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Electrical Spare Parts Demand Forecasting

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***Abstract*—In this paper is presented a research of electrical spare parts demand forecasting through application of conventional (moving average, exponential smoothing and naive theory), more sophisticated forecasting techniques (support vector regression, feed-forward neural networks) and adaptive model selection methodologies. Electrical spare parts demand forecasting is a fundamental task that should be performed in order to improve SCM (supply chain management). If it would be possible to know what the demand for electrical parts will be in the future, the logistics of the companies that manufacture electrical parts or retailers could be managed more accurately: selection of appropriate warehouse safety limits for each part and ability to plan the resources more precisely. Customer sales and marketing departments always perform formal forecasts, this is usually done through application of conventional methods in order to prepare future plans. Experimental results reveal that application of SVR technique guarantees the best and precise results of forecasting of weekly and daily demand of electrical parts. Furthermore, application of adaptive methodology in order to select adaptive model allowed substantially to increase forecasting accuracy.**

***Index Terms*—Demand forecasting, support vector machines, neural networks.**

I. Introduction

In order to increase a profit, manufacturing companies, wholesalers or retailers should be able to increase their productivity in the supply chain management (SCM), i.e., logistics. A supply chain is a system of organizations, people, activities, information, and resources that are involved in the process of product or service movement from supplier to customer. Electrical spare parts demand forecasting is crucial task that should be accomplished by electrical components manufacturer in order to solve a problem of logistics optimization. The more precise forecast is the better savings of electrical spare parts logistics will be achieved. Future demand of electrical spare parts could be estimated basically in two ways: 1) either using historical demand (end customers) data; 2) or modelling electrical parts' life cycles and estimating electrical parts demand in the future in accordance with prediction of electrical part's fault time. The latter option could be applied in order to optimize electrical devices service, but it's effect in regard of retailer's (manufacturer's) logistics is not direct, this is in contrary to the first option which is characterized by direct effect in regard of retailer's (manufacturer's) inventory. In this paper historical electrical parts demand data (first option) was used in order to forecast future demand and to optimize logistics.

Historical electrical parts demand is typically lumpy and intermittent. W. Romeijnders *et al* [1] propose two-step forecasting method, which takes into account additional repair information unlike conventional Croston's method which takes into account only intermittent information and information about demand amount that is needed for forecasting. It is assumed that intermittency evidences due to repair of a particular part and lumpiness evidences because multiple parts are needed to complete the repair. Z. Jiantong and L. Biyu [2] use grey modelling to forecast intermittent demand. Authors use Croston's suggestion for individual forecasting of intermittent interval and demand series.

More sophisticated forecasting method, such as support vector regression (SVR), was successfully adapted in manufacturing of semiconductor. P. Chittari and N. R. S. Raghavan [3] show that SVR technique is superior to conventional ARIMA demand forecasting techniques in this field. L. Yue *et al* [4] proposed the model SHEnSVM (Selective and Heterogeneous Ensemble of Support Vector Machines) and applied it during demand forecasting of one retail company that works in the field of beer supply. Results showed that accuracy has increased due to proposed model that was used instead of SVM model. K.-Y. Chen [5] used SVR technique with Generic Algorithm in order to optimize SVR parameter and to forecast reliability in engine systems. Author shows that SVR model is more precise than ARIMA and several other neural network architecture models in this field. For forecasting of spare parts consumption Y. Huang *et al* [6] use hybrid grey relational analysis and SVM approach. This technique takes into account influence factors (after grey relational analysis) as an input to SVM model. Yanling *et al* [7] proposed adaptive neural network model that is applicable for forecasting of logistics demand, it indicates that more accurate forecasting results are achieved by using proposed approach instead of conventional neural network. The results that are presented in the paper by F. Qi *et al* [8] show that a hybrid method which combines Grey Model and artificial neural networks yields more accurate results in forecasting of logistics

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demand in comparison with individual use of methods. M. R. A. –Naseri and B. R. Tabar [9] compare various neural network architectures, Croston's and Syntetos-Boylan approximation methods in lumpy demand forecasting for spare parts in process industries. Their results show that RNN (Recurrent Neural Network) model is the most precise using spare parts demand data from Arak Petrochemical Company.

This paper is structured as follows. After introduction and short problem formulation in this section, in the section two are presented the methods of spare parts demand forecasting, in the section three is described forecasting precision metric, in the section four are discussed experimental data processing and investigation results. Finally, the conclusions are presented.

