PRODUCTION ASSIGNMENT PROBLEM WITH THE OBJECTIVE OF MINIMIZING DEFECTS

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INTRODUCTION

The textile sector has a great importance in most of the country's economy with both the added value it provides and high export rates. Moreover, the socks industry in Turkey is a country frequently preferred by international brands. The brands that are responsible for providing this quality expect the same care from the socks factories they have contracted with. Dönsa Textile is a socks factory established in 1987 in Istanbul. It exported 25 million pairs of socks in 2018. It aimed to increase its production capacity by establishing the second factory in Yozgat in 2019. The Yozgat factory operates on a total area of 20,000 square meters, of which 12,000 square meters is covered. The factory, which has 297 socks knitting machines, has the capacity to produce 20 million pairs of socks in 2021. Dönsa Textile exports 90% of the socks it produces to the leading brands of the industry.

SYSTEM UNDER CONSIDERATION

In the current system, production planning takes place by assigning weekly incoming orders by considering machine and operator availability. The number of products to be produced is calculated by adding a certain defect ratio to the demand amount to prevent incomplete and faulty production. This rate is fixed as %3 for all type of product. However, the complexity of socks designs, the number of yarns used, the experience of the machine operator and other factors do not keep the defect ratio change them significantly. Thus, the defect ratio can be underestimated or overestimated and results in underproduction or overproduction If the defect ratios are higher than the tolerance, it may cause the yarns to be insufficient or the production to be completed later than planned. Products that reach the customer later than the deadline can lead to breach of contract and reduce the reputation of the company in the eyes of the customer. On the other hand, the firm increases the labor, time and raw material costs by overproduction. In addition, the production planning department gives the work orders of the socks without considering the defect ratios according to the machines and operators.

Figure 1. Production Line and Knitting Machine Illustration

PROBLEM DEFINITION

Current average defect ratio in company is %14. This undesired number of defective products are causing rework, waste of materials and workforce. In addition, it is decreasing the overall productivity of the production and causing delay of orders. The estimated annual loss of company caused by average %14 defect ratio is around ₺3.310.243 (including raw material, production expenses). The aim of project is to minimize the defective products produced caused by the production planning. As a first step, predictive modelling will be conducted to analyze historical defective data to estimate the defect ratio that will arise from combinations of different product, operator and machine groups. Then, using the insights from the predictive models, an assignment optimization model will be built with the objective of minimizing the total defective produced.

METHODOLOGY

Methodology begins with data collection, exploration. Then creating a machine learning model for prediction of defect rates. The output of the machine learning model, the defect ratio arised in different combination of product type, operator and machine group, will be used as parameter the optimization model Finally, optimizing the assignment in production that will give the minimum the defect ratios that may occur by considering demand of product, time available in shift.

DATA EXPLORATION

Data exploration is provided in various groups, including defect quantities, operator experience time, machine groups, design number-related data, data necessary for calculation of defect ratios. An example image of the table obtained after data collection is given below.

Table 1. Example of Data Collected

Cycle Time	Color	Size	Texture of Sock	Type of Sock	Number of Yarn	Pattern Intensity	Machine Group	Operator Experience Level	Defect Rate
129	BLUE	39-42	NORMAL	WOMEN SHORT	17	3	C4	18	0.37
115	WHITE	33-35	NORMAL	TEENAGE SHORT	23	4	D4	15	0.32

The Cycle Time shown in the first column of this table is in seconds and shows how many seconds a single sock is knitted in one machine. Color, Size, Texture of Sock and Type of Sock columns are design related features of a product. These data give detailed information about the properties of the socks. Machine group, on the other hand, represents the name of the group formed by 15 machines coming together. Based on the name of the operator responsible for the defect, the Operator Experience Time data was obtained by calculating the experience period on a monthly basis over the employment date of that operator. The last column, the Defect Rate, was found by dividing the Defect Amount and the Production Amount.

OPERATOR EXPERIENCE TIME

Operators tend to produce more faulty socks when they start to work in the company as a freshman. For this reason, the starting dates of the operators in the textile sector are collected. After collecting these data, the total number of months they worked in the textile industry was calculated.

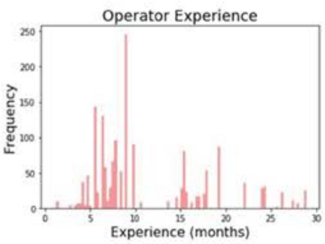

Figure 2. Operator Experience Indicator

MACHINE GROUPS

The brands, and ages of the machines in each group may differ. The names of the machine groups in production section, which consists of 15 machines by each are arranged as follows: A1, A2, A3, A4, B1, ..., E4. In Figure 3, it is seen that the machine group with the highest defect ratio is C3, E3 and E4. It can be concluded that the groups with the higher defect ratio are the groups which has older machines.

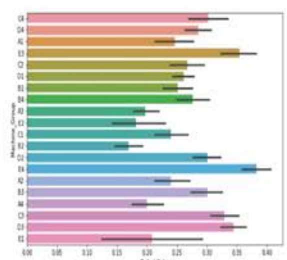

Figure 3. Machine Group with Defect Ratio Comparison

OPTIMIZATION MODEL OUTPUT

In this optimization model, defect ratio that arises with the different product, operator and machine group combination is going to be used as parameter. However, there are not enough historical data that can generalize the defect ratio for each combination because number of machine groups, operators and product types can make more than 150.000 combinations. In the real life, not all these combinations are made in production planning since the facility is operating for past 2 years. Instead, by using the predictive machine learning model that is built, the defect ratios for the combinations that are required-to-known can be obtained. Thus, an input data as shown in table below, is created to make predictions in Random Forest Regression Model.

