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Prediction of customer demands for production planning – Automated selection and configuration of suitable prediction methods

Bernd Scholz-Reiter (1)[a,*], Mirko Kück[a], Dennis Lappe[b]

[a] University of Bremen, Bremen, Germany
[b] BIBA – Bremer Institut für Produktion und Logistik GmbH, University of Bremen, Bremen, Germany

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ABSTRACT

Demand planning is of significant importance for manufacturing companies since subsequent steps of production planning base on demand forecasts. Major tasks of demand planning are the selection of a prediction method and the configuration of its parameters subject to a given demand evolution. This paper introduces a novel method for the automated selection and configuration of suitable prediction methods for time series of customer demands. The research investigates correlations between dynamic time series characteristics and forecasting accuracies of different prediction methods. The evaluation of the method on a database comprising real industry data confirms excellent prediction results.

1. Introduction

Production planning is an important task for manufacturing companies. In particular, demand planning, which is premised on forecasts of future customer demands, is the main basis for all following planning steps [1]. Since no single prediction method outperforms all other methods for all cases of time series [2], two major tasks have to be fulfilled. At first, a suitable prediction method must be selected. Subsequently, the parameters of this method have to be configured to match a current demand evolution. Commonly, manufacturing companies select a few prediction methods, configure their parameters and compare the training results to select the best of the considered methods. In an extreme case, only one prediction method is selected and configured with respect to a current demand evolution. The advantage of this approach is the quick establishment of forecasting results. Nevertheless, the probability of poor results in comparison to other prediction methods is high. The other extreme is to configure various prediction methods to the current demand evolution and to select the method with the lowest training error. This approach can lead to more accurate predictions. However, it requires either a high amount of expert knowledge or automated algorithms to find appropriate parameter configurations of the applied prediction methods. Moreover, it takes much time to configure the different prediction methods and to compare the prediction results. Besides, the increasing number of product variants in recent years further complicates demand planning [3].

The paper at hand presents a novel data-driven approach for the automated selection and configuration of suitable prediction methods. Thereby, sophisticated predictions are calculated quickly. By using machine learning methods, correlations between time series characteristics of demand evolutions and the accuracies of different prediction methods are analysed. Here, measures of recurrence quantification analysis are incorporated in addition to common time series characteristics. Furthermore, the study includes several established prediction methods which model time series evolutions locally or globally as well as linear or nonlinear. After setting up a knowledge base, a suitable prediction method for an unknown time series of customer demands is selected and configured automatically. The remainder of this paper is structured as follows. Section 2 gives a theoretical background. The new automated selection and configuration approach is detailed in Section 3. Section 4 describes an evaluation on real time series data of the M3-competition [4]. Conclusions and an outlook on further research directions are given in Section 5.

2. Theoretical background

2.1. Demand planning and time series

Manufacturing companies must solve demand planning problems for every product they sell. In particular cases, additional information can be incorporated to improve forecasts of future customer demands, but in general, univariate time series of past customer demands are the main basis for the predictions. A time series of customer demands for a specific product is an ordered sequence of points $\mathbf{y} = \{y_1, \ldots, y_T\}$ measured in time steps of equal length. The time distance between consecutive points is called a planning period. Each point of the time series represents an amount of customer demands within a period.

Demand planning can be conducted for different prediction horizons. However, the most important and most frequently performed planning step is planning one period into the future, denoted as a one-step-ahead forecast. In this paper, one-step-ahead demand planning problems are considered. These can be defined as follows: *For a given time series* $\mathbf{y} = \{y_1, \ldots, y_T\}$ *of past*

* Corresponding author.

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customer demands for a specific product, predict the unknown future demand y_{T+1}. In order to obtain meaningful results, in this paper, one-step-ahead demand planning is performed for subsequent time steps. This means, after predicting y_{T+1} based on $y_1, \ldots, y_T$, predict y_{T+2} based on $y_1, \ldots, y_{T+1}$ and so on. In this second prediction step, y_{T+1} is known and is included into the prediction of y_{T+2}. This procedure is iterated h times. The prediction accuracy is computed as the average error of the predicted values $\hat{y}_{T+1}, \ldots, \hat{y}_{T+h}$ compared to the true future values $y_{T+1}, \ldots, y_{T+h}$.

In general, many different demand planning problems have to be solved at each period. Thus, usually a high amount of time has to be invested to find individually suitable prediction methods for the demand evolutions of different products. Model selection is an approach to achieve sophisticated predictions in shorter time.

2.2. Selection of prediction methods

In order to obtain sophisticated forecasts of time series, a suitable prediction method has to be selected. For this purpose, different approaches exist which can be divided into expert systems and data-driven approaches [5]. Since expert systems [2] are generally static and inflexible, data-driven approaches in terms of machine learning methods were studied in the recent years [5–7]. These methods achieve an automated selection of a prediction method by linking time series characteristics (features) to the accuracies (labels) of different prediction methods. In this way, a higher flexibility is accomplished [5]. However, most of the proposed model selection methods base either on a small amount of considered features [6] or a small number of prediction methods as possible labels [7]. Hence, Wang et al. developed a data-driven approach which incorporates 13 time series characteristics as features for the selection of one of four prediction methods by a decision tree [5]. This approach showed great potential for a sophisticated model selection. In the paper at hand, a classification approach by linear discriminant analysis is proposed which considers measures of recurrence quantification analysis in addition to the features proposed by Wang et al. [5]. Moreover, prediction methods of nonlinear dynamics are incorporated beside the common prediction methods. Recurrence quantification methods and nonlinear dynamics base on the theory of dynamical systems which is outlined in the next subsection.