II. Electrical Parts Demand Forecasting Methods

In this section we present brief description of forecasting methods used for electrical spare parts demand forecasting. Further in this section 5 forecasting methods are described.

A. *Support Vector Machine*

The basic idea of SVM is that it maps the training data from the input space into a higher dimensional feature space via kernel function $\phi(\mathbf{x})$ and then constructs an optimal separating hyperplane with maximum margin in the feature space. In this experiment *v-SVR* regression algorithm was used. In this experiment radial basis kernel function was used. Given the set of data points such that $\mathbf{x}_i \in R^n$ is an input vector (i-th observation n-dimensional vector) $y_i \in R^1$ is a target output, the optimization problem for *v-SVR* algorithm is formulated as follows

$$\min_{\mathbf{w},\varepsilon,\xi,\xi^*,b} \left\{ \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\left[\nu\varepsilon + \frac{1}{l}\sum_{i=1}^{l}\left(\xi_i + \xi_i^*\right)\right]\right\}$$

$$\text{subject to} \begin{cases} \left[\mathbf{w}^T\phi\left(\mathbf{x}_i\right)+b\right] - y_i \le \varepsilon + \xi_i, \\ y_i - \left[\mathbf{w}^T\phi\left(\mathbf{x}_i\right)+b\right] \le \varepsilon + \xi_i^*, \\ \xi_i, \xi_i^* \ge 0, \\ \varepsilon \ge 0, \end{cases} \tag{1}$$

where $\mathbf{w}$ is n – dimensional hyperplane model parameter vector; b is separating hyperplane bias parameter; ξ_i^***,** ξ_i are upper and lower training errors (slack variables) subject to ε – insensitive tube; C is a cost parameter, that controls trade off between allowing training errors and forcing rigid margins; v is regularization parameter that controls parameter ε.

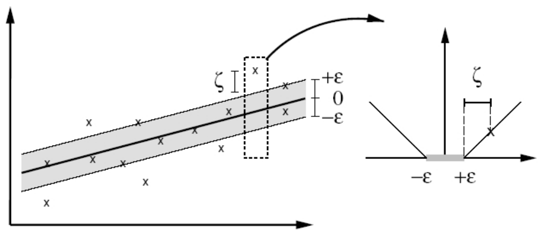

Fig. 1. A graphical illustration of soft margin loss function, the linear SVM case [10].

The equation (1) clearly reveals that a minimization problem is a quadratic optimisation problem, which means that the local optimum is always a global optimum.

B. *Feed-Forward Neural Network*

Feed-forward neural network is the most widely used artificial neural network architecture for nonlinear function approximation problems. This algorithm is inspired by biological neural networks (brain) and models the interconnection of neurons that can compute values from inputs by feeding information through the network.

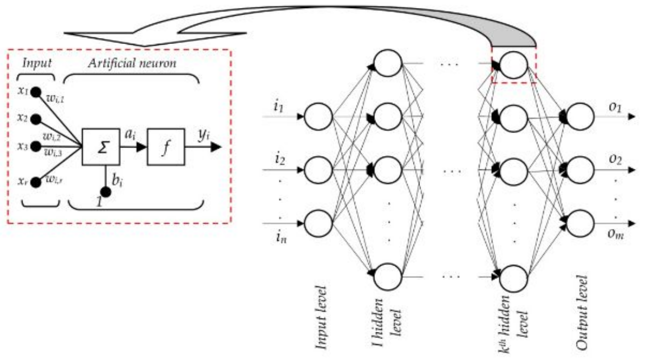

Fig. 2. An illustration of feed-forward neural network architecture.

In this experiment logarithmic sigmoid transfer function was used in the hidden levels and linear transfer function in the output level. Logarithmic sigmoid transfer function output of input variable a is equal to

$$y = \log\left(\frac{1}{1+e^{-a}}\right). \tag{2}$$

In this paper regularized back-propagation algorithm was used for feed-forward neural network model training.

C. *Moving Average*

Conventional 5-point moving average forecasting algorithm was used, in order to forecast one-step ahead on the basis of last five point data

$$y_i = \frac{\sum_{j=1}^{5} y_{i-j}}{5}. \tag{3}$$

D. *Single Exponential Smoothing*

Exponential smoothing is a special case of moving average, when the data points are multiplied by weights that decay exponentially. A simple exponential smoothing (SES) forecasting technique is formulated as follows:

$$\begin{cases} s_1 = y_1, \\ s_i = \alpha\, y_{i-1} + (1-\alpha)\, s_{i-1}, \end{cases} \tag{4}$$

where s_i is the SES i-th forecasted value; y_i is the i-th true value; α is a smoothness parameter.

E. *Naive Theory*

It assumes that the future forecasting value is equal to the past forecasting value. This approach is usually applied in order to benchmark other forecasting methods and we have involved it in our investigation. Another reason is that the customer didn't provide information about the methods used by companies' ordering engineers, so we decided to use naïve theory, such as engineer's decision equivalent.

F. Adaptive Forecasting

In the methodology proposed all methods are applied adaptively. The methodology allows to change adaptively the certain forecasting model according to forecasting accuracy on historical data. The best model for every electrical part is selected according to minimum historical error during defined optimal time period and is used to forecast demand in the future. The only additional parameter which must be defined for every part individually is the optimal time interval of historical data.

III. FORECASTING PRECISION METRICS

In this topic we discuss in brief the forecasting precision metrics that are used in this research. There prevails an opinion that there is no single best forecasting method and therefore can't be single best accuracy measure. Despite the fact basically there are known four types of forecast error metrics: Scale-dependent (MAE), percentage error (MAPE), relative error metrics and scale-free error metrics (MASE).

A. Mean Absolute Percentage Error (MAPE)

Mean absolute percentage error (MAPE) is the most widely used forecasting precision metric and has an advantage of being scale independent. Also it has one disadvantage of being infinite if there are zero values in data. This metric is formalized as

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|, \tag{5}$$

where A_t is the actual value and F_t is the forecasted value.

B. Mean Absolute Scaled Error (MASE)

This novel forecasting accuracy metric was proposed by J. R. Hyndman and A. B. Koehler [11]. This metric doesn't confront the problems that are common during application of other forecasting metrics when intermittent data is used, it also allows to compare precision between forecasting models more accurately. The metric is formulated as follows

$$MASE = \frac{1}{n} \sum_{t=1}^{n} \left(\frac{|A_t - F_t|}{\frac{1}{n-1} \sum_{i=2}^{n} |A_i - A_{i-1}|} \right), \tag{6}$$

where A_t is the actual value and F_t is the forecasted value.

IV. EXPERIMENTAL DATA AND RESULTS

In order to perform experimental investigation the data concerning electrical spare parts demand of coffee vending machines was used. The data was provided by customer service company. Collection of the data lasted for approximately two years, it varies depending on time the certain component was added to the database. Historical data about 3342 spare parts in total was provided, but most of the data was ordered once or twice per time period. Some spare parts were rejected and the data about 100 sorts of the most frequently ordered parts (ordered almost every day) was selected for analysis. On the client's request two cases of forecasting were investigated: daily and weekly. Also the comparison of proposed adaptive forecasting methodology and individual models is done.

A. Daily Electrical Parts Demand Forecasting Results

One-step ahead forecasting was done using all 5 forecasting techniques. In order to capture possible daily, weekly or monthly demand seasonality for SVR and FFNN models, the following inputs were selected:

1. Month number;
2. Day number of the month;
3. Weekday;
4. Week number (even/odd);
5. Sum of parts demand for the last several days.

The 4th input was selected because of specific electrical parts ordering on even and odd weeks, and this information was provided by the customer.

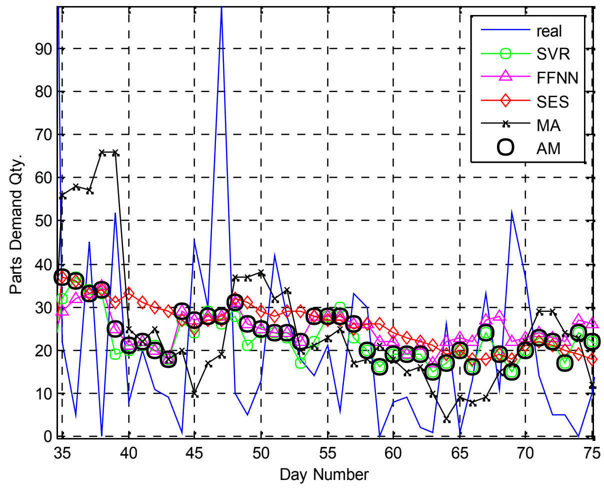

Fig. 3. Daily forecasting results for one spare part by all forecasting methods investigated.

Forecasting models were trained with historical data records and then they were used in order to forecast the daily demand for every spare part. The precision metrics were estimated for following 70 days. The average daily forecasting accuracy evaluations by both metrics are provided in Table I. Graphical results are presented in Fig. 3.