Table 2. Input Data

Cycle Time	Color	Size of Sock	Texture of Sock	Type of Sock	Pattern Intensity	Number Of Yarn	Machine Group	Experience
145	MAVİ	39-42	HAVLU	BAYANPATİK	3	17	A1	4.79
145	MAVİ	39-42	HAVLU	BAYANPATİK	3	17	A1	17.84
145	MAVİ	39-42	HAVLU	BAYANPATİK	3	17	A1	30
145	MAVİ	39-42	HAVLU	BAYANPATİK	3	17	A1	25
145	MAVİ	39-42	HAVLU	BAYANPATİK	3	17	A1	13
145	MAVİ	39-42	HAVLU	BAYANPATİK	3	17	.	15
145	MAVİ	39-42	HAVLU	BAYANPATİK	3	17	.	79
145	MAVİ	39-42	HAVLU	BAYANPATİK	3	17	B3	24
145	MAVİ	39-42	HAVLU	BAYANPATİK	3	17	B4	14

The input data transformed into required form by using one-hot encoding and scaler. Then, defect ratios are obtained for the combinations in the input data. This output is taken to excel file to be used later in optimization model as parameter, to get optimum assignment for the production planning.

PRODUCTION PLANNING OPTIMIZATION MODEL

Indices

- i order(product type) index
- j machine index
- m machine group index
- k operator index

Parameters

- D_(i,m,k) Defect ratio of order (product type) i in machine group m with operator k
- C_i Cycle time of order (product type) i (seconds)
- Q_i Quantity of demand of order (product type) i
- T Duration available in a shift (28,800 seconds)

Decision Variables

- X_(i,j,k) Amount of socks produced with style code (order) i is assigned to machine j with operator
- Y_(i,m,k) If style code(order) i is assigned to machine group m with operator k 1 o.w 0

Objective Function

$$Min\ Z = Z^{*} = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} X_{i,j,k} * D_{i,j,k}$$

Constraints

$$\sum_{j}^{n}\sum_{k}^{n} Y_{i,j,k} = 1 \qquad \forall i \qquad (1)$$

$$\sum_{j}^{n}\sum_{k}^{n} Y_{i,j,k} = 1 \qquad \forall i, \qquad A1, A2, \ldots E4 \in j \qquad (2)$$

$$X_{i,j,k} \leq M * Y_{i,j,k} \qquad \forall i, k \quad A1, A2, \ldots, E4 \in j \qquad (3)$$

$$\sum_{i}^{n}\sum_{k}^{n} X_{i,j,k} * (C_i) \leq T \quad \forall j \qquad (4)$$

$$\sum_{j}^{n}\sum_{k}^{n} X_{i,j,k} \geq Q_i \qquad \forall i \qquad (5)$$

The objective function minimizes the total number of defective socks produced. Constraint (1) restricts model to assign each order (product type) to 1 machine group and operator. Constraint (2) restricts model to assign one operator to each machine group and each order (product type). Constraint (3) is a connection between decision variables are built. If given order (product type) is not assigned to machine group that includes the machine, model does not assign any amount of demand in that machine with that operator. Constraint (4) shows the time capacity for each machine in one shift. Constraint (5) shows the demand requirement for each order (product type).

RESULTS

Machine Group	Real Life Defect Ratio	Optimization Model Defect Ratio
A1	0,1524	0,1123
A2	0,1706	0.08429
A3	0.124	0.1112
A4	0.2238	0.1096
B1	0,14	0.0984
B2	0,03	0.0981
B3	0,1125	0,1075
B4	0,2523	0.0902
Average Defect ratio	0,2038	0,0986
Total Number of Defect	7294	2984

The following table shows the defect ratio of real life and optimization model for the in the given machine groups. The optimization model defect ratio is calculated by diving number of defects produced in the machine groups to number of demand of order (product type) that is assigned to that machine group. When we compare the average defect ratio among the machine groups in real life and optimization model, it is seen that with the use of optimization model average defect ratio is decreased %55 percent. Total demand is 32.590 for the taken week. When we compare total number of defective socks produced in real life and in optimization model, there is 4310 products saved from scrap.

CONCLUSION

This study represents the idea of using predictive machine learning and prescriptive operations research method in optimizing and minimizing the defect rate in the production plan department. Moreover, the assignment optimization model was done using GAMS and the defect ratio is to be found using Python software. The predictive model was evaluated and compared through different types of regression methods and the one with the best accuracy was taken. Furthermore, defect ratio that arise with different product, operator and machine group combination was used as parameter. In order to achieve and compare the current system the data has been filtered and reprocessed resulting in removing the out-of-range values and all irrelevant data. Finally, to conclude with the used of proposed optimization model the company can have a lower average defect ratio and may reach the objective of having 1% defect ratio. In addition, by waste elimination, company can save from raw material, work force and production related costs which is more than ₺400.000 annually.

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