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Applying frequency based forecasting for resource allocation

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Abstract

Soaring complexity in supply chains with more fluctuations and ever increasing uncertainty in demand puts an increased focus on flexibility and changeability in manufacturing. Thus, it is increasingly important to determine the right change type, such as changes in the number of employees or overtime, at the right time in order to be able to react appropriately and sustainably to changes in demand. The developed approach uses frequency analysis to predict future changes in demand in different frequency ranges in order to assign appropriate change types to them and optimize the change intensity for each change type and time step. The foundation of the related algorithm is a discrete Fourier analysis that extracts relevant frequencies and assigns change types using generative algorithms to enable cost-minimizing production. The algorithm is validated against LSTM and ARIMA forecasting in a use case with seasonal time series including different noise levels.

Keywords: Frequency, Fourier analysis, Resource allocation, LSTM, ARIMA, Generic Algorithm

1. Introduction

Globalization, individualization, and the shortening of product development cycles are creating new challenges in terms of changeability [2]. The so-called change drivers, such as fluctuating demand and uncertainty in the supply chains, are increasingly putting pressure on production adaptation. Changeability and flexibility are the main enablers for the adaptation of manufacturing systems under uncertainty [29]. Flexibility represents the change in predefined corridors without changing the basic structure of the system [28] and to operate at low cost [9]. Therefore, the term changeability is introduced in the literature, which is the answer to uncertainty and goes beyond the concept of flexibility [4]. Wiendahl and Hernández [30] define changeability as the potential to efficiently respond to planned and unplanned changes throughout the factory [30]. The adaptation of manufacturing is enabled by different change types. Depending on the selected change type, different costs and different implementation times arise [31]. The presented concept represents a new method for the identification of suitable change types to enable better changeability and flexibility while minimizing the incurred cost. The basic assumption is that information regarding changeability is to a large degree contained in past data and can be extracted by frequency analysis to make decisions for the future. The approach thus assumes that the different changeability types can be mapped to frequency components generated by frequency analysis on demand data.

This article is structured as follows: Section 2 introduces the current state-of-the-art in enabling changeability, frequency based resource allocation and frequency based forecasting. Subsequently, in Section 3 the proposed algorithm and the comparison method are presented. An evaluation of the frequency based forecasting is executed with a case study in Section 5. In Section 6 the findings are discussed and followed by a subsequent summary and outlook in Section 7.

2. Related Work

In the three-part literature review, the general analysis of changeability is addressed in the beginning. Then, existing frequency-based analyses in the manufacturing environment are reviewed and finally, existing frequency-based forecasting research and the fundamentals of ARIMA and LSTM as state-of-the-art methods are discussed.

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2.1. Changeability evaluation

Changeability evaluation methods are usually multi-stage evaluation methods, which consider both monetary factors and non-monetary factors; see Heger [9]. The goal of changeability evaluation methods is to provide a framework, which defines the optimal degree of changeability. The field of application ranges from single reconfigurable machines, see Scholz-Reiter et al. [20], to global production systems, as introduced in Sudhoff [24]. Scholz-Reiter et al. [20] present a concept that, based on reconfigurable machines and over time, attempts to regulate throughput while keeping inventory as constant as possible. The analysis and optimization are done by linear programming and simulation. Another approach for the monetary assessment of changeability is presented by Moser et al. [18]. The aim of the work is the identification of risk-efficient changeability enablers to achieve the ideal degree of changeability in a production network, based on the steps of reconfiguration analysis, preselection of enablers, estimation of cost potentials and associated risks [18]. Sudhoff [24] on the other hand focuses on the impact of mobility as a degree of freedom for the global production system under uncertainty. The analysis of changeability is validated by optimizing investment strategies and considering opportunities and risks.

Human resource allocation is a part of the changeability literature in which human resources are used to respond to environmental influences in the context of flexibility. Human resource allocation can be subdivided into different model areas. Stochastic human resource allocation analyzes turnover behavior of employees and other problems via stochastic formulation; see Robbins and Harrison [19]. Deterministic human resource allocation has similarities to existing aggregate production planning. The latter type of human resource allocation is the frequency-based approach, which is discussed in more detail in the next section.

