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Long Term Demand Forecasting System for Demand Driven Manufacturing

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Abstract. Demand-Driven Manufacturing (DDM) is the solution that most companies are heading to in our days. Although this strategy consists of producing goods based on what consumers demand, companies should also rely on accurate forecasting systems to prepare their production chain for such an operation by supplying enough raw material, increasing production capacity to fit the desired demand, etc.... However, due to the fact that most companies have been relying on massive production, most sales forecasting systems usually used rely on sales data of previous years that, not only contain the actual demand, but takes into consideration the marketing strategy effects like massive promotions. Hence, the resulting forecasts do not mainly reflect consumers' demand. For this reason, a switch to demand forecasting, instead of sales forecasting, is essential to ensure a good transition to DDM. This paper proposes an artificial intelligence based demand forecasting system that aims to determine "potential sales", mainly reflecting consumers' demand, by correcting historical sales data from external variables' effects. A comparison with other sales forecasting models is performed and validated on real data of a French fashion retailer. Results show that the proposed system is both robust and accurate, and it outperforms all the other models in terms of forecasting errors.

Keywords: Demand Driven Manufacturing · Sales forecasting · Demand forecasting · Historical sales correction

1 Introduction

For many years, the market of consumer goods relies on overconsumption with mass production and aggressive marketing campaigns. This approach requires the companies to focus on low cost production with off-shore sourcing and involves both high volume purchases and long lead time [1].

Due to the needs for more personalized products and environmental awareness of the consumers, this strategy reaches its limits in many industrial and commercial sectors [2]. Consequently, many companies move toward a Demand Driven Manufacturing (DDM) strategy [3]. DDM strategy aims to produce goods based on consumers' demand instead of sales or target forecasts [4]. According to Gartner, nearly 90% of production

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industries which are not demand-driven, are planning to be [5]. This is mainly because of the benefits a DDM approach could offer, such as increasing profitability, reducing wastefulness, and most importantly improving customers' satisfaction.

Even though a DDM strategy relies on flexible and reactive production and supply chain, companies still require accurate forecasting systems to anticipate their raw material supplies, production capacity, ... and meet the consumer expectations in terms of lead time. However, current sales forecasting techniques do not reflect exactly consumer's demand since they rely on historical data including the constant discounts or commercial offers. Moreover, in a DDM approach, only goods that are going to be sold are produced, which implies the application of a totally different marketing strategy. Hence, in order to ensure a successful transition to the DDM strategy, companies should switch from a sales forecasting system to a demand forecasting system.

Recently, Artificial Intelligence AI techniques have presented great improvements in many fields and especially in forecasting [6, 7]. In fact, with the AI techniques and the heterogeneous data sources available nowadays, new forecasting systems can be developed to determine consumer demand by modeling the impact of the different exogenous variables on sales.

This paper proposes a demand forecasting system that aims to correct historical sales, using AI techniques, by removing the influences caused by external factors, such as promotions, before moving to the prediction process. In fact, by modeling the impact of the previous discount strategy, historical sales could be corrected, presenting then potential sales that mainly reflect consumers' demand. This results in an accurate and robust forecasting model which can be an additional tool to help companies better react to the rapidly changing market, and meet the demand of materials, warehouses, etc... for the production process.

The following parts will be structured as follows. A brief literature review about existing sales forecasting systems is presented in Sect. 2. Section 3 describes the proposed methodology in detail. Results and discussion are presented in Sect. 4. The conclusion is presented in the last section.

2 Literature Review

Retail companies, based on a mass production strategy, generally rely also on sales forecasting systems in order to optimize their production and supply chain. Hence, sales forecasting has been always studied by researchers in the literature, which presents a wide variety of sales forecasting systems, adapted to different contexts [8–10].

The most commonly used methods for sales forecasting are statistical time series analysis tools that primarily seek to identify trends and seasonality. Among the existing statistical methods, “Auto-Regressive Integrated Moving Average” ARIMA and “Seasonal Auto-Regressive Integrated Moving Average” SARIMA are widely used for sales forecasting [11]. Similarly, SARIMAX is an extension of SARIMA when explanatory variables are available. Moreover, deep learning has recently shown promising results in nonlinear sequence learning problems. Notably, Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) networks are popular deep learning techniques and have outperformed popular machine learning methods for time series forecasting [12]. RNN and LSTM networks, unlike other neural networks, have the property of retaining information over time.