Forecasting results with proposed adaptive methodology (AM) revealed that optimal time interval for model selection varies for every electrical part in wide range. It varies from 2 to 55 days (according to the length of test data). The average percentage of the days for all data set when one or other model has been used for forecasting is as follows: SVR – 62 %, FFNN – 18 %, SES – 19 %, MA – 1 %.

TABLE I. DAILY DEMAND FORECASTING RESULTS.

Precision metric	SVR	FFNN	SES	MA	AM	Naive
MAPE	75 %	81 %	82 %	84 %	71 %	103 %
MASE	0,73	0,77	0,81	0,81	0,7	1

B. *Weekly Electrical Parts Demand Forecasting Results*

The data needed for evaluation of weekly forecasting accuracy was prepared with one week discretization step. For the FFNN and SVR models the following three inputs were selected:

1. Month number;
2. Even/odd week number;
3. Sum of parts demand for last five weeks.

The precision metrics were estimated for following 30 weeks.

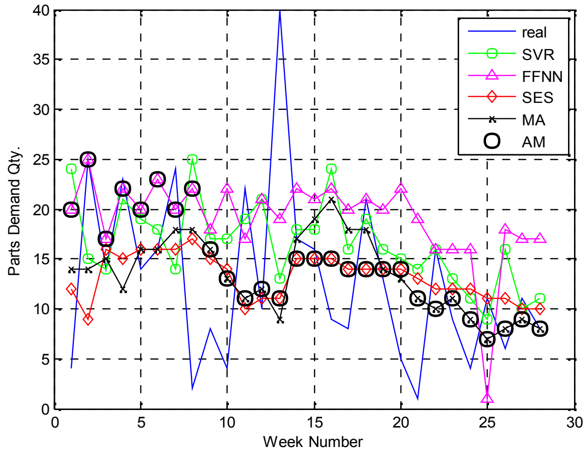

Fig. 4. Weekly forecasting results for one spare part by all forecasting methods investigated.

Experimental results revealed that optimal time for adaptive methodology interval varies from 2 to 11 weeks (according to the length of testing data). The average percentage of the weeks for all data set when one or other model has been used for forecasting is as follows: SVR – 42 %, FFNN – 33 %, SES – 16 %, MA – 9 %.

The weekly forecasting accuracy evaluations by both metrics are provided in Table II.

TABLE II. WEEKLY DEMAND FORECASTING RESULTS.

Precision metric	SVR	FFNN	SES	MA	AM	Naive
MAPE	43 %	44 %	47 %	44 %	39 %	57 %
MASE	0,74	0,77	0,83	0,76	0,69	1

V. CONCLUSIONS

Experimental investigation and analysis of forecasting results revealed that the best precision on real spare parts demand data was achieved through application of support vector regression (SVR) technique. If this model is applied individually. It is worth to mention, that all forecasting methods are superior to the naive forecasting approach which was engineer decision equivalent. The results revealed that weekly forecasting doesn't improve the model predictive capabilities (MASE is almost the same), instead it slightly worsens the forecasting accuracy for SVR and SES models. The proposed adaptive methodology produces better average results than any other model alone. SVR model was most frequently selected for demand forecasting (both weekly and daily forecasting). Also it was defined that time period for model selection varies for every electrical part in wide range and it should be selected individually.

However the use of more sophisticated forecasting methods (SVR and FFNN) and adaptive model selection methodology (AM) didn't show a significant forecasting improvement compared to conventional methods (SES and MA) as it was expected. Despite extensive attempts to tune up the models, experiments could not approve these expectations. Such an outcome occurred because the demand process was affected by some constraints: 1) a certain part could be ordered only when it is in the warehouse, this leads to peak and zero periods (all the customers receive that certain part on the same day despite the fact that demand for that part was expressed on different days); 2) customers are divided into groups of regions, i.e. one group can order the parts only on even days and another group – on odd days; 3) There was no information about sell-out days, other special days that might be applied as an input to forecasting models; 4) there is no information available about repairs done per specific coffee vending machine (it reflects the age of particular equipment) or regions of machines distribution or information that would reveal what group serves whichever region. The forecasting results could be undoubtedly improved if the data about historical electrical parts demand wouldn't be affected by the constrains of the process mentioned above or would be available raw from the engineers that serve coffee vending machines.

To sum up, the adaptive model selection methodology provide better results than each model alone regardless quality of data available and is appropriate for use.

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