2.2. Frequency concepts for human resource allocation

Frequency analysis considers a function of the form $x(t)$, with time t as an independent variable, which is designated in the time domain. This function can be transformed by frequency analysis into the form $X(k)$. Variable k represents a frequency index [25]. When considering finite and discrete values in the time and frequency domain, the analysis is called Digital Fourier Transform/Transformation (DFT), which can be often found in digital systems due to its simplicity [25].

The consideration of resource allocation from the point of view of frequency analysis is a fairly new approach. Fisel et al. [7] use discrete Fourier transformation to extract information from highly periodic and non-periodic demand trajectories. The goal of their approach is to map three change types: temporary workers, overtime and subcontracting to demand fluctuations. A solution has been developed that creates the link between frequency and change type. Therefore, the frequency band is divided into low, medium, and high frequencies and mapped to the 3 change types. This approach considers neither optimization, determining when to make a change, nor any type of cost function [7]. The approach presented by Echsler Minguillon et al. [3] extends the results of [7]. The goal of this approach is to find a cost-efficient resource allocation using frequency analysis. The input values are historical demand data and a linear cost function, upper- and lower bounds for the changeability types and an amplitude for the resources is applied. The following five resources can be allocated: Overtime, permanent employees, contract employees, relocation of employees, outsourcing and no change. Based on serving input values, the demand is transformed into the frequency domain using DFT. The problem is formulated as Mixed-integer linear programming (MILP) and the solution of the allocation is performed in Matlab. After transforming back to the time domain, an optimization is performed using a slack variable to obtain a cost-efficient allocation. The approach is applied to highly periodic data [3]. A graphical representation of the two studies is shown in Figure 1.

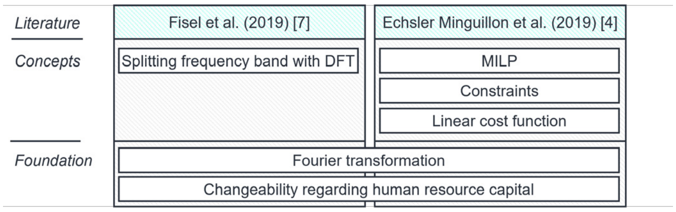

Fig. 1. Comparison of frequency concepts in the literature

2.3. Forecasting using frequency analysis

The use of frequency analysis for forecasting is uncommon in current research. The work of Beiraghi and Ranjbar [1] attempts to predict the monthly variation of the peak electricity load in the national power grid using DFT. The concept introduces the use of DFT analysis as input to an autoregressive integrated moving average (ARIMA) model [1]. Also in the energy sector, [14] developed an approach that applies DFT and afterward a neural network predicts the sunshine hours for the next day. Another example, where DFT is implemented as the basis for a neural network, can also be found in the research by Shu and Gao [22]. The approach extracts the five most dominant frequencies in a stock price and uses these values for forecasting with a a long short term memory (LSTM) network.

3. Frequency-Based (FB) Algorithm for Resource Allocation

The algorithm is based on using frequencies to determine an optimal resource allocation. In the first step, a Fourier analysis is performed. Afterwards for each frequency, the phase angle is calculated and based on the knowledge of the phase the forecasting is determined. In the next step, the extracted frequencies are assigned with the help of an evolutionary algorithm to the different change types. Subsequently, each change type and the associated frequencies are solved separately using a heuristic. The algorithm is in Figure 2 and described in more detail in the following. The algorithm is applied on a rolling basis for each forecast period.

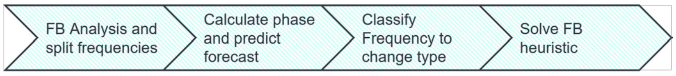

Fig. 2. Steps of the developed frequency-based (FB) algorithm

3.1. Cost model

The model used to evaluate the costs is a linear resource allocation model with the decision variables employee, subcontract and change type. The model used is based on the publications of Wang and Liang [27] and Mokhtari [17]. The mathematical formulation of the problem is defined as follows:

$$\begin{aligned} Cost(u,x) &= u_{employee} * h_{employee} * c_{employee} * u_{overtime} + \\ &\quad u_{subcontract} * h_{subcontract} * c_{subcontract} * u_{overtime} \\ &\quad + f_{inventory}(x_{inventory}) + f_{backlog}(x_{backlog}) + \\ &\quad f_{overtime}(x_{overtime}) + f_{change}(u) \\ Output(u,t) &= u_{employee} * o_{employee} * h_{employee} * u_{overtime} \\ &\quad + u_{subcontract} * o_{subcontract} * h_{subcontract} * u_{overtime} \\ x_{inventory,t} &= x_{inventory,t-1} - x_{demand,t} + Output(u,t) \end{aligned} \tag{1}$$

The overall optimization goal is reducing the total costs over the entire period: $\min Cost(x,u)$.

3.2. Frequency-based analysis

The calculation of the Fourier transformation is based on the discrete Fourier transformation (DFT) over the last n-values. Due to the day-by-day data and the discrete Fourier transforms, the frequencies cannot be resolved exactly, so a function consisting of all frequencies is resolved into several frequency intervals after the frequency analysis according to the minima in the frequency analysis. An example is shown in Figure 3.

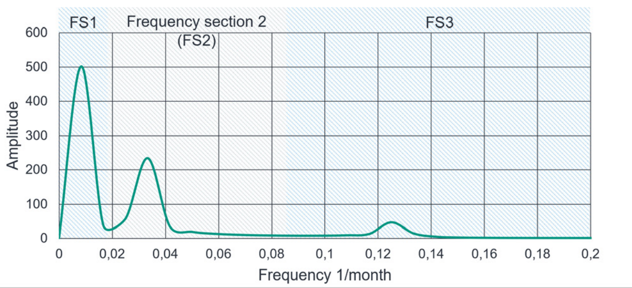

Fig. 3. Example for frequency analysis

3.3. Phase detection - Forecast

The calculation of the phase is one of the most elementary steps in finding an optimal solution. The determination of the phase per frequency lays the foundation for the forecasting calculation. Because the frequencies cannot be resolved exactly, a simple calculation via the calculated frequency and amplitude is not possible. The use of the calculated frequency and amplitude would lead to an unprecise forecast. For this reason, an evolutionary algorithm is used to determine the phase. For each frequency, one time period is defined per population from the past data. The evolutionary algorithm determines an optimal interval section per frequency, which leads to a minimum Mean absolute percentage error (MAPE) over the entire past horizon; see Fildes [6]. The selected period can then be used to determine the phase and to calculate associated forecasts per frequency. The algorithm is illustrated in Figure 4, note that the evolutionary algorithm population of individual phase estimates is randomly initialized and evaluated with the root mean squared error (RMSE).

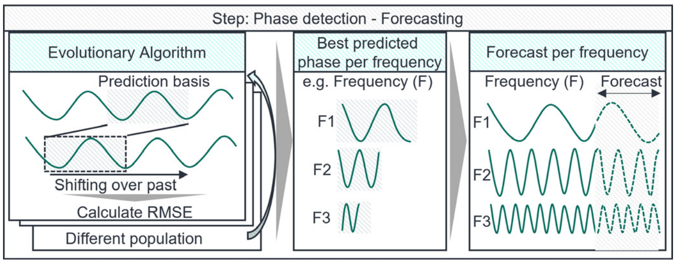

Fig. 4. Algorithm step for phase detection and forecasting

3.4. Resource assignment

The idea behind the algorithm is that every frequency is assigned to a change type. Specifically, this means that low frequencies are automatically assigned to the change type employee and high frequencies are assigned to overtime. Another influencing factor is the amplitude, small amplitudes are filtered out and high amplitudes are assigned according to the best fitting change type. The optimal selection of the assignment of change type and frequency is done by an evolutionary algorithm. Each population represents an assignment for all frequencies and based on the assignment the costs are calculated via an heuristic. Therefore, the fitness is selected according to the minimum total cost over the forecasting range. The classification is performed for each forecasting step since the frequencies change over the solution period and therefore the best assignment must be determined at each forecasting cycle. The algorithm is illustrated in Figure 5.

