Spare Parts Demand Forecasting and Stock Management

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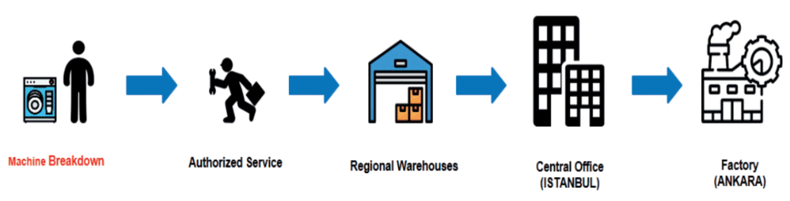
INTRODUCTION

Spare part demand plays a significant role almost in every industry. Companies are responsible of providing these spare parts most of the time. For white goods industry in Turkey, the manufacturer has to supply spare part demands for at least ten years by the laws. This is one of the reasons for spare parts to be important. These demands have several features. Firstly, they could be intermittent which is mostly random demands with lots of zero values. Secondly, historical data for spare part demands are limited. Lastly, there could be high variability between non-zero values. In the light of these information, forecasting spare part demands is considered one of the challenging subjects in the literature. What makes spare parts special is because these parts are not often used in production line of manufacturers and they even have sub-industries that just produce spare parts. In addition, forecasting the spare part demands yields at most %70 accuracy in the literature. Moreover, stock management for spare parts demands become significant since it requires storage area, some amount of investment, e.g. holding cost, production cost. Overall, being able to manage spare part demands plays significant role for almost every industry in terms of forecasting spare parts and managing stock of companies.

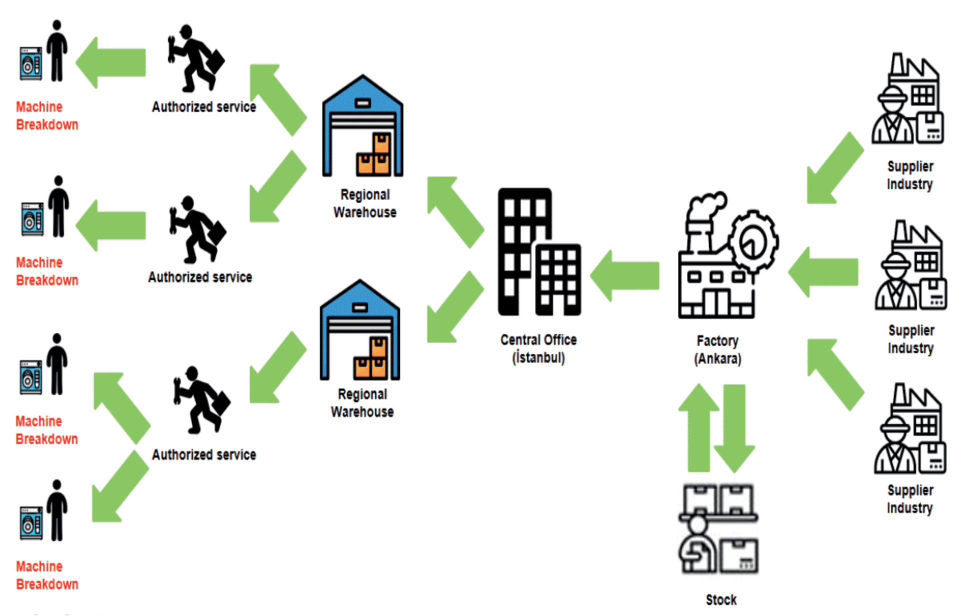
CURRENT SYSTEM

Based on the demands from dishwasher customers all over the world, authorized technical services determine the spare parts requirement by making the necessary examinations. They report this need to the regional warehouses. Regional warehouses meet the part requirement if available in their existing stocks, otherwise they will report this request to the center (Istanbul). The center first collects the demands of spare parts from all regional warehouses, then predicts the amount of future demand, and finally, orders them to the Dishwasher Plant. Following figure represents the flow of spare parts demand determination from customer to the plant.



According to the Consumer Protection Act of the Republic of Turkey, the demand of customers who need service must be met within 20 working days. Otherwise, sanctions such as refund or exchange with a new product may be imposed. In this context, the Dishwasher Plant is responsible for meeting the daily spare parts order from the center as soon as possible (between 3 and 7 days).

