk pooling [2]. Predictions made on quarterly basis for siphons are plotted in Figure 6. These predictions were then divided by three to move back to monthly basis.

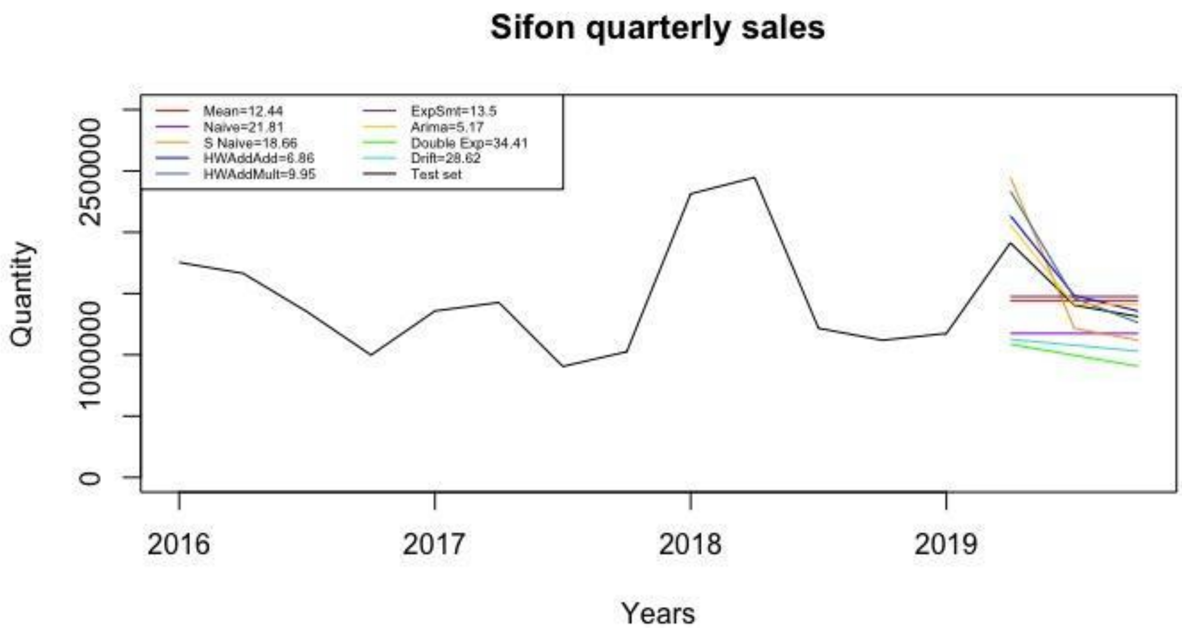


Figure 6: Siphons Sales Predictions Generated on Quarterly Basis

Although altering time resolution resulted in great improvements in some product types, it was not as successful for others. For example, predictions for shower and bathtub siphons are plotted in Figure 7. For such product types that were not well predicted with quarterly resolution, information lost was concluded to be not justified. Final predictions to be given to the LP model were kept on a monthly basis.

Consequently, the basis for each product type was specified depending on the significance of improvement yielded by shifting to quarterly resolution. Predictions were made on the specified basis of the product type, and best performing methods were chosen likewise. In case of close scores or ties, the decision was made in favor of the simpler method.

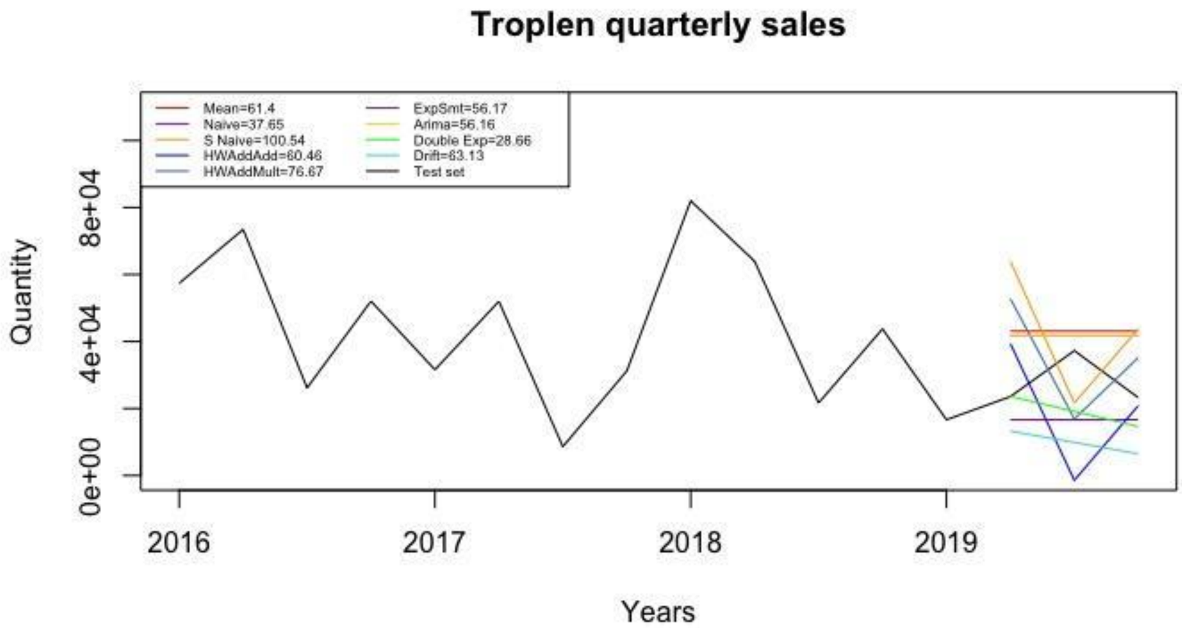


Figure 7: Shower and Bathtub Siphons Sales Predictions Generated on Quarterly Basis

Mildly disappointed with the forecasting accuracy, the team decided to supply best case and worst-case scenarios to be used for sensitivity analyses. One way of doing so was to use confidence intervals suggested by the best performing method. However, some forecasting methods —such as naive and seasonal naive— were not able to provide any confidence interval. In addition, placing too much reliance on the best performing method itself was refrained from.

