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Comparison of Demand Forecasting Techniques for Determination of Stock Inventory Levels: An Application in Kitchen Furniture

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Abstract: *Customer-oriented and complex competitive environments are significant problems for operational excellence (OpEx). It is possible to correctly forecast requests to provide a high customer service level in organizations that manufacture according to customer-oriented demand. Material requirements planning (MRP) is employed in deterministic demand and supply timings, and failing to meet customer demand on time has negative consequences for businesses. With the company's operational profitability, it can provide a high customer service level. Effective material management, which accounts for 40% of the company's capital, is a critical component of operational excellence.*

This study aims to apply Demand Driven Material Requirements Planning (DDMRP) to sustain both customer satisfaction and the average on hand at the required level. In this paper, we focus on exploring the average on-hand and operational profitability in the kitchen cabinet industry by modeling data from past to calculate daily usage with artificial neural networks (ANN). Then we compare DDMRP and ANN results. As a result of this application, we obtain more acceptable inventory level using data handled by ANN.

Keywords: *Demand forecasting, DDMRP, ANN*

1. Introduction

MRP enables companies to improve the quality and effectiveness of planning their dependent demand. It supports the determination of more reliable schedules and payment dates depending on the need dates of the customers. It provides managers with a conclusion to evaluate the potential impact of proposed changes, while determining when orders should be placed to ensure materials arrive exactly when they are needed. MRP helps create an integrated system where changes at any level will lead to potential changes other levels.

Recent advancements in the practical world, such as Lean Systems and Theory of Constraints, have highlighted the need to radically rethink the logic of MRP. Furthermore, these changes called into question some of MRP's fundamental assumptions, leading to the replacement of static safety stocks with dynamic buffers. As a result of these advances, a new technique, Demand-based MRP (DDMRP), has emerged [1].

Demand-Driven Material Requirements Planning DDMRP provides an advantage at the stock inventory level by separating it from the pull feature, which eliminates the dependency of classical material requirements planning (MRP) on the bill of materials. DDMRP not only deals with the pull according to the promised customer demands and the actual stock status, but also combines the push with the forecasting of future demand. With the buffer model of the theory of constraints (TOC), which has been used since 2011, it is possible to manage the material stock level in a certain flow with appropriate stocks with DDMRP.

Using only MRP for effective positioning of stock policies in customer-oriented and make-to-order companies. is managed. With the increase in materials procured from abroad, longer lead times affect the level of customer service. Table 1 shows the supply chain characteristic:

TABLE I**:** Supply Chain Characteristics [2].

Supply chain characteristics	**1965**	**Present**
Supply chain complexity	Low	High
Product lifecycles	Long	Short
Customer tolerance times	Long	Short
Product complexity	Low	High
Product personalization	Low	High
Product variety	Low	High
Long lead time parts	Little	A lot
Prediction accuracy	High	Low
Goal of Keeping Less Inventory	Low	High

DDMRP is superior to MRP by separating supply and demand. It prevents fluctuations between suppliers, customers, production, warehouse, accounting, and financial management departments. Thus, it eliminates the "bullwhip effect" throughout the supply chain. Using the customer's welcome time in cases where the product's total supply chain time is shorter and there is variation in demand also contributes positively to the competitive advantage of the company.

2. Methodology

2.1. Demand Driven Material Requirements Planning (DDMRP)

With its strategic positioning function, it is an instrument that enables the setting up of stock buffers in particular areas. It combines aspects of six sigma, the theory of constraints, materials requirements planning (MRP), and distribution requirements planning (DRP). Consequently, it allows it simpler to eliminate uncertainties caused by variability [2].

1. Strategic positioning: This phrase refers to the process of determining strategic objects at critical points within an organization. Positioning is determined by the following decomposition factors based on the notion of constraints, customer tolerance time, market response time to enable for price increases and customer acquisition through existing or new channels for customers, demand and supply variability, inventory flexibility, critical operational processes [3].

2. Creating a Buffer Profile: This is the stage in which the buffer profile of the inventory that will be kept in stock is created. Its fundamental mechanics are determining the buffered items and modifying the buffers.

Calculating the green zone: Maximum (Yellow zone x Delivery time factor, MOQ-minimum order quantity, EOQ-economic order quantity, average daily usage x planned supply cycle).

Calculation of the yellow zone: Average daily usage x Decoupled lead time.

Calculation of the red zone: Red zone safety + Red zone base.

Red zone base: Yellow zone x Lead time factor (LTF).

Red zone safety: Red zone base x Variability factor (VF).

Users decide whether the lead time factor should be short, medium, or long.

Users decide whether the variability factor should be high, medium, or low.