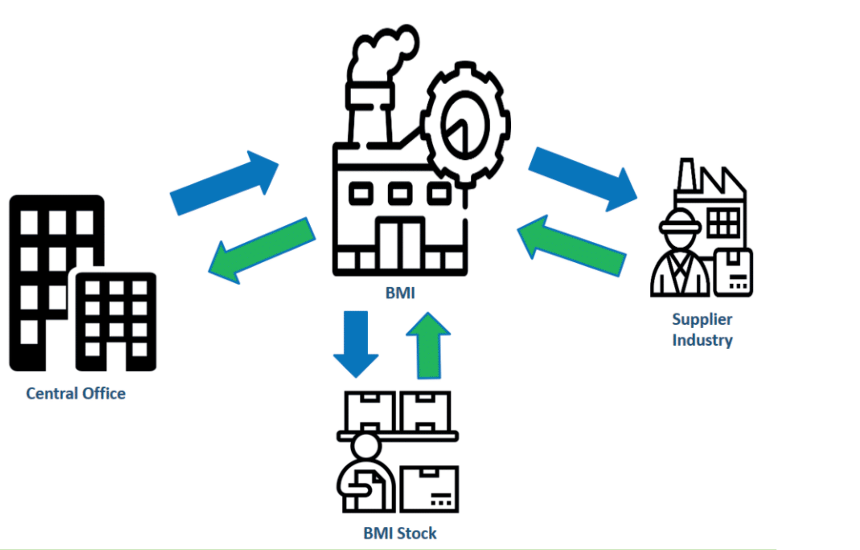
The plant meets the orders coming from the center by supplying it from its own stock, or from the supplier industry if it is not in stock. Spare parts coming to the center from the plant are sent to the relevant regional warehouses. Afterwards, the regional warehouses deliver spare parts to their customers through authorized services. Following figure displays the process of meeting spare parts demand.



PROBLEM DEFINITION

The plant needs to meet the demand of spare parts of various dishwasher brands and models in a limited period by using stock or having them produced in the sub-industry quickly. The demand has to be met within three-working days. In other words, Dishwasher Plant has to send demands to Center Office in three days and Center Office to send them as soon as possible to customers. In some extreme cases, this period could be extended to seven days, however the ideal period of sending demands is three days. Dishwasher spare parts are produced in various sub-industry companies by the request of the plant. Dishwasher Plant keeps various spare parts in stock as it will be difficult to meet the demands from the sub-industry within a limited time period. Due to the variety, production and stock cost of the spare parts, it is very difficult to keep all parts in stock and have them produced on time. For this reason, the company wants to increase the coverage rate from stock by forecasting future spare parts demand. In addition, the company will be able to reduce the production costs of the parts produced in the sub-industry, shorten the delivery time and thus increase customer satisfaction with this forecasting. Since there is no existing estimation and decision system, the current process is carried out based on experience.

There are more than 10,000 different kind of spare parts for the dishwashers produced in the last five years. Stocking, controlling and distributing them from one facility is a huge burden for the company and the aim of our project is to help Arçelik for (i) forecasting the number of spare parts for the following years to decrease the cost and time of delivery to increase the customer satisfaction, (ii) determining the optimal number of spare parts stocked in the factory per year and finally (iii) designing a decision support system which helps them to do the calculations of forecasting and determination of optimal number of spare parts.



INDUSTRIAL ENGINEERING

arçelik

METHODOLOGY

DATA DESCRIPTION

Raw Data 60 Months (BMI) 2015-2019

Movement Type	Material Code	Quantity	Unit	Unit Price (TL)	Currency	Date of registration	Hour	Year
643	A2-10939	-8	ADT	-16	TRY	1.03.2017	17:01:06	2017
643	A2-10939	-8	ADT	-15.2	TRY	7.02.2017	18:27:48	2017
352	A2-13666	2	ADT	2.68	TRY	29.04.2018	21:04:12	2018
352	D3-10660	45	ADT	386.5	TRY	29.04.2016	15:05:57	2016
352	E1-13391	10	ADT	303.4	TRY	29.04.2015	21:04:12	2015
643	Y1-7403	-80	ADT	-22.07	TRY	12.09.2019	17:27:34	2019

Categories

Order Frequency (Month)	Type Name
60-46	Fast moving
45-31	Medium moving
30-16	Slow moving
15-0	Very slow moving

Demode / Current Data

Type Name	Demode	Current	Total
Fast moving	86	155	241
Medium moving	438	398	836
Slow moving	973	750	1723
Very slow moving	4531	2755	7286
Total	6028	4058	10086