The team invented an alternative solution. This solution includes making predictions using all forecasting arsenal, and then creating a pessimistic set with the minimum predicted value for each month or quarter. Optimistic set is obtained in the same manner with the maximum predicted values. This method accounts for different characteristics of data detected by different forecasting methods. It includes many “what if” questions. Optimistic, realistic and pessimistic prediction sets for shower and bathtub siphons are plotted in Figure 8. These procedures were followed for each product type. Prediction sets of three scenarios were prepared. The project continued with the estimation of other parameters.

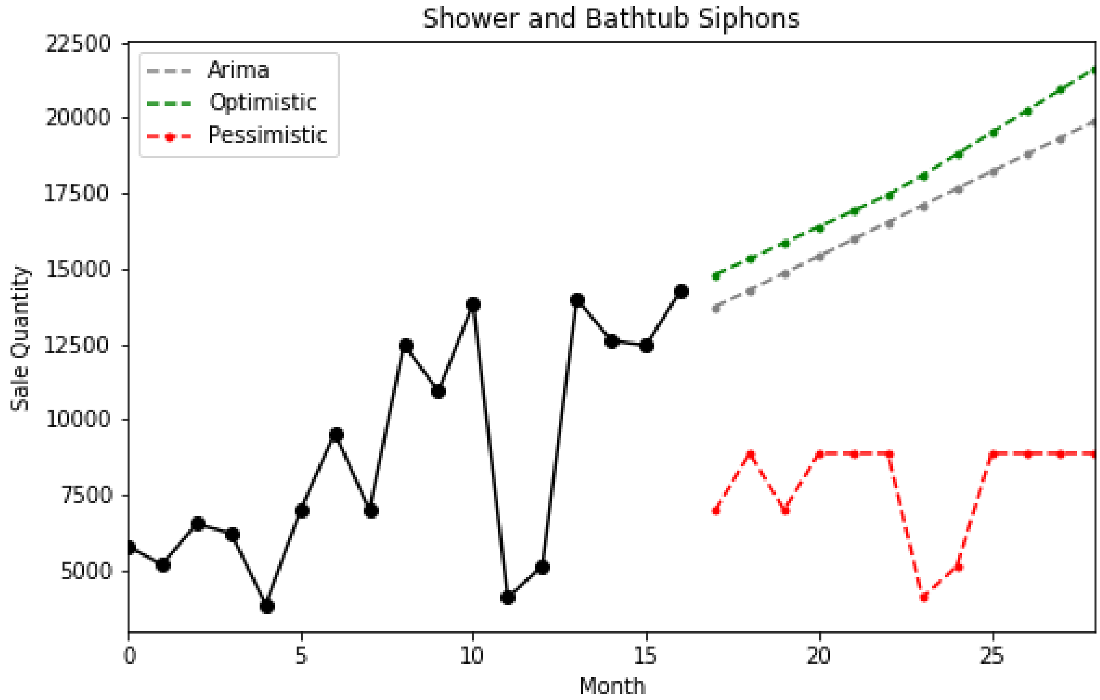


Figure 8: Optimistic, Realistic and Pessimistic Predictions for Shower and Bathtub Siphon Sales

3.3. Other Parameter Estimations

There were several parameters in the LP model that were needed to be estimated by using the data gathered from Nova and by using other techniques. These parameters were: demand, machine loads (per product group), total machine hours available, subcontracting price (per machine group), inventory holding cost (per product group), labor load (per product group), regular hourly labor cost, overtime hourly labor cost, extra hourly labor cost, total regular labor hour available and total overtime labor hour available.

- **Demand** parameter was estimated by using the output from the forecasting phase. Realistic, minimum, and maximum demand cases were used at the sensitivity analysis.
- **Machine load** parameter was estimated for each product group separately. By gathering the machine load for each specific product type and by considering the sales data of last year for product groups, a weighted average machine load was found for each generic product group.

- For **total machine hours available**, there are 6 machine groups: 90 T, 120 T, 160 T, 200 T, 320 T, 500 T. To find total machine hours for each group, the following formula was used: Total machine hours = # of machines * # hours per day (24) * # of days per month (30) * OEE * available portion of a week (6/7)

  Overall Equipment Effectiveness *(OEE)* is a metric that accounts for availability, performance and quality rates of a machine **[14]**. Its value was given by the company as 85% for the first four machine groups and 80% for the 320 T and 500 T machine groups.
- **Subcontracting prices** for all machine groups were received from the company.
- **Labor hour load per product group** was calculated by gathering the data from the company for each product. Sales data of the recent year was used to calculate the weighted average of labor hours for each product group.
- **Regular hourly labor rate** parameter was calculated by dividing minimum wage by the total working hours per month.
- **Overtime hourly labor rate** parameter was calculated by increasing the regular hourly labor rate by 50%.
- **Extra hourly labor rate** parameter was set to prevent infeasibility of the model. It was set at a much higher price than overtime and regular hourly labor because it has nothing to do with the current situation of the company.
- **Regular total hours available** parameter was calculated by using the following formula:

  # of workers * hourly working limit per week (45h) * weeks per month (30/7)
- **Overtime total hours available** parameter was calculated by dividing the regular total hours by 3, which is the maximum limit that can be assigned as overtime labor.
- For **inventory holding cost**, a different approach was used. Since it was not possible to gather exact data from the company, literature search was done first. Then an approach was developed which was also used at the sensitivity analysis part.