The methods already mentioned are likely to be adequate to learn seasonality in a time series. However, in the context of sales forecasting, there are many exogenous variables that can influence the predictions. Thus, several hybrid methods that can take advantage of both time series analysis and explanatory variables are proposed in the literature [11]. Punia et al. [13] proposed a new forecasting method that combines LSTM, to model the time aspect of the input series, and Random Forest (RF), to predict the impact of explanatory variables not detected by LSTM. The obtained results showed that their method outperformed other methods, ARIMAX, LSTM and RF. Another more interpretable working methodology is to correct the sales history by removing the impact of explanatory variables before making the prediction of the time series, as proposed by Thomassey et al. [14].

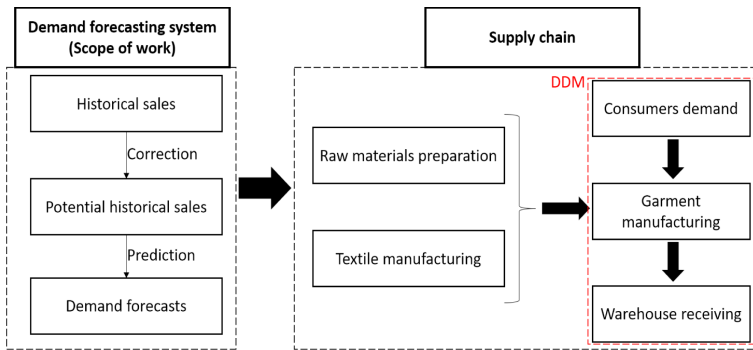


Fig. 1. Demand forecasting based DDM approach

3 Methodology

The main goal of this paper is to build a demand forecasting based DDM approach as illustrated in Fig. 1. Using the demand forecasts, production managers can better manage the supply chain by anticipating the required raw materials and adapting their production capacity to meet actual consumers' demand.

The approach adopted in this paper was inspired by the forecasting system proposed in [14] in which a fuzzy logic system is optimized to predict the influences of the explanatory variables on sales. The work done in this paper uses a similar approach for correcting historical sales (year $\in [1, \dots, n]$) by removing the influence of external variables before predicting sales for year $n + 1$. The following parts describes in details the proposed methodology as well as the learning process.

3.1 Global Forecasting System

The proposed forecasting system, presented in Fig. 2, is composed of three main stages:

- The influences of explanatory variables are removed from historical sales data using the Influence Capturing System ICS ,
- The resulting historical potential sales are used to make predictions for next year's potential sales,
- The final sales predictions are obtained by adding the influences of explanatory variables corresponding to the next year to the previous predictions using ICS^{-1} .

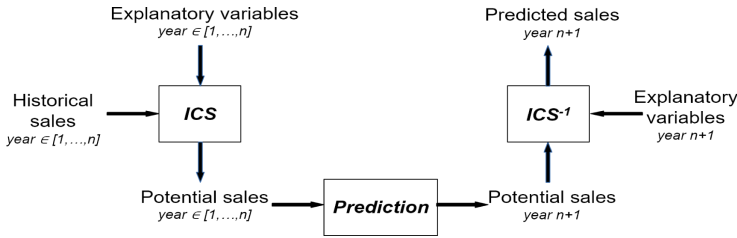


Fig. 2. Global forecasting system

3.2 Learning Process

The Influence Capturing System ICS is designed to predict, using the explanatory variables, a coefficient that has a role of correcting the historical sales, generating then a series of historical potential sales. We used a simple neural network NN (a perceptron) to predict these correction coefficients, based on the assumption that a NN can learn to generate efficient and sophisticated rules for prediction.

Thereafter, for predicting the potential sales of the next year, we applied the seasonality average, which is one of the simplest time series forecasting methods. We selected this basic model in order to check the ability of the model in the optimization of the correction coefficients, without having additional parameters to adjust, which increases the complexity in the overall learning process.