Analyzed Data

Material Code	Price	Current/Demode	Type	2015-01-01	...	2019-12-01
A5-13481	13	current	Medium Moving	196	...	0
P5-13515	0	demode	Fast Moving	770	...	0
A2-13642	7	demode	Very Slow Moving	0	...	0
T4-10729	21	current	Slow Moving	0	...	0

The last five years (2015-2019) movement data of Arçelik Dishwasher Plant has been provided. Movement Type, Quantity, Date of Registration, Hour of spare part movement data has been taken from SAP, and the unit price information has been added by renaming the materials code for our project. Real Material codes have been replaced with phantom codes to avoid privacy issues and data exchange as fast as possible.

In order for the data obtained from the Arçelik Dishwasher Plant to be used in the project, it is necessary to extract the spare part output data from the plant and turn this data into a monthly data form. In addition, combining the current and demode information, used by the plant for the classification of spare parts, with the data to be used will help to analyze the results.

In the next step, it was divided into the categories of data we have, both to choose the trial set and to evaluate the results more accurately. FSN (fast-slow-nonmoving) analysis was used for categorization. This analysis is a very important method in stock management and plays a major role in determining the status of the products at hand.

FORECASTING SYSTEM

For fast moving and medium moving, 7 different forecasting models are used. Since slow moving and slow moving product categories requires special attention and work, weighed moving average method is used in order to come up with reasonable forecast of these categories.

For fast moving and medium moving, 7 different forecasting methods are used. These methods are Moving Average (MA), Simple Exponential Smoothing (ES), Double Exponential Smoothing or Holt's Method (HM), Triple Exponential Smoothing or Holts-Winter Method (HWM), Autoregressive Integrated Moving Average (ARIMA), and Prophet (PRO) developed by Facebook. Following table illustrates these seven methods.

Method Names	Abbr.	Inputs	Explanation	Mathematical Model	Innovative Future	Limitations
Single Exponential Smoothing	ES	- Historical Data - Smoothing Constant (α)	It adopts a smoothing constant (α) of the real demands.	Exponential Smoothing	- adapt to small period of forecasts - easy calculation	- Deterministic model - few fields of applicability
Moving Average	MA	- Historical Data - window size	Mean of the past n demands	Arithmetic mean	- adapt for the constant demands - easy calculation	- Deterministic model - few fields of applicability
Holt's Method	HM	- Historical Data - Smoothing constant (α) - Trend constant (β)	It adopts a smoothing constant (α) and trend constant (β) of the real demands.	Exponential Smoothing	- small and medium period of forecasting - easy calculation	- Deterministic model - few fields of applicability
Holt-Winters Method	HWM	-Historical Data - Smoothing Constant (α) - Trend constant (β) - seasonality constant (γ)	It uses ES method with Smoothing (α), trend (β) and seasonality (γ).	- Exponential Smoothing - components (α, β, γ)	- effects of seasonality (α, β, γ additive)	- Failure to cope with spare parts seasonality - Deterministic model
Grey Method	GM	- Historical Data	With probabilistic basis this algorithm forecast though the use of cumulative demand and least square method to minimize the error.	- accumulative generating operation - least squares method	- Ideal when there are few historical data. - it performs good in low period forecasts.	- not well performing in the medium and long term.
Autoregressive Integrated Moving Average	ARIMA	- Historical Data - p (AR) - q (MA) - d (residual differencing)	It combines autoregressive and moving average models in an iterative way until the best forecasts are produced.	- Autoregression - weighted average of residuals	- Iterative way until find best forecast - possibility to consider non-stationarity and seasonality in long and short term.	-- It requires a lot of historical data to give good results. - It takes lots of time to find orders (parameters p, d, and q)
Prophet (Facebook)	PRO	- Historical Data	Returns the forecast value by using trend and seasonality components together.	- can add components (trend and seasonality)	- ability of medium and long term forecasts	- short term predictions are bad.

Lumpy and intermittent demand requires special attention while forecasting these categories. In order to find the forecast result of slow-moving and very slow-moving categories, Croston Method, Teunter, Syntetos & Babai (TSB) Method, and weighted moving average with trend methods are applied. Based on results of these three methodologies, moving average with trend yields better forecasting results compared to Croston and TSB method. Hence, moving average with trend method is applied for slow-moving and very slow-moving categories. After having year 2020 forecast, the result is divided by 12, which is the number of months, in order to allocate yearly forecast to monthly forecast. Hence, forecast of each month is the same.