To determine the inventory holding cost, several approaches were tried. First, a behavioral economics approach was experimented. The aim was to get the insight of managers regarding the parameter by delivering them a survey that asks more or less the same question from different angles. An example question of this survey can be seen below:

“Assume the average cost of one unit of reservoir to the company is 90 TL. Say we produced 10 units today to stock. Which of the two orders would you prefer?

a) 10 reservoirs for 1000 TL to deliver tomorrow

b) 10 reservoirs for 1250 TL to deliver one month later

If you choose a) how much an increase to the amount in b) will make you indifferent”

However, it did not produce meaningful results. Basically, managers were indifferent in answering most of the questions. So, literature search was done to try different approaches. After doing some literature search, a multi-case study article showed that in Italy, inventory holding cost has a significant yearly percentage around 25% [15]. Nevertheless, after discussing these cases for a while, it was seen that they do not have much relevance for a company in Turkey. It was decided to come up with a lower limit for the inventory holding rate, specifically considering the opportunity cost of capital that is invested in stock. By taking the average interest rate on TL (up to 1 month term) from the Central Bank, for the 6 months period (10/2019-03/2020), and after using compounding formula; a lower limit was calculated for the monthly inventory holding rate. It was calculated in the following manner:

$$(1 + h)^{12} = \bar{\iota}$$

Where h is the monthly inventory holding rate and $\bar{\iota}$ is the average interest rate on TL [16].

In the sensitivity analysis part, this inventory holding rate was used with the lower limit, 2x and 4x cases to determine its significance. So, it was satisfactory in the approach to set a lower limit first and then increase it to check the importance.

4. Output Analysis

After estimating all necessary parameters, the LP model was ready to be solved and it was time to derive inferences. This task was carried out in the following order. Firstly, the model was solved by plugging the baseline values estimated for all parameters. Then to check the robustness of the results, sensitivity analyses were performed on parameters which were thought to have significant influence on the outcome. Last phase was the discussion regarding some economic decisions and further work to strengthen the analysis.

4.1. Output Analysis for the Baseline Case

The baseline case is using the parameters that we estimated and using the realistic demand as demand parameter. The output is evaluated from different perspectives namely the objective value and the level of decision variables.

The baseline case resulted in:

- Zero inventories.
- Zero subcontracting for any of the machine groups.
- Machine utilization percentages ranging from 19% to 84%, they are illustrated in Figure 9.
- Zero overtime labor utilization and regular labor utilization ranging from 51% to 53%. They can be observed in Figure 10.
- Total cost is 3,104,471.74 TL and it consists of 100% regular labor cost. Cost structure is available in Figure 11.