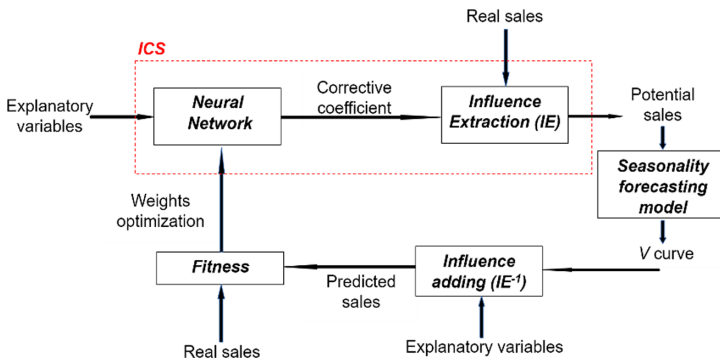


Fig. 3. Learning process

Figure 3 above presents the learning process of the proposed system in detail. In fact, the NN must be optimized in order to predict the most reliable and efficient correction coefficients. To do so, we used a genetic algorithm GA where each chromosome is formed by real genes representing the weights of the neural network. The learning loop is composed of the following important steps:

- Using the explanatory variables as inputs, the NN predicts the corresponding correction coefficient (cc), which is considered to be a multiplicative coefficient that quantifies the impact of exogenous variables on sales,
- The Influence Extraction function IE calculates the potential sales as input to the prediction model,
- The V-curve is the predicted life curve obtained from the potential sales (without influences of the explanatory variables),
- The influences of the explanatory variables are re-added to the obtained V-curve, using IE^{-1} , to perform the final prediction,
- The GA's fitness function is calculated from the sales thus predicted and the actual sales by calculating the root mean square error RMSE:

$$fitness = 1/RMSE \quad (1)$$

- The GA sets new weights for the neural network to increase the value of the fitness function,
- The optimal parameters of the neural network that allows the determination of the optimal life curve V^* (corrected historical sales) are obtained when the maximum number of iteration of the GA is reached.

Once the optimal ICS model is obtained, the final forecast is calculated by adding the influence of the explanatory variables of the future season (the 52 weeks to be predicted), to the optimal life curve V^* .

4 Results and Discussion

4.1 Data Used

The proposed forecasting system was applied to real world data of a French fashion retailer. It was tested to perform a one year sales prediction (52 weeks) of a T-shirt's family of products. We used three years of historical sales data (2016, 2017, 2018) for the learning process, and one year, 2019, for testing.

In order to test the ability of the proposed system to capture the influence of the explanatory variables on the sales, those variables have to be wisely selected and must be the most significant ones. Therefore, since obtaining the influence of promotions on sales was important to our industry partners, the explanatory variables chosen were:

- The average percentage of discount per family of products,
- The type of commercial operation OP applied (no OP, winter/summer sales of long duration, or 10-days winter/summer sales of short duration),

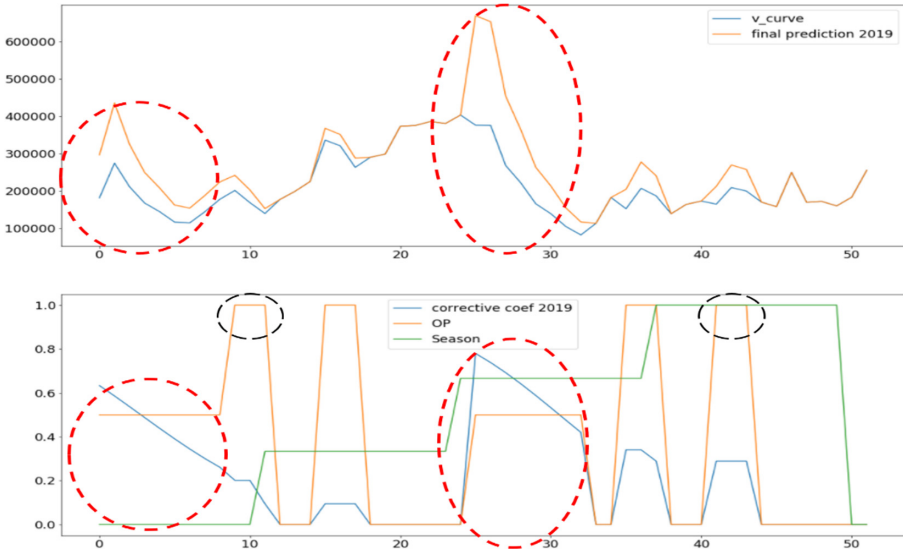


Fig. 4. Corrected sales (v-curve) and final prediction (top), correction coefficient (bottom) (Color figure online)

- The season (fall, winter, spring, summer),
- The remaining duration of the sale period (100% at the beginning of the sale and 0% at the end) to locate at which phase of the sales period we are.

