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Artificial intelligence-based hybrid forecasting models for manufacturing systems

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Highlights

- In the paper 4 new hybrid forecasting artificial intelligence-based models are proposed.
- A problem of defining explanatory variables when access to data is limited is addressed.
- Study fills in literature gap of hybrid forecasting application in manufacturing systems.
- The presented case studies cover production planning, maintenance and quality control.
- Algorithm for forecasting accuracy assessment and optimal method selection is presented.

Abstract

The paper addresses the problem of forecasting in manufacturing systems. The main aim of the research is to propose new hybrid forecasting models combining artificial intelligence-based methods with traditional techniques based on time series – namely: Hybrid econometric model, Hybrid artificial neural network model, Hybrid support vector machine model and Hybrid extreme learning machine model. The study focuses on solving the problem of limited access to independent variables. Empirical verification of the proposed models is built upon real data from the three manufacturing system areas – production planning, maintenance and quality control. Moreover, in the paper, an algorithm for the forecasting accuracy assessment and optimal method selection for industrial companies is introduced. It can serve not only as an efficient and costless tool for advanced manufacturing companies willing to select the right forecasting method for their particular needs but also as an approach supporting the initial steps of transformation towards smart factory and Industry 4.0 implementation.

Keywords

artificial neural network, support vector machine, extreme learning machine, hybrid forecasting, production planning, maintenance, quality control.

1. Introduction

In many enterprises the issue of making accurate business decisions often depends on the quality of demand forecasts for manufactured products. “Demand forecasting is crucial for decision making and operations in organisations” [38]. In the era of globalization, market uncertainty, and growing supply chain complexity the need for integrated and efficient planning increases [55]. Predicting future demand values provides the basis not only for proper production planning, but also for preparing precise material, financial and employee demand schedules. The proper resources management is a challenging task in every manufacturing company [25]. The accurate demand forecasting for the manufactured products allows reducing inventory and improving order indicators, whereas “inaccurate forecasts can be costly for company operations, in terms of stock-outs and lost sales, or over-stocking, while not meeting service level targets” [39]. Forecasting is widely used not only in production planning, but also in maintenance – it enables the companies to predict failures or demand for spare parts (examples of forecasting applications in maintenance-related problems include for instance time-based machine failure prediction in multi-machine manufacturing systems [75] or lifetime prediction of bearings or bearing-based systems [4]). In manufacturing processes the quality of the end product is in general defined by multiple critical outputs or responses and therefore, the efficient forecasting of quality is both critical and challenging for practitioners [72]. In fact in every single area of activity of a manufacturing company, for which it is possible to collect the appropriate dataset and it is necessary to make effective decisions regarding future operations, accurate prediction techniques should be implemented.

In [29] Hall discusses a number of cases presenting how improvement of forecasting influences profitability of companies – for example Hyundai Motors has reduced delivery time by 20% and increased inventory turns from 3 to 3.4, whereas Reynolds Aluminum has reduced forecasting errors by 2%, which in turn caused a reduction of 1 million pounds in inventory. Moreover, Unilever has reduced forecasting errors from 40% to 25%, which has brought multi-million dollar savings. SCI Systems on the other hand has reduced on-hand inventory by 15%, which resulted in annual savings of 180 million dollars. It is also worth mentioning that Virgin Atlantic Cargo – being one of the largest air freight operators in the world – has identified forecasting accuracy as of strategic importance to its operational efficiency, due to the reason that efficient predictions ensure to have the right resources available at the right place and time [37].

Another important area of forecasting implementation in manufacturing companies is spare parts management. According to Suomala et al. the impact of the spare parts business is significant in terms of

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a company's profit [76]. "Strategically aligned and efficiently implemented spare parts logistics can differentiate a business from its competitors, lower costs, increase revenues, and thus help firms generate greater value for customers and ultimately increase profits"[80]. In consequence it can be stated that improvement of processes related to spare parts management is a matter of great importance for many industrial companies. Especially challenging is the issue of lumpy and intermittent demand forecasting – a sort of demand typical for spare parts, which can be observed in aerospace, automotive, mining and railway industry as well as in advanced manufacturing or electronics. Forecasting the failure rate of machines based on data obtained from the monitoring systems is an extremely important solution for maintenance departments, which goal is to minimize the number of failures. When weighing these considerations against industrial implementations results, it can be noticed that predictive maintenance reduces the time needed for planned machinery maintenance by 20-50%, equipment availability can be increased by 10-20%, whereas overall maintenance costs can be reduced by 5-10% [17].