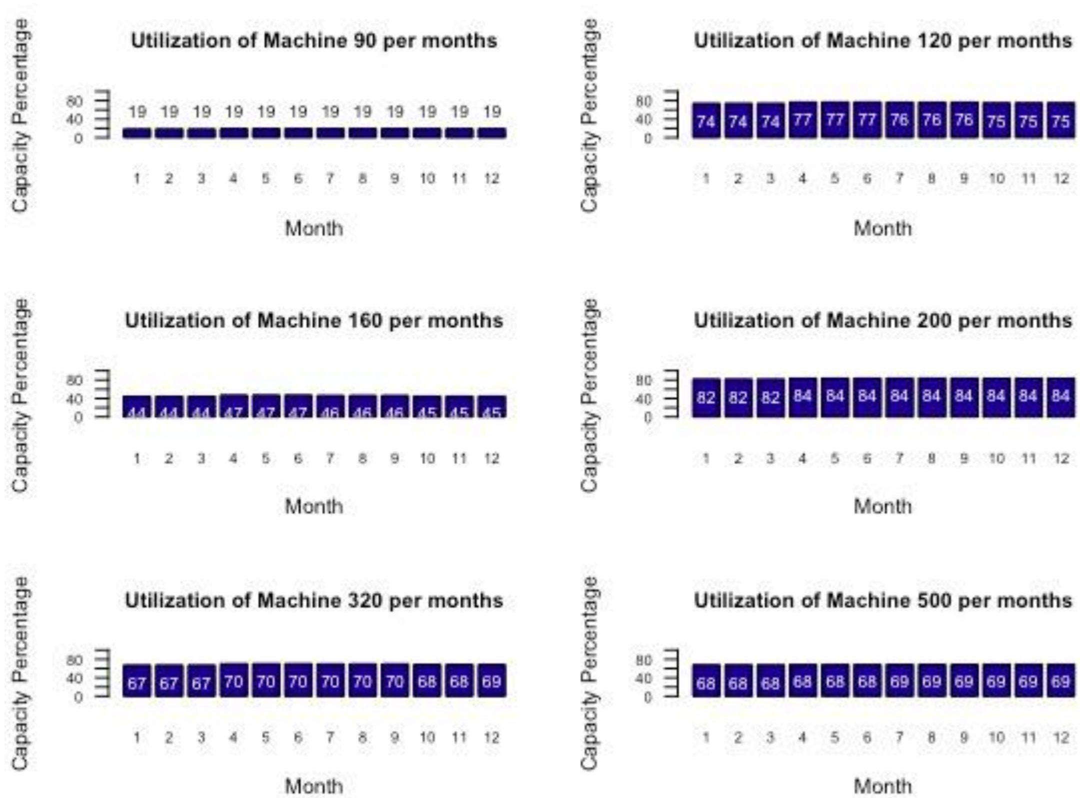


Figure 9: Utilization of Machines in Baseline Case

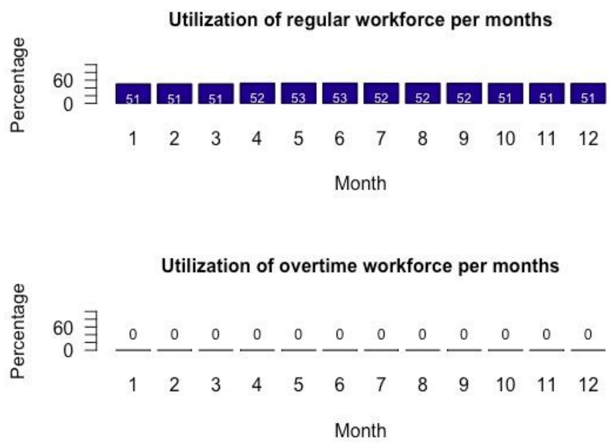


Figure 10: Regular and Overtime Labor Utilization

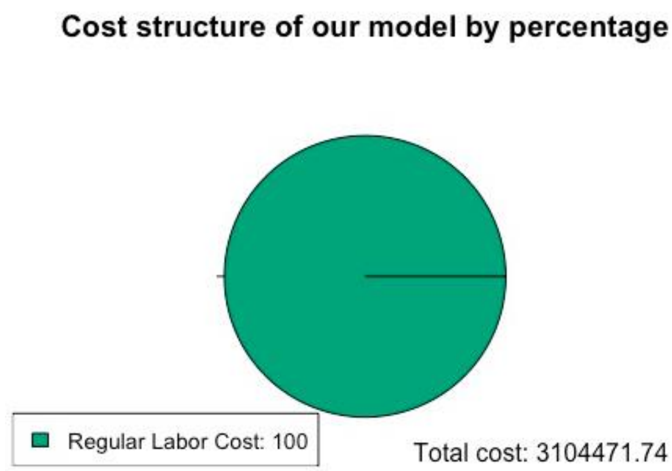


Figure 11: Cost Structure for the Baseline Case

It is important to mention that only the relative shares of cost items are emphasized with a plot like the above one. Since the production cost was not included in the model, it is not expected to get a realistic number with the total cost figure.

4.2. Sensitivity Analysis

The sensitivity analysis was done for four different parameters which are:

- Demand, inventory holding cost, subcontracting price and hourly labor rate.

These parameters could be changing by nature and it is important for the company to be prepared against unstable parameters.

i) Demand

Sensitivity analysis for demand was done for the three cases which were received as the output from forecasting. They are minimum (pessimistic), baseline, and maximum (optimistic) demand cases. The minimum demand case was more or less the same as the baseline case except for production volumes, they had no inventories, no overtime labor and no subcontracting. In this case:

- Machine utilization rate dropped, ranging from 10% to 67%.
- Regular labor utilization dropped, ranging from 26% to 40%.
- Total cost reduced to 2,097,568.25 TL, which consists of regular labor cost as plotted in Figure 12.

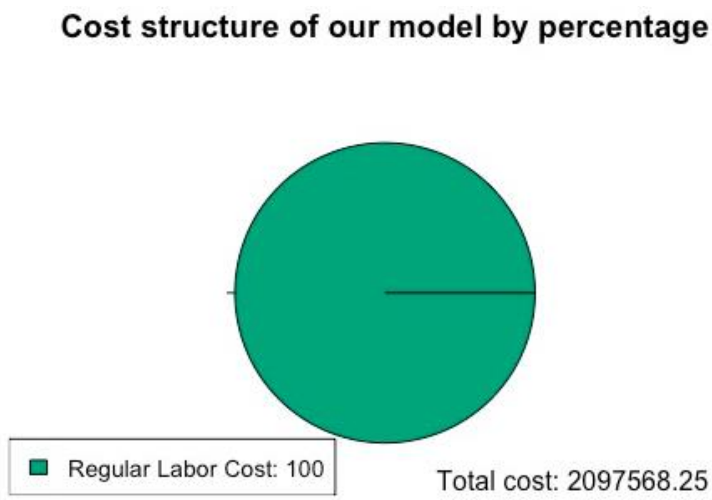


Figure 12: Cost Structure for the Pessimistic Case

The maximum (optimistic) demand case had significant outcomes:

- Siphon had 16,500 units of inventory in March and toilet seats had 3,993 inventories in June. These inventory levels are depicted in Figure 13.
- Machine 200 used all of its capacity and had a subcontracting rate for all months ranging from 7% to 12%. Subcontracted hours as percentage of capacity are available in Figure 14.
- There is no overtime labor and the regular labor utilization increased slightly ranging from 60% to 69%.

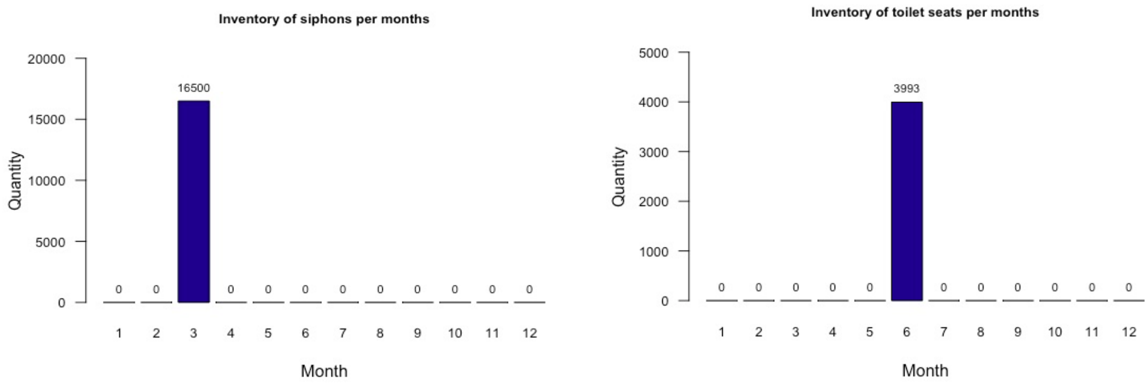


Figure 13: Inventory Levels of Siphons and Toilet Seats in the Optimistic Case

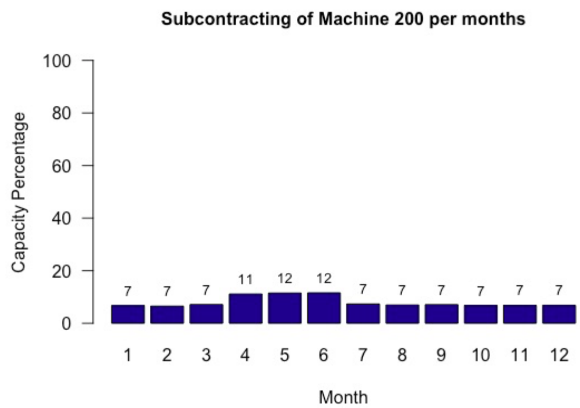


Figure 14: Subcontracting of Machine 200 T in the Optimistic Case

- Lastly, the total cost increased to 3,900,219.58 TL with regular labor cost, 200 T subcontracting cost, inventory holding cost for siphon and for toilet seats. Total cost and cost share are shown in Figure 15.