2.2. Artificial Neural Networks (ANN)

Artificial neural networks (ANN) have been developed biologically inspired by the study of the human brain. They are mathematical computer programs in which learned information creates memory through weighted connections. ANN can adapt to a new environment thanks to its adaptive and learning capabilities. Even if ANN does not guarantee the best solutions, it gives acceptable solutions. Artificial neural networks consist of five elements: inputs, weights, summation functions, activation functions, and outputs. Artificial neural networks develop solutions with the method of experiencing data, called "learning" from past data. After the random determination of the connection weights, the process of obtaining the output begins. Learning is done within certain rules. Examples such as Kohonen learning rule, Adaptive Resonance Theory Network learning rule, Hebb learning rule, Hopfield learning rule, Simple perceptron learning rule, Delta learning rule can be given as learning rules. The methods obtained by supervised learning, unsupervised learning, supportive learning, and their hybrid models are expressed as learning methods. In the process of "training" the artificial neural network, random initial weight values are given to obtain the desired value to be given in the output of the data shown as input to the network before. These weights are not fixed, by continuing the learning process in the network, weights that will give the least error are created. It is possible to represent the elements of artificial neural networks with more than one model according to the processing or learning method and rule. The most used models are single-layer perceptrons, multi-layer perceptrons, Adaline / Madaline model.

3. Application

The applied company is a pioneer in its field in Turkey, producing kitchen furniture. To fulfil on-time deliveries to domestic as well as overseas clients, the company employs a customer-oriented make-to-order strategy. In some circumstances, the order is expected to be backed by customer-specific non-standard raw materials or procedures.

The properties of the chosen material group

- Long lead time (21 days or more)
- Suitable for stock cutting issues (waste material)
- Taking up space in the warehouses (volume)
- Inventory occupying space (cost)
- Prolonged manufacturing process (3 days or more)
- Price rises that are irregular (at least three price hikes per year)

The performance parameters of one provider of panel materials from five distinct sources were assessed. For 11 distinct materials, inventory positioning was created. The buffer zone parameters as below.

- The Average Daily Use (ADU) is deterministic.
- The Decouple Lead Time (DLT): The DDMRP literature states that the longest cumulative time between the buffer and the prior references must be chosen, but in our case study, planning lead time (30 days) is what is important.
- The Lead Time Factor (LTF) is a measure of lead time uncertainty with long level is 0.25.
- The Variability Factor (VF) is the uncertainty factor of demand is changeable.
- Suppliers and the company need restrictions define the Minimum Order Quantity (MOQ) and Economic Order Quantity (EOQ).

The performance factor, determined from Green Zone/2+Red Zone, is average on hand.

According to the horizon, the average daily consumption is determined as 125 days, and artificial neural networks are used to create forecasts. Table 2 shows the parameters of Variability factors and Lead time factors for the calculation.

TABLE II: Parameters for DDMRP

Variability factors	Value	Lead time factors	Value
X (low)	0,25	**E (short)**	0,75
Y (medium)	0,50	**F (medium)**	0,50
Z (high)	0,75	**G (long)**	0,25

Figure 1 shows 11 materials that were calculated using historical data between 1.1.2022 and 30.6.2022. Figure 2 shows 11 materials that were forecast using Matlab 2019a Artificial Neural Network (ANN). The average Daily usage are predicted by each other daily usage because of the using in the same bill of materials. Normalization function is calculated in the below formula. Training Function is selected as Trainlm in Matlab 2019a. Table:3 is illustrated parameters both DDMRP and ANN.

$$\min\max normalization = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

TABLE III: Parameters

					DDMRP-calculation		**ANN - calculation**			
	DLT	**LTF**	**VF**	**MOQ**	**ORDER CYCLE QTY**	**ESM**	**ORDER CYCLE QTY**	**Neurons**	**Validation**	**Test**
Printpan1	30	0,25	0,25	735,00	2.940,00	12.495,00	3.675,00	15	10	10
Printpan2	30	0,25	0,75	735,00	2.205,00	12.495,00	1.890,09	25	10	10
Printpan3	30	0,25	0,75	735,00	2.205,00	12.495,00	1.470,00	25	10	10
Particleboard1	30	0,25	0,50	1.004,67	15.070,05	2.210,27	15.672,85	25	10	10
Particleboard2	30	0,25	0,50	1.152,90	7.147,98	2.305,80	6.917,40	25	10	10
Particleboard3	30	0,25	0,50	1.152,90	7.378,56	2.305,80	6.686,82	25	10	10
Particleboard4	30	0,25	0,50	1.004,67	1.808,41	2.411,21	1.406,54	25	10	10
Particleboard5	30	0,25	0,75	1.004,67	1.808,41	2.210,27	1.406,54	25	10	10
Particleboard6	30	0,25	0,50	1.004,67	1.205,60	2.411,21	401,87	25	10	10
Particleboard7	30	0,25	0,75	683,20	819,84	1.366,40	683,20	25	10	10
Particleboard8	30	0,25	0,75	882,00	322,64	882,00	303,42	25	10	10