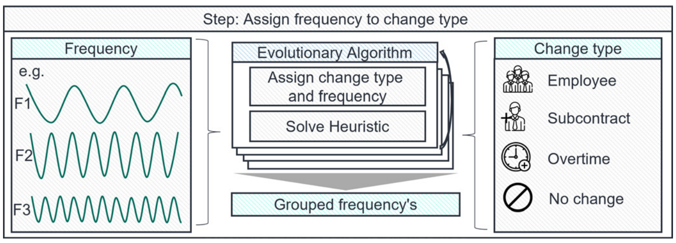

Fig. 5. Algorithm step for assigning a frequency to a change type

3.5. Frequency-based heuristic

The heuristic calculates the concrete number of employees, subcontracts, and overtime for the given forecast values. The overall goal of the heuristic is the minimization of the inventory, based on the standard heuristics from Jacobs et al. [12]. The only difference is that each change type with the frequency is evaluated separately in descending order based on the change rate. In this case, the number of employees is determined first and the open inventory due to integer values is transferred to the next change type, the subcontractors. By this procedure, a minimization of the inventory is ensured despite separate considerations of the change types. The process is visualized in Figure 6.

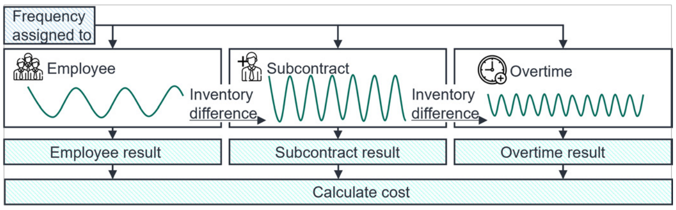

Fig. 6. Heuristic procedure for the frequency-based concept

4. Comparison Methods

4.1. ARIMA

The first comparison algorithm is based on the forecast using ARIMA and the heuristic proposed in Jacobs et al. [12]. Together with Exponential Smoothing, ARIMA, which stands for Autoregressive (AR) integrated (I) moving average (MA), is a widely applied forecasting method [15]. ARIMA describes the autocorrelation of data combined with differencing and moving average [11]. The mathematical representation of the degree of similarity between a given time series and a lagged version is called autocorrelation [11]. The formulation of AIMRA for the first derivative is:

$$\begin{aligned} y'_t =& c + \phi_1 * y'_{t-1} + ... + \phi_p * y'_{t-p} \\ &+ \theta_1 * \epsilon_{t-1} + ... + \theta_q * \epsilon_{t-q} + \epsilon_q \end{aligned} \tag{2}$$

This ARIMA Model is often given in the following form: $ARIMA(p, d, q)$, where p is the order of autoregressive parts, d the degree of differentiating involved and q the order of moving average part. By extending seasonal covariates, ARIMA will also be able to detect seasonal trends [26]. For the determination of the resource allocation based on ARIMA, in the first step. The optimization algorithm for the parameter set is based on Akaike Information Criterion [21] and the differencing test Kwiatkowski-Phillips-Schmidt-Shin [13]. Akaike Information Criterion describes how well the calculated model fits the generated data. The best-selected model according to the Akaike Information Criterion is the one that has the best maximum likelihood estimate and uses the fewest independent variables [21]. The null hypothesis Kwiatkowski-Phillips-Schmidt-Shi test calculates whether the observable series oscillates stationary around a deterministic trend [13]. After the optimal ARIMA parameter set is defined, the forecast for the next ten days is performed, Afterward, the implemented heuristics determine the best resource allocation.