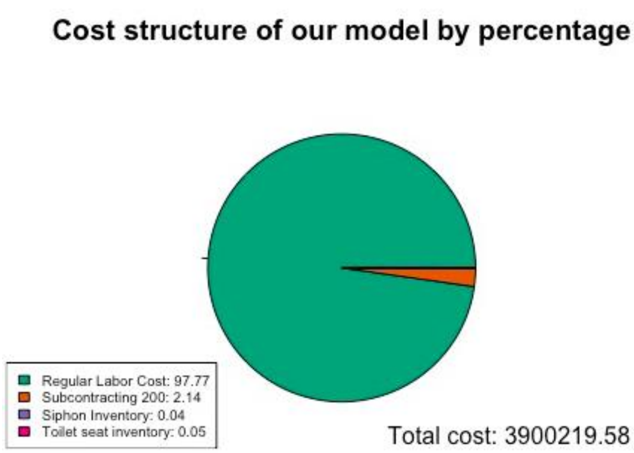


Figure 15: Cost Structure for the Optimistic Case

These three cases did not lead to divergent results, so lastly the 1.5x of maximum demand case was solved. This extreme case showed a cost distribution with different cost items. In this extreme case, total cost had increased to 8,560,966.19 TL with subcontracting cost, inventory holding cost, regular labor and overtime labor cost. Further analysis can be done in this extreme case scenario. Share of these cost elements are given in Figure 16.

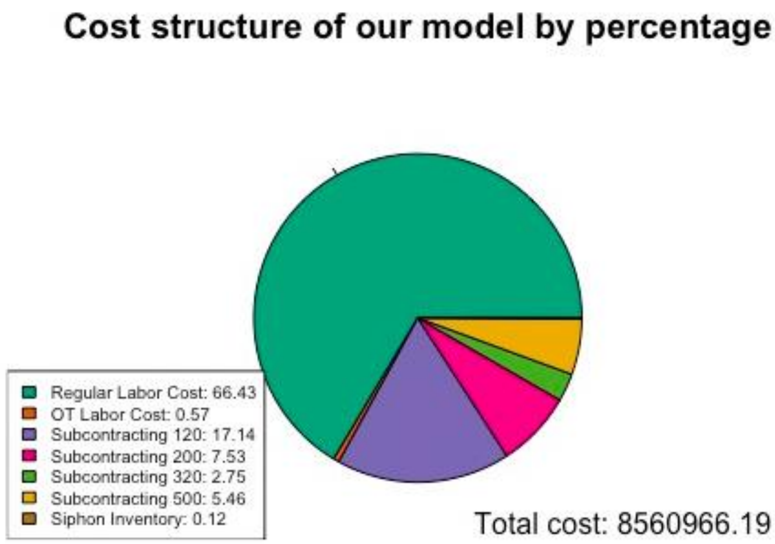


Figure 16: Cost Structure for the Extreme Demand Case

ii. *Inventory Holding Cost*

The sensitivity analysis for inventory holding cost was done by comparing the baseline with 2x and 4x cases. Demand for these models were used from the maximum (optimistic) demand case. The 2x inventory holding rate scenario only changed in increased inventory costs for siphon and toilet seats, but all the other values remained the same.

The 4x inventory holding rate scenario had slightly different outcomes. In this case, siphon had zero inventory compared to 16,500 units of inventory in the base scenario. Toilet seats inventory remained the same. This decreasing siphon inventory led to a slight 1% increase of subcontracting for machines 120 T and 200 T in April. Also, machine utilization has increased around 1-2% for machines 160 T and 320 T. Lastly, regular labor utilization had decreased 1% in March and increased 1% in April. The total cost has slightly increased around 8,000 TL to 3,908,086.68 TL and the cost distribution is displayed in Figure 17.

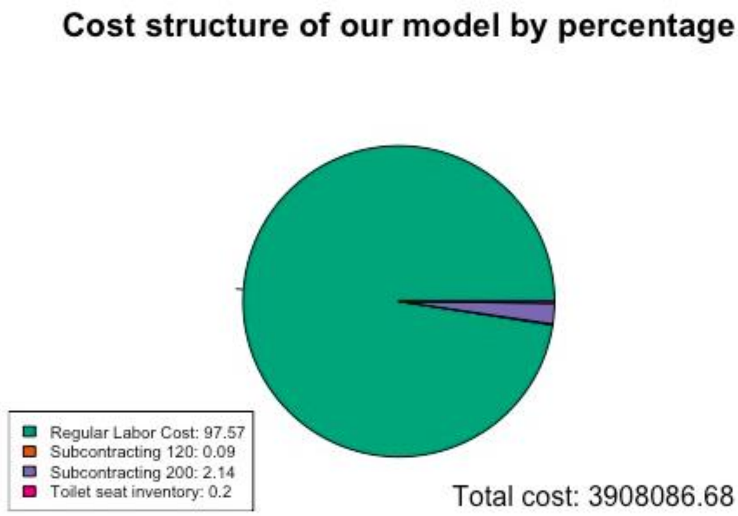


Figure 17: Cost Structure for the Extreme Inventory Holding Cost Case

iii. *Subcontracting Price*

The subcontracting price cases were done for maximum (optimistic) demand scenario with 0.5x cases and 1.5x cases. The outcome did not show any significant changes. Only difference was in the cost distribution. Percentage of subcontracting costs decreased and increased respectively with 0.5x and 1.5x cases.

iv. *Hourly Labor Rate*

The analyses for this parameter were also done for maximum (optimistic) demand scenario with 0.5x cases and 1.5x cases. The outcome for both cases didn't show any significant changes. Only difference was in the cost distribution which is caused by an increase and decrease in the regular labor cost.