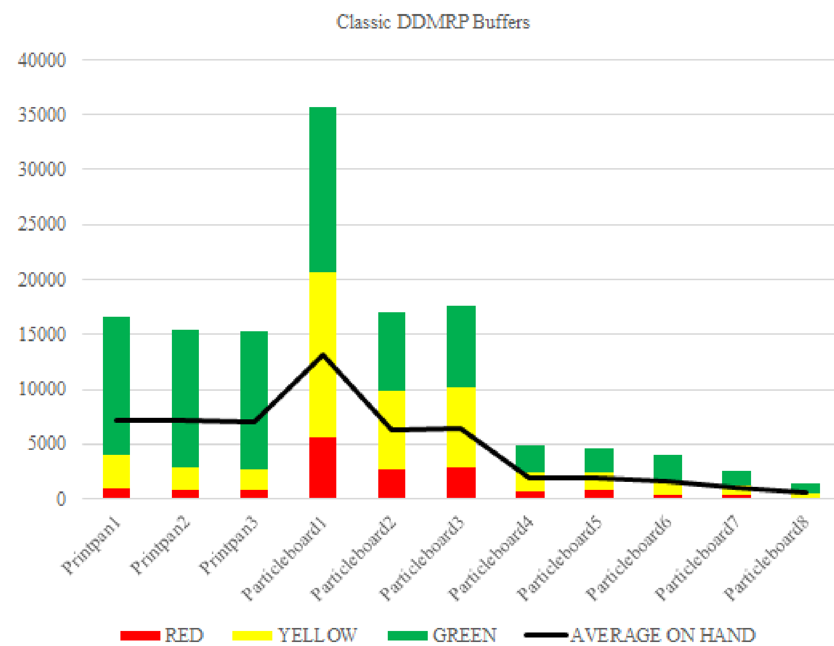

Fig. 1: Classic DDMRP Buffer Levels

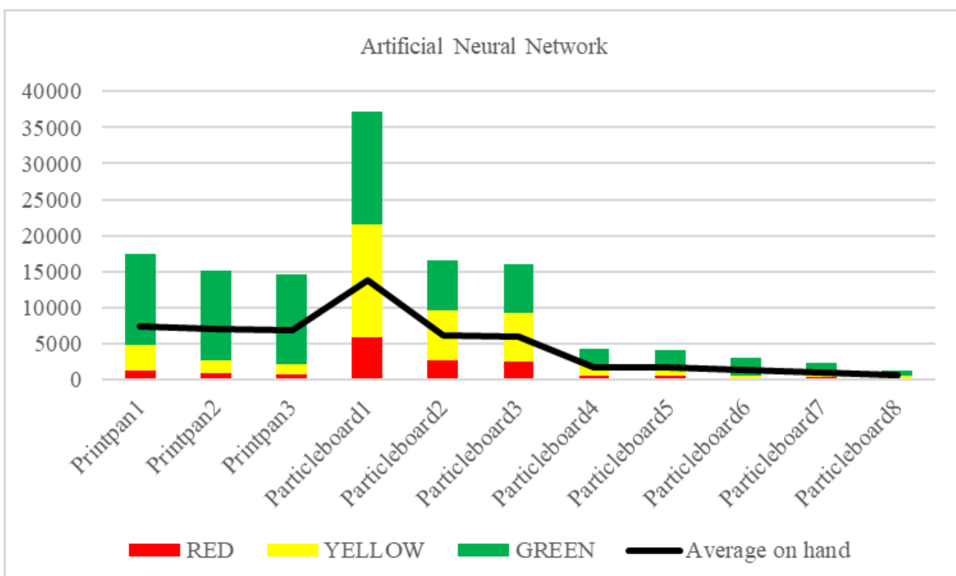

Fig. 2: ANN-DDMRP Buffer Levels

4. Conclusion

Selecting the materials to be used with DDMRP is a strategical decision. It provides a way to solve the issues with MRP that need to be resolved. With DDMRP, it aims to identify missing materials, delayed order fulfillment for customers, improper material planning, and uncertainty in demand projections. DDMRP and ANN were used to estimate the parameter for average daily consumption quantity. In this paper, it was compared to the DDMRP stock buffers and average on-hand with different average daily usage calculations both DDMRP and ANN. Though not obviously, artificial neural networks have produced better results.

Future research may compute the average daily consumption amount and use DDMRP methodology using forecasting techniques like ARIMA and the exponential smoothing approach. DDMRP will therefore be able to eliminate the uncertainty of the estimates. The average on-hand value can be decreased by calculating lead time factor and variability differently. As a result, stock management will be completed successfully and effectively.

5. References

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