4.2. LSTM

Besides ARIMA, which is based on autocorrelation, a forecasting method based on a neural network is used. A long short term memory (LSTM) network is an extension of recurrent neural networks (RNN) and enables the storage of past information over a long period. A recurrent neural network is a special case of a neural network aiming at forecasting the next step in a sequence based on the previous observed steps [23]. For this, past values are remembered to learn from the observations to predict future trends. The storage of the information happens in the hidden layer and the name recurrent comes from the recurrent performance of the same tasks for each element in the input vector [32]. Since RRN are not able to learn long time series, the LSTM has been developed [23]. Compared to a recurrent network, the LSTM offers the following advantages: First, it solves the vanishing gradient problem of RNN. Additionally, it allows predicting non-linear trends based on large parameter sets with high dimensionality due to the non-linear activation function in each layer [5]. LSTM is widely used and finds application among others in language model tasks and speech recognition [8, 10]. The structure of a single LSTM cell consists of three types of gates and is composed of input, forget, and output gates [5]. In the forget layer irrelevant information is filtered, relevant information is used in the next step to update the state value and the output gate provides the link to the outside [5]. A comparison of ARIMA and LSTM in various publications including Fan et al. [5], May et al. [16] and May et al. [15] show that LSTM outperforms ARIMA on average across different data sets [5, 16, 15, 23].

The application of LSTM for resource allocation start with learning the LSTM model based on existing past values. Before learning and predicting with the LSTM model, every value is scaled to a number ranging from 0 to 1. After learning, the past 50 demand data are used for forecasting the next ten days. The forecasting result is then applied for the calculation of the resource allocation with the same heuristic used with the ARIMA comparison method. Thus, the two comparison methods differ mainly in the generation of the forecast and the respective input vector for the generation of the forecast, illustrated in Figure 7.

5. Case Study

The evaluation of the designed frequency-based (FB) algorithm is compared with the comparison methods ARIMA and LSTM on the basis of three seasonal data sets including noise. The noise is based on Gaussian noise with a variance, given as RMSE between 25 and 200. The exemplary data sets used are

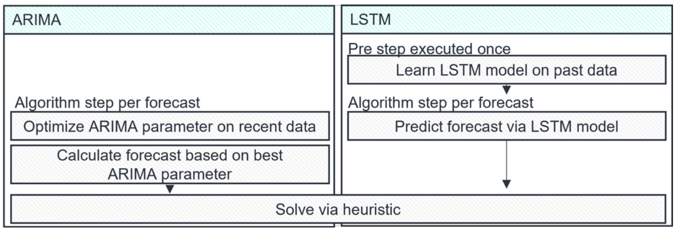

Fig. 7. Algorithm steps of the two comparison methods

shown in Figure 8. The objective of the analysis is to compare the total costs and the forecasting error via MAPE across the different methods.

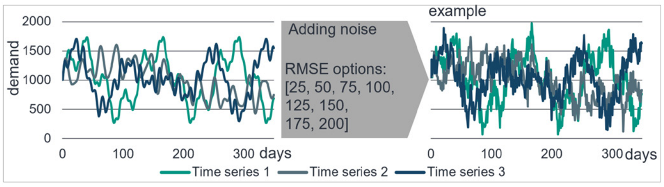

Fig. 8. Exemplary view of the applied data

The results are visualized in Figure 9. The analysis results are shown per time series and consider the average costs per noise level and evaluation type.