4.3. Discussion and Remarks

Overall, above analysis showed that the model outcomes are robust to parameters other than demand. Only extreme demand shocks may justify the distortion of the status quo with different policies. Moreover, the team did not find enough justification in favor of purchasing a machine. Only in the optimistic (maximum) demand scenario, very little need for subcontracting 200 Tons machine capacity came out. Most of the capacity was found to be idle in the baseline scenario. Therefore, a new math programming formulation that focuses on how to get the most out of this capacity slack was decided to be solved. This is the subject of section 5.

5. Extended Model

After realizing that a big portion of the capacity remains idle in the baseline parameter scenario, the team decided to extend the analysis by looking for ways to benefit from this projected capacity slack. For that purpose, a new LP model was formulated with the objective of producing the most profitable product mix given the idleness in capacity. An estimation for profit margins of product groups were received from the company. Of course, demand balance constraint was discarded here. Also, the cost of inventory keeping was ignored for this model.

The result of optimization suggested the production of three product groups. These are built-in reservoirs, shower and bathtub siphons, and toilet seats. Their individual share in total revenue is depicted in Figure 18.

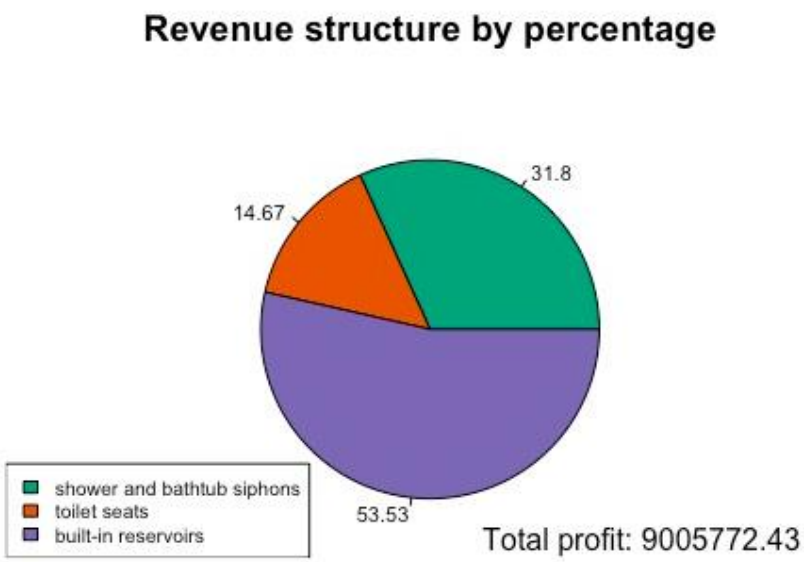


Figure 18: Share of Product Groups in Revenue

The results state that by utilizing slack capacity in the suggested manner for the following year, the company could make additional production that brings around 9,000,000 TL additional profit when all of them are sold. In fact, the exact number is not very meaningful. What can be derived from the analysis is that there is room for scalability even with the current resources when a proper capacity planning is done.

One final remark was made with the extended model. Even if the suggested production was realized, 75% of 90 tons machine capacity and 50% of 160 tons machine capacity would remain idle. In that case, management could consider other options such as subletting excess capacity and serving as a subcontractor.

6. User Interface and Implementation

It is important for the company to repeat the steps in a cyclical manner to guarantee the stability of improvement. The team advises the company to build an aggregate production plan once a month. An example case for Sales and Operations (S&OP) cycle is provided by Nahmias and Olsen [2]. Its overview is reprinted in Figure 19.

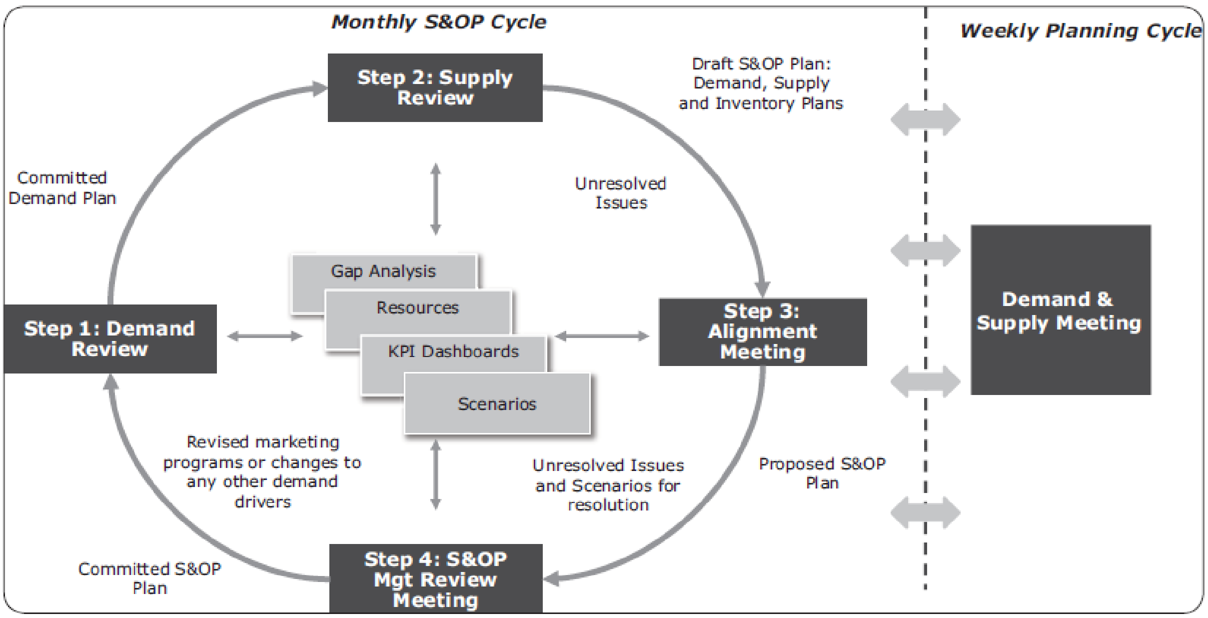


Figure 19: An Example Case of S&OP Cycle. Reprinted from *Production and Operations Analysis* (p.132), by Steven Nahmias and Tava Lennon Olsen, 2015, Copyright 2015 by Steven Nahmias and Tava Lennon Olsen[2].