4.2 Prediction Results

Figure 4 shows, for the year 2019, the optimal V-curve representing the prediction without the influence of exogenous variables, the predicted sales after reinjection of these influences, the corresponding predicted corrective coefficients for each week, as well as a visualization of some of the explanatory variables used. The results obtained demonstrate the effectiveness of the proposed method as well as the ability of the neural network, combined with GA, to model the influences of the explanatory variables. It is clear from Fig. 4 that during winter/summer sales (shown in red dashed circles), the influence of the explanatory variables is more visible than in normal weeks. The correction coefficient is at its highest at the beginning of the winter/summer sales, and decreases continuously throughout the promotions period: we can clearly see in the predictions for the year 2019 that the peak in weeks 26 and 27 is caused by the beginning of the summer sales (corrective coefficient, in this case, is equal to 90%). This correction is of less importance during 10-days sales (shown in black dashed circles), which is logical since during this type of operation, promotions are not applied on the entire collection which explains the lower peaks in those periods.

We evaluated our proposed methodology by comparing it to three other forecasting methods in terms of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). We used for comparison two of the classical time series forecasting methods, SARIMA and SARIMAX. In addition, we

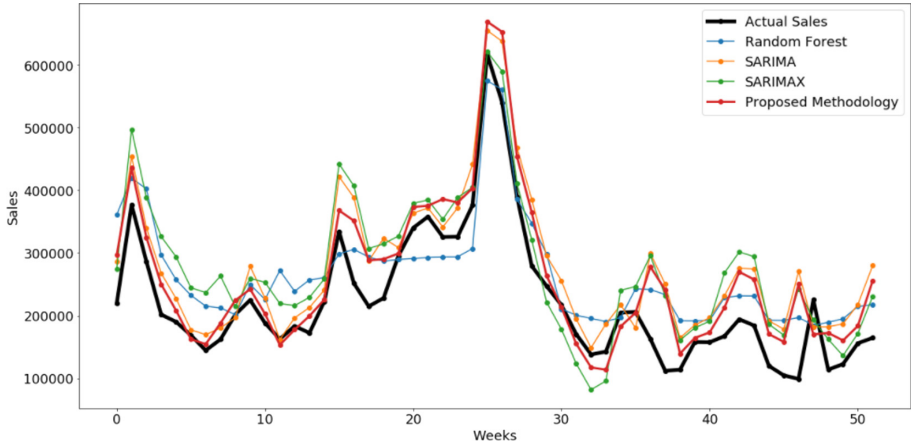


Fig. 5. 2019 sales predictions for the different methods

Table 1. Results on 2019 test data.

	RMSE	MAE	MAPE
SARIMA	67970	56109	31.01
SARIMAX	73133	62710	34.57
RANDOM FOREST	63451	55825	31.97
PROPOSED METH.	56135	43908	23.89

applied the Random Forest, a popular machine learning algorithm, to our forecasting problem by adding the week number as an additional input to the other explanatory variables used. Results shown in the following table (Table 1) show that the proposed methodology yielded better results when applied to 2019 test data, by having the lower forecasting errors for the three of the metrics used. Figure 5 shows a comparison of the prediction results obtained by the different methods mentioned above.

5 Conclusion

This paper presents a demand forecasting system that is able to correct historical sales by eliminating the effect of marketing strategies such as promotions. The proposed system plays a vital role for companies when shifting to DDM strategy. It helps them optimizing the supply chain by adapting their resources to the demand. It was shown that it is able to perform well compared to other existing sales forecasting systems due to the fact that it relies on potential sales to perform the predictions. This system can be improved with the help of experts in fields like marketing, fashion, ... in order to add additional features to the learning process for obtaining potential sales that better reflect consumers' demand.

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