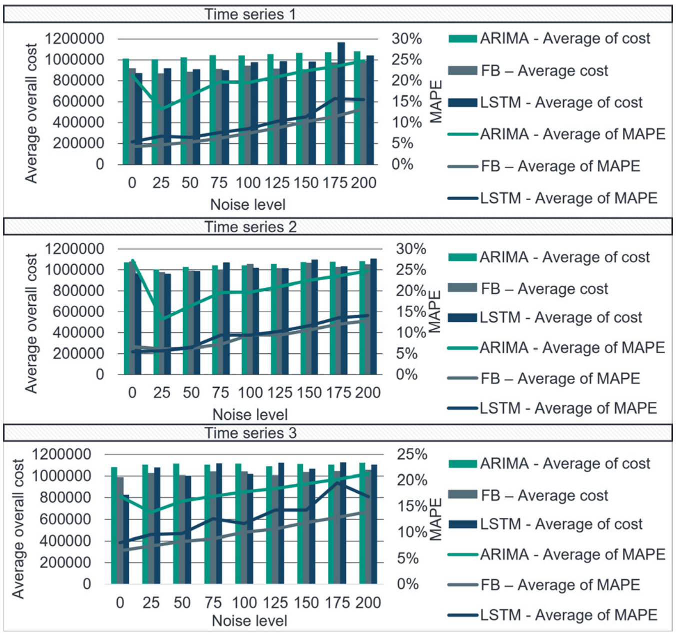

Fig. 9. Comparison of the developed FB algorithm with the comparison method

The analysis based on three time series shows that FB outperforms ARIMA for all evaluations presented. The three time series are shown in 8 and each of these time series is based on three frequencies with different phases. The difference in MAPE between FB and ARIMA lies between 10%-15%, which means that depending on the data set, the cost of using ARIMA is between 5-15% higher than the FB algorithm. The higher total costs are mainly related to the consistently worse forecasting result. A worse forecasting result leads to an increased inventory. Since inventory is one of the key costs that can be minimized, the overall cost increases with a higher inventory. Costs related to the workforce level and the resulting costs are nearly identical for forecast and evaluation data because the number of producing parts is nearly identical due to the seasonal data. The differences between LSTM and FB are smaller because the forecasting error difference is smaller. When analyzing the results, it can be seen that LSTM and FB produce quite similar results for low noise data and with increasing noise FB outperforms LSTM. Furthermore, it is noticeable that the selection of the FB plays a greater role in the comparison of FB and LSTM. The forecasting results for time series 2 are very identical, while for time series three there are more significant differences.

6. Discussion

The comparison of the FB algorithm with the comparison methods LSTM and ARIMA shows that for seasonal data including noise, the forecasting error is lower for the FB algorithm. For ARIMA, the result is significantly worse for all cases in terms of MAPE and total cost. When using LSTM, the performance of the FB algorithm increases with increasing noise. There are cases for LSTM with low noise, where LSTM provides the best solution due to the better forecast, which leads to lower inventory costs and finally lower total cost. The advantage of the algorithm is the good independence from noise compared to the comparison algorithms for seasonal data sets.

Furthermore, the use of the frequency-based approach allows a better traceability of the results. By splitting the demand data into the different frequencies, it is easier to understand which periodic trends are reflected in the solution. The biggest limitation of the algorithm is the limitation to seasonal data sets. The integration of trends is not possible at the current time. Furthermore, due to the discrete analysis and the resulting inaccuracy, a forecasting error of around four percent remains even for seasonal data without noise.

7. Summary & Outlook

The increasing complexity in supply chains leads to new requirements regarding fluctuation of demand and the possibility to react to changes with the appropriate change type. The developed algorithm determines the relevant frequencies by frequency analysis and calculates the forecast. By decomposition into frequencies, individual change types are assigned to the different frequencies. Therefore, the currently developed frequency-based algorithm represents a proof of concept and lays the foundation for further research. The current investigation is based on seasonal data with Gaussian noise which shows good results regarding cost-minimal resource allocation compared to the state-of-the-art ARIMA and LSTM.

In the next step, an adaptation of the concept for trend data, other types of noise and data with ramp-up will address a wider range of applications and real-world use cases. In a much broader sense, stronger integration of control methods for filtering and sorting frequencies could allow a more mature use of frequency in problem-solving. Current prediction and classification are based primarily on the use of Generic Algorithms and are performed largely in the time domain. The idea behind the frequency-based algorithm is to take advantage of the benefits of frequency analysis in terms of parameter reduction, and better ability to filter.

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