To make the processes of the project available to the Production Planning Department of Nova, the team designed and developed a graphical user interface (GUI) to be delivered to the company. It was coded on Python, considering availability of packages needed to satisfy requirements —namely forecasting, LP solving and GUI. Also, the manager of the Production Planning Department declared familiarity with the language, which is expected to ease implementation.

The planning cycle can be considered in two phases. The first phase is making forecasts. Its working mechanism is drawn in Figure 20. For this phase, some inputs are read from Excel files —provided that their format and names match the requirements— and some inputs are specified by the user on the fly. These inputs are taken by the core application code “App.py”. It later calls functions from the forecast module. Predictions are generated after this procedure. They can be illustrated on the interface, and also can be exported to an Excel file. The user can choose to download forecasts from all the methods or just the ones that correspond to the chosen scenario.

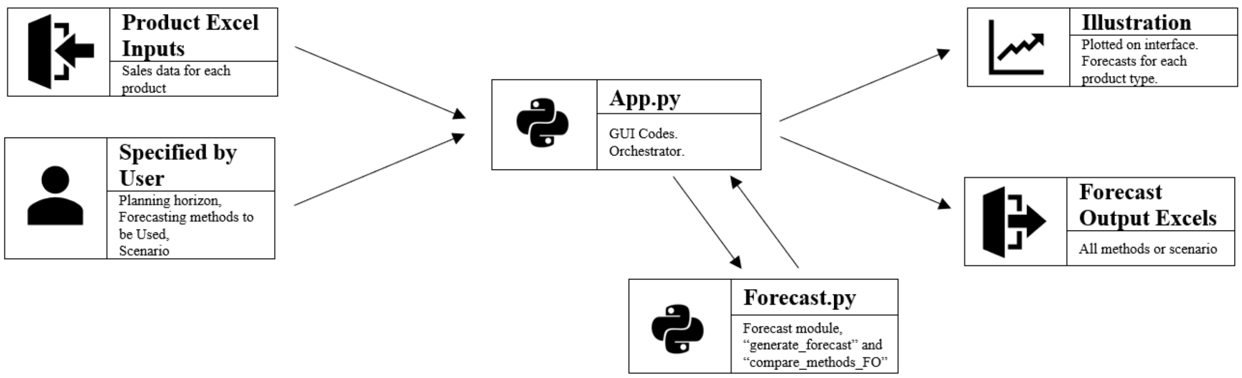
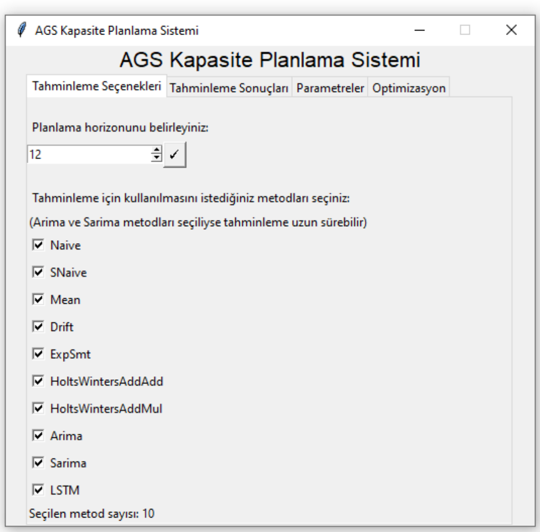
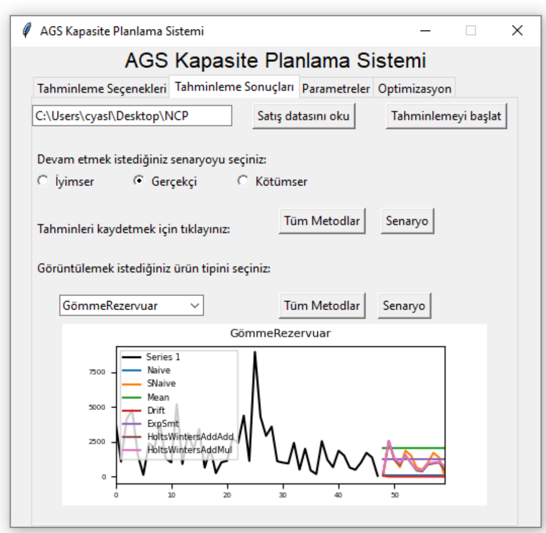


Figure 20: Diagram of the Working Mechanism for the First Phase

The first phase is represented by the first two tabs in the GUI. Screenshots of these two tabs are given in Table 3. In the first tab, the user selects the forecasting methods to be employed. In the second tab, the user specifies the path of Excel files containing sales data. The user can display predictions and export them as an Excel file.

Table 3: The First Two Tabs of the Application

<table>
<tr><th>The First Tab: Forecasting Settings</th><th>The Second Tab: Forecasting Results</th></tr>
<tr><td>
</td><td>
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</table>

The second phase is handling other parameters and solving the LP model. Its working mechanism is drawn in Figure 21. In this phase, there are also two types of parameters. Just as the first phase, some inputs are required as an Excel file in a specific format. Other parameters —such as inventory costs, number of machines— are built in in the system, yet the user is free to observe and make changes on them. Similar to the first phase, these inputs are collected by the application code. It calls the optimization function from the LP module with given parameters. After completion of LP solving procedure, it provides the user with some illustration and opportunity to save output as excel.