ERROR METRICS

In the spare part demand estimation, the average absolute error percentage may be insufficient for the accuracy assessment due to the possibility of intermittent demand of the products. Therefore, the average absolute error percentage (AMAPE), and root mean square error (RMSE) were used for the accuracy assessment of the developed models. The formulas AMAPE and RMSE are given below, respectively.

$$AMAPE = \frac{\frac{\sum_{t=1}^{N} |A_t - F_t|}{N}}{\frac{\sum_{t=1}^{N} A_t}{N}} * 100 \qquad RMSE = \sqrt{\sum_{t=1}^{N} \frac{(F_t - A_t)^2}{N}}$$

At real demand value in time t
Ft forecast demand value in time t

MATHEMATICAL MODEL

Sets

i months

j products

Parameters

P_j Price of Product j (TL)

$TotalCost_i$ Total stock cost in month i (TL)

V_j Volume of product j (cm^3)

$TotalVolume_i$ Total stock volume in month i (cm^3)

D_{ij} Forecast value of product j in month i (units)

Decision Variables

x_{ij} Total number of product j to be held in stock in month i (units)

a_i Coverage ratio from stock, or forecast values, in month i

There are two indices; i represents months and j defines different spare parts. Price of spare parts, which is denoted by Pj; maximum cost of holding spare parts in stock, represented by TotalCosti are provided. Month-based forecast values of each product, which is denoted by Dij, are gathered via results of forecasting system that is developed in Python®. In order to manage the stock properly, depot volume and volume of each product become essential in order to have more feasible stock management methodology and application.

In this model, there are two decision variables. First one, xij, determines the total number of each product that should be held in stock in each month in units. Second decision variable, ai, represents the ratio of holding the forecast values of product for each month.

Formulation

Objective Function

$$Maximize \sum_i a_i \tag{1}$$

Constraints

subject to:

$$\sum_j a_i * D_{ij} = \sum_j x_{ij}, \qquad \forall_i \tag{2}$$

$$\sum_j x_{ij} * P_j \leq TotalCost_i, \qquad \forall_i \tag{3}$$

$$x_{ij} - D_{ij} \leq 0, \qquad \forall_{i,j} \tag{4}$$

$$\sum_j x_{ij} * V_j \leq TotalVolume_i, \qquad \forall_i \tag{5}$$

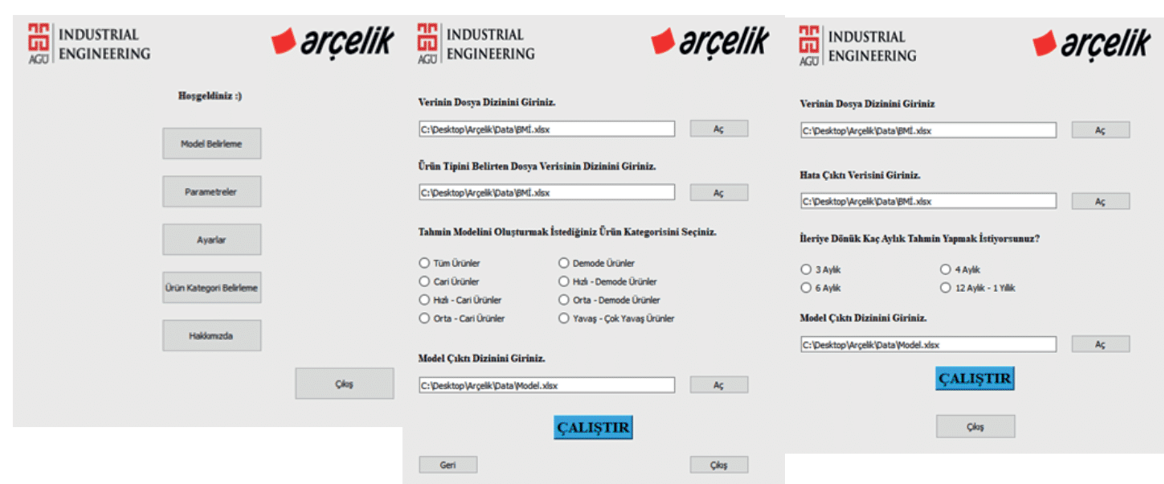
$$x_{ij} \geq 0, \qquad \forall_{i,j} \tag{6}$$

$$x_{ij}\ integer \qquad \forall_{i,j} \tag{7}$$

$$a_i \geq 0, \qquad \forall_i \tag{8}$$

The objective of the mathematical model, shown as equation 1, is to maximize total month-based coverage ratio in terms of forecast results. Equation 2 defines decision variable ai as the ratio of forecast result of products to total number of products to be held in stock in each month. Equation 3 defines the total cost for holding products in stock in each month. Equation 4 sets the maximum number of each product that will be kept in stock in each month. Equation 5 defines the total cost for holding products in stock in each month. Equation 6, 7, and 8 are variable definition constraints.

GRAPHICAL USER INTERFACE



FINDINGS

In the forecasting system, the best forecast model is found by trying all the forecast models for all spare parts with using RMSE and AMAPE metrics. After finding the best forecast models, forecast values are obtained for each spare part.

Sample Output of Model Determination Program

Product	Best Method	Best Error (RMSE)
X-11464	ARIMA	2.0
S2-6654	ARIMA	96.9
P5-7842	GM11	9.8
S5-11613	ARIMA	11.6
P5-10627	HWM	11.3
S5-5790	ARIMA	26.9
Y1-12911	ARIMA	72.1
H1-2868	ARIMA	1241.8
X-7676	HWM	15.9
S2-10533	PRO	52.3

Sample Output of Forecast Program

Material Code	Jan 2020	Feb 2020	Mar 2020	...	Nov 2020	Dec 2020
X-11464	6	6	6	...	6	6
S2-6654	388	341	320	...	349	352
P5-7842	31	32	33	...	41	42
S5-11613	34	35	35	...	35	35
P5-10627	34	32	44	...	45	41
S5-5790	83	112	114	...	106	95
Y1-12911	145	201	149	...	128	134
H1-2868	5181	3123	5952	...	5493	3290
X-7676	62	50	55	...	61	50
S2-10533	157	271	209	...	225	231

Forecasts from AMAPE and RMSE metrics for fast and medium moving spare categories are combined with the forecasts of 4 scenarios created for slow and very slow moving spare categories. Then 4 alternatives are obtained with respect to total number of different products and minimum pieces in stock.Then 4 alternatives are obtained with respect to total number of different products and minimum pieces in stock.

4 Alternatives for All Spare Parts (10,086)

	Alternative 1 (Min 1 Piece)	Alternative 2 (Min 1 Piece)	Alternative 3 (Min 5 Pieces)	Alternative 4 (Min 5 Pieces)
Total # Different Products	4581	7124	4581	7124

The stock coverage rate of Arçelik Dishwasher Plant for March 2020 and the stock coverage rate of March forecasts based on RMSE are compared. As a result, considering the demand data for Alternative 1, the margin coverage ratio is increased from 33.9% to 55.6% in March. An improvement of 64.01% was observed for this alternative. For Alternative 2, the margin coverage ratio increased from 33.9% to 62.4%, with an improvement of 84.16%. In Alternative 3, the stock coverage for March is calculated as 65.5% and an improvement of 93.22% is observed. In the Alternative 4, the ratio of coverage from March stock is calculated as 73.0% with an improvement of 115.34%.

Comparison of Coverage Ratio with Actual Demand Data in March, AMAPE

Month	Alternative 1	Alternative 2	Alternative 3	Alternative 4
Mar 2020	50.12%	56.98%	60.32%	68.46%
Improvement	48.28%	68.57%	78.46%	102.54%

Comparison of Coverage Ratio with Actual Demand Data in March, RMSE

Month	Alternative 1	Alternative 2	Alternative 3	Alternative 4
Mar 2020	55.57%	62.43%	65.56%	73.04%
Improvement	64.40%	84.70%	93.66%	116.09%

CONCLUSIONS

MARCH 2020

CURRENT	FORECAST	IMPROVEMENT
33.8%	65.46%	93.66%

In the light of the results, Alternative 3 is recommended to the company, considering the cost of the forecasted spare parts, the cost of the transfer to the next month, forecasted safety stock cost, and the stock coverage ratio based on March demand data. However, since the developed forecasting system is a system that will help the decision maker to make decisions, other alternatives are also accounted for. Since only the spare part forecasting from the industrial engineering perspective will not be sufficient for stock management, a mathematical model is developed in which the stock volume and total stock cost constraints could be taken into consideration. However, the model could not be applied to all spare parts since the company could not provide volume information for stock and spare parts. This mathematical model is tested as described in the methodology section and it is proposed to apply this model.