2.3. Dynamical systems and phase space reconstruction

In general, customer demands for a specific product depend on various influences, like the amount of substitute products, the success of competitors, changing social or ecological conditions, or general agreements [8]. Here, methods of nonlinear dynamics have shown potential to model complex dependencies in production networks [9,10]. These methods base on dynamical systems which are also applicable to model a customer demand evolution together with its influencing forces. In order to reconstruct the dynamical properties of the system, the method of delay coordinate embedding is applied [11]. This method maps the time series into a so-called phase space. A vector

$$\mathbf{v}_{t,y}^{m,\tau} = [y_{t-(m-1)\tau}, y_{t-(m-2)\tau}, \ldots, y_{t-\tau}, y_t] \quad (1)$$

is called delay coordinate vector of length m corresponding to time point t. The delay time τ is a multiple of the sampling time of the time series $\mathbf{y}$. The length m is called the embedding dimension. By building all delay coordinate vectors $\mathbf{v}_{1+(m-1)\tau,y}^{m,\tau}, \ldots, \mathbf{v}_{T,y}^{m,\tau}$ of length m with successive time distance τ, the dynamical properties of the whole dynamical system can be reconstructed if the parameters m and τ are chosen appropriately. Rules of thumb values for the parameters can be obtained by the fnn-algorithm and the first minimum of the average mutual information [11]. In order to build a prediction method based on the dynamical system reconstruction, the parameters have to be chosen more sophisticatedly, like described in Section 3.2.

3. New approach for model selection and configuration

This section describes the new approach for the automated selection and configuration of suitable prediction methods. The process for the creation of the proposed prediction framework is illustrated in Fig. 1. Characteristic measures are computed for a given training set of time series. After performing a principal component analysis (PCA) on these measures, the principal components are stored in a knowledge base. Besides, the time series are predicted by different prediction methods. The rankings of the different prediction methods for each time series are also stored in the knowledge base. Thus, the knowledge base comprises the principal components of the time series characteristics (features) as well as the most appropriate prediction methods for each time series (labels) of the training set. By performing a linear discriminant analysis (LDA), a classifier is created which relates the features to the labels. The proposed automated prediction method consists of this classifier as well as a parameter configurator. If an unknown test time series has to be predicted, firstly, the classifier recommends a prediction method. Secondly, the parameter configurator optimises the parameters according to the time series evolution. After these two steps, the resulting model can be used to predict the time series into the future. The next subsections describe the three main components of the proposed method, the features, the labels and the classifier.

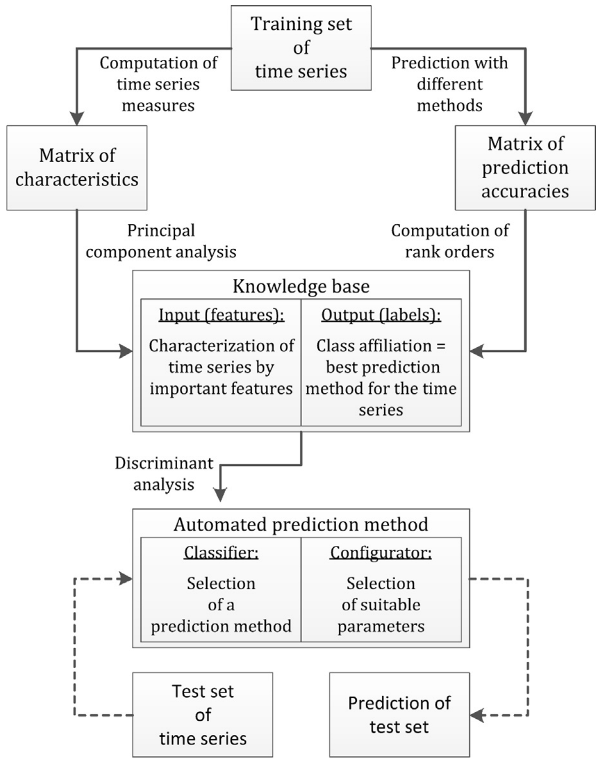

Fig. 1. Creation of the proposed automated prediction method.

3.1. Time series characteristics (classification features)

In order to describe given time series by informative characteristics, different measures are calculated. Fig. 2 shows the 26 characteristics which are considered as classification features in this paper. These are 14 common time series measures as well as 12 measures derived from recurrence quantification analysis (RQA).

Wang et al. [5] propose a set of 13 common metrics to quantify the global characteristics of univariate time series. Nine characteristics are measured on the raw time series $\mathbf{y}$. Furthermore, four characteristics are measured on the remaining time series $\mathbf{y}'$ after detrending and deseasonalising. In this paper, the proposed 13 characteristics are incorporated as well as the length of the considered time series as 14th measure.