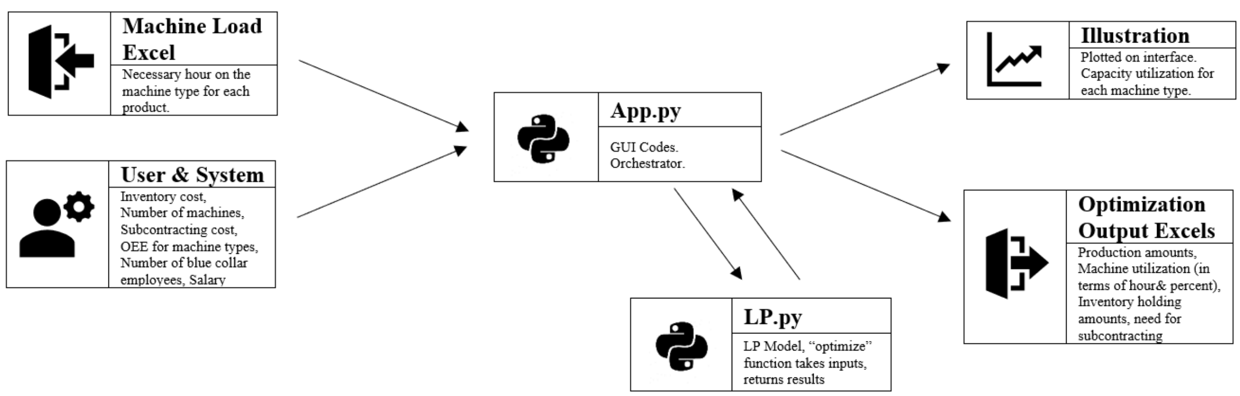
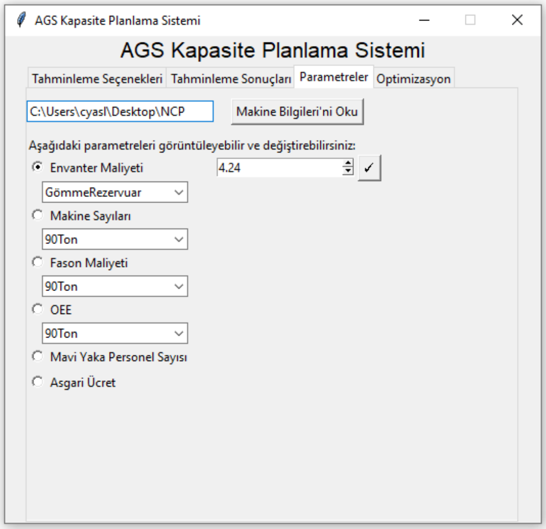


Figure 21: Diagram of the Working Mechanism for the Second Phase

The second phase is completed through the third and fourth tabs of the GUI. Screenshots of these two tabs are given in Table 4. In the third tab, the user enters the path to an Excel file in which machine and labor loads per unit product for each product type should be provided in a strict format. The user is free to inspect built-in parameters and alter their values. In the last tab, the user starts the optimization process. When it is completed, the user can download the results as an excel file and display capacity utilization for each machine type.

For a successful implementation process, the team had a meeting with the manager of the Production Planning Department. Feedbacks regarding the design were received and necessary actions were taken. For example, the initial design did not include taking paths as inputs for the Excel files. This feature was added accordingly. It was also stated that the company would prefer getting this service as a web application. However, this task is not yet completed due to time limitations. Along with the application, a user manual document will be delivered to the company.

Table 4: The Third and The Fourth Tabs of the Application

<table>
<tr><th>The Third Tab: Parameters</th><th>The Fourth Tab: Optimization</th></tr>
<tr><td>


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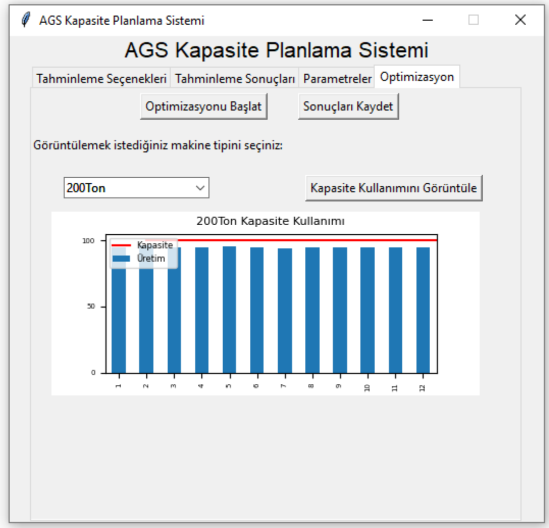

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7. Conclusions and Discussion

After analyzing the data, it was seen that sales data exhibits no seasonal character. It can be concluded that, given the validity of the data received, minimal inventory levels should be satisfactory for the following year. Also, the results obtained from the extended model show that; taking advantage of planning in advance, the company can benefit from the idle portion of the capacity.

There are a few points that the company should pay special attention to. First and foremost, proper data keeping is indispensable to determine parameters of models — especially for detecting trend and seasonality in sales. So, it is essential to keep the data in a proper and punctual basis. Further recommendation to the company is that they should use the application regularly and the process should be repeated once a month to be aware of the capacity.

Throughout the project several industrial engineering tools were integrated. At first, data analysis, time series analysis and forecasting were used to understand the data, manipulate it, and afterwards generate accurate forecasts. Later, mathematical modelling — linear programming in particular— was used to construct the model and to conduct sensitivity analysis on it. Several concepts from engineering economics were also visited when estimating the inventory holding rate. Lastly, object-oriented programming was adopted to develop the user application.

One advantage brought by the project is that the user application provides the company with the opportunity of repeating the design process on demand. This contributes to continuous improvement in capacity planning. Moreover, the forecasting phase was approached diligently. Various statistical models permit a wide coverage of different characteristics in sales data.

Upon the implementation of this project on the shop floor, it is expected to achieve positive economic impact in a few senses. Its explicit implication will be on resource planning. Although the exact savings implied by the optimization figures may not be very realistic, it will give valuable insight to decision makers towards conscious policies. Regular revisit to the application will make the company more aware of how much and what it is capable of producing. By doing so, due date promising trouble can be put behind. Hence, the unnecessary variation in the order lead time could be minimized.

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