In the era of Industry 4.0, which can be defined as "an integration of intelligent machines, systems and the introduction of changes in production processes aimed at increasing production efficiency and introducing the possibility of flexible product changes"[70], the issue of accurate forecasting becomes especially important. The impact of new technologies like Big Data, Industrial Internet of Things and Cloud Computing, which are considered to be the pillars of Industry 4.0, changes the way how manufacturing companies operate. Especially "the field of big data time series has dramatically evolved in the last years"[56]. Cloud Computing "has become a new type of Internet service because of its high scalability, flexibility, and cost-efficiency"[9]. What is more, "from an ICT point-of-view, during the last decay, "Data, Information and Knowledge" (DIK) became a central capital with a critical value. ICTs introduced huge changes in Knowledge Management (KM) and AI applications"[8]. Flexible Manufacturing Systems - representing an opportunity for shifting from fixed to customized production - when associated with computational technology they lead to industry of the future [47]. According to a report on Industry 4.0 by PricewaterhouseCoopers huge data volumes generated by control systems, which are currently used mainly to monitor the state of technological processes, in the future will enable predicting their behaviour and product quality parameters, as well as global production control. Therefore it is expected that manufacturing management processes will be subjected to major changes [88]. In consequence, currently, a number of manufacturing companies are facing the challenge of transforming into so-called smart factory or factory of the future. In Poland, as most companies are currently at the stage of the third industrial revolution, the process of implementing Industry 4.0 technologies is still ahead. As the increasing amount of collected data requires effective analytical tools [41], there still is a need to develop new ways and models enhancing this transformation process. As Frank at al. underline "the effective implementation of Industry 4.0 technologies is still a subject of research"[22].

A properly constructed database is a key aspect of effective forecasting. Collecting data of adequate quality is a prerequisite for building accurate models. Currently, due to advanced information and manufacturing technologies, companies have the opportunity to gather a huge amount of data that characterize the work of machines, their technical condition and production processes. These data can be collected, for instance through sensors that are installed in particular machines and devices. In consequence, production management based on digital data allows adding value in the areas of production and logistics mainly due to very precise forecasting of demand and making manufacturing process more flexible, reducing failures by implementing predictive models in maintenance as well as elimination of root causes of defects through intelligent quality assurance processes.

As an access to data is getting easier in manufacturing systems, the companies are willing to possess the knowledge hidden in the data and develop efficient predictions. On the other hand, obtaining appropriate data to build accurate forecasting models is still rather challenging – especially, when data characterizing explanatory (independent) variables are desirable. Often companies interested in effective forecasting face the problem of lack of available, reliable, complete and comparable statistical data. Therefore there still is a need to develop approaches allowing the companies to create a set of potential explanatory variables when access to data is limited and to develop new ways enhancing companies in transformation to Industry 4.0. To answer this need the Author proposes new hybrid forecasting models dedicated to manufacturing systems.

2. Literature review on hybrid forecasting

Literature review on forecasting problems shows that nowadays research on the application of artificial intelligence methods is developing very dynamically. According to Hall "a new generation of artificial intelligence technologies have emerged that hold considerable promise in helping improve the forecasting process including such applications as product demand, employee turnover, cash flow, distribution requirements, manpower forecasting, and inventory" [29]. Typically manufacturing/distribution planning decisions focus on achieving following goals: "(1) set overall production levels for each product category for each source (manufacturer) to meet fluctuating or uncertain demands for various destinations (distributors) over the intermediate planning horizon and, (2) generate suitable strategies regarding regular and overtime production, subcontracting, inventory, backordering and distribution levels, thereby determining the appropriate resources to be utilized"[46]. Increasing number of decision-making problems related to manufacturing systems (e.g. production scheduling or optimal arrangement of machines) can be solved with the use of algorithms like genetic algorithm, Artificial Bee Colony Algorithm [50] or Tabu Search [13]. There is also a significant number of papers focusing on the application of the artificial intelligence methods for prediction of different aspects related to manufacturing processes (e.g. artificial neural networks (ANN) for predictive compensation of thermal deformations of ball screws in CNC machines [62] or for prediction of average surface roughness and formability [51]) or maintenance in general (e.g. forecasting of mains reliability [77], intelligent forecasting of automatic train protection system failure rate [35], modified convolutional neural network for intelligent fault diagnosis of industrial gearbox [45], ANN-based failure modeling of classes of aircraft engine components [2] or hybrid fault diagnosis of railway switches [54]).

Simultaneously it can be observed that a number of publications on hybrid forecasting is growing rapidly [28]. It is said that hybrid modelling is developed to improve the accuracy of forecasts obtained through the use of individual models. What is more, it is assumed that the forecasts based on combining several methods are simply more accurate than individual ones. According to Hajirahimi and Khashei main advantages of hybrid forecasting models listed in a number of research papers include: "improving forecasting accuracy due to comprehensive pattern detection and modeling", "reducing the risk of using inappropriate model due to the combination of forecasts" and "simplifying the procedure of model selection due to the use of different components"[28].

In [28] Hajirahimi and Khashei performed an in-depth analysis of hybrid forecasting structures on the basis of 150 research papers focused on various hybrid models in time series modeling and forecasting domains. They proposed a classification of hybrid models covering three main combination structures, namely: parallel, series, and parallel-series [28]. This study presents a very detailed and up-to-date review on hybrid forecasting approaches. Nevertheless, taking into account forecasting fields addressed in the analyzed papers, namely [28]: stock market, interest rate, bank circulation, oil price and demand, wind energy, power and speed, tourism and passenger, stream flow, traffic flow, exchange rate, weather and pollutant, GDP, throughput, solar, health, sales and demand, production, hot rolling, internet

Table 1. Review on hybrid forecasting approaches

Hybrid approach	DM	ANN	TQTF	QLF	OM	Implementation area	Source
Combining a multi-layered perceptron neural network and a traditional recursive method		x			x	Spare parts demand forecasting in process industries	[5]
Combining Support Vector Machine (SVM) as a classification tool and autoregressive integrated moving average (ARIMA) model	x		x			Remaining useful life prediction for real-time monitoring of the manufacturing process	[42]
Integrating "the demand autocorrelated process and the relationship between explanatory variables and the nonzero demand of spare parts during forecasting occurrences of nonzero demands over lead times"			x			Spare parts lumpy demand forecasting in the petrochemical industry	[30]
Using SVM model to forecast occurrences of nonzero demand of spare parts and then integrating the forecast being an output from the SVM and the relationship of occurrence of nonzero demand with explanatory variables	x		x			Forecasting intermittent demand of spare parts	[31]
Outputs of moving average (MA) and exponential smoothing as inputs to an ANN model		x	x			Sales forecasting in furniture industry	[66]
Combining Syntetos-Boylan method (being a modification Croston's method) and exponential smoothing			x			Spare parts demand forecasting	[10]
Two-stage approach to forecast intervals of market clearing prices (MCPs) – at first extreme learning machine (ELM) is used to estimate point forecasts of MCPs, next the maximum likelihood method is applied to estimate the noise variance	x				x	Forecasting of electricity prices	[81]
Historical sales data, popularity of article titles, and the prediction result of a time series based on ARIMA are inputs to backpropagation neural network (BPNN)		x	x			Sales forecasting in the publishing industry	[52]
Hybrid of ARIMA model and ANN model		x	x			Short-term price forecasting in deregulated market	[6]
Integrating empirical mode decomposition (EMD), long short-term memory (LSTM) and ELM	x				x	Forecasting of biofuel production	[85]
Hybrid feature selection method (HFS) combining Cuckoo search-based feature selection with singular spectrum analysis and SVM	x				x	Short-term electricity price forecasting	[86]
Combining seasonal autoregressive integrated moving average (SARIMA) model in the ANN model		x	x			Number of inspections forecasting	[67]
Combinations of Kalman filtering (KF), Wavelet Neural Network (WNN) and ANN schemes	x	x				Short-term load forecasting	[3]
Combining adaptive Fourier decomposition, quantitative identification of the average periodicity length and the sine cosine optimization algorithm to select the penalty and kernel parameters of SVM	x		x		x	Electricity demand time series forecasting	[44]
Combining the ARIMA model with time delay neural network (TDNN) and with nonlinear support vector regression (NLSVR) model.	x	x	x			Production forecasting	[60]
Merging the principal component regression method (PCR), the partial least squares regression method (PLSR) and the modified partial least squares regression method (MPLSR).			x		x	Forecasting of product quality evaluation	[84]
Consisting of an ARIMA model and feed-forward, backpropagation network structure with an optimized conjugated training algorithm		x	x			Quality prediction	[53]
Combining Stepwise Regression Method and RBF Neural Network		x	x			Production forecasting	[83]
Combining nonlinear autoregressive with exogenous input (NARX) model and autoregressive moving average (ARMA) model for long-term machine state forecasting based on vibration data.	x		x			Long-term machine state forecasting	[58]
Combining the SARIMA and computational intelligence techniques such as ANN and fuzzy models	x	x	x			Production value of machinery industry forecasting	[36]
Combining traditional forecasting techniques based on time series with artificial intelligence-based methods (ANN and SVM)	x	x	x			Spare parts demand forecasting in mining industry	[64]
Hybrid SVM-based models where three optimization algorithms: gray wolf optimization, whale optimization algorithm and moth flame optimization where applied to optimize the hyper-parameters of the SVM	x				x	Advance rate forecasting of a tunnel boring machine	[87]
Combining a Mahalanobis–Taguchi System (MTS), support vector regression (SVR), bootstrap prediction interval (PI), and derivative-free Nelder-Mead (NM) optimisation strategy.	x				x	Prediction-based multivariate manufacturing process quality control	[72]

traffic, morbidity, birth immigration, NN3 competition, electricity, energy consumption, computer science, rainfall, drought, quality, inflation, solid waste generation, machine state, property crime rates, tidal current, inspection, price, it can be noticed that little research has been done on forecasting dedicated to manufacturing systems. Considering above-listed fields it can be indicated that only a few of them are directly or indirectly related to manufacturing systems – in this aspect forecasting of sales, demand, throughput, production, energy consumption, quality, machine state, inspection and price is significant and should be further investigated.

In general, it can be stated that researchers merge predictive methods and models in very different ways. Table 1 presents an analysis and summary of research results related to hybrid forecasting, which can be applied to specific areas of manufacturing systems. The first column contains a brief description of each hybrid approach, columns 2-6 summarize type of calculation techniques addressed in particular approaches (ANN stands for artificial neural networks, DM stands for data mining techniques (other than ANN), TQTF stands for traditional quantitative forecasting methods, QLF stands for qualitative forecasting methods and OM stands for other methods), whereas the column 7 indicates the implementation area.

According to [28], in general, hybrid forecasting models can be divided into four main groups – data preprocessing based hybrid models, parameters optimization based hybrid models, component combination based hybrid models, and post processing based hybrid models. Analysis of the Table 1 in turn leads to a conclusion that the majority of proposed hybrid methods which can be applied to forecasting manufacturing-related phenomena combines ANN models with traditional quantitative forecasting techniques (especially ARIMA). Quite common is also merging data mining techniques (other than ANN, like e.g. SVM) with ANN models and TQTF. Another noticeable trend is combining DM with other classical mathematical or statistical methods. Very rare is on the other hand combining ANN and qualitative forecasting techniques. "The possibility of generalization of knowledge on new data (that were not presented in the learning process) is an essential characteristic that distinguishes artificial neural networks (ANN)" and thus makes ANN models very often used in hybrid forecasting [63].

Apart from the above-presented analysis which focuses on hybrid forecasting applied to different areas of manufacturing systems, interesting research on hybrid forecasting can be found in results of the M4 Competition, which "follows on from the three previous M competitions, the purpose of which was to learn from empirical evidence both how to improve the forecasting accuracy and how such learning could be used to advance the theory and practice of forecasting" [48]. "The field of forecasting has progressed a great deal since the original M Competition, which concluded that "more complex or statistically sophisticated methods are not necessarily more accurate than simpler methods", and over time, new methods have been proposed that have clearly proven to be more accurate than simpler ones"[48]. From the point of view of the research discussed in this paper the most interesting results following from the M4 Competition include a hybrid and hierarchical forecasting method, which "utilizes a dynamic computational graph neural network system that enables a standard exponential smoothing model to be mixed with advanced long short term memory networks into a common framework" [74] and "a combination-based approach that combines statistical and machine learning techniques" presented in [34].

"Controlling production systems to match supply and demand in an uncertain environment received considerable attention in the manufacturing systems literature"[49], however results of the above-presented literature analysis show that although increasing number of scientific papers is focusing on hybrid approaches, rather little research has been done on hybrid forecasting models dedicated to manufacturing systems. Therefore this paper aims to fill in this gap. The main goal of the study presented in this paper is to propose new artificial intelligence-based hybrid forecasting models and assess their accuracy in comparison to traditional techniques. The research focuses on solving the problem of limited access to explanatory (independent) variables. The research covers three areas of manufacturing, namely: production planning, maintenance and quality control. In order to verify the forecasting accuracy, real data coming from different manufacturing companies are used.

3. Research methodology

Based on the literature review conclusions and bearing in mind experiences gained from cooperation with industrial companies, in this paper new hybrid models are proposed – their goal is to obtain more accurate forecasts in comparison to traditional prediction methods. What is more, the new approach is aiming at solving common problems which still exist in industrial practice (especially in manufacturing companies aiming at transformation into Industry 4.0) – the limited access to data or simply the lack of available data (particularly in terms of explanatory, independent variables). The models are dedicated to forecasting challenges of the manufacturing systems. In the paper four hybrid forecasting models are proposed:

- a Hybrid forecasting econometric model (hybrid_ECO),
- a Hybrid forecasting artificial neural network model (hybrid_ANN),
- a Hybrid forecasting support vector machine model (hybrid_SVM),
- a Hybrid forecasting extreme learning machine model (hybrid_ELM).

The research methodology is schematically presented in Fig. 1. It is composed of 4 main steps: (1) preparation phase, (2) forecasts computation based on traditional forecasting methods, (3) hybrid forecasting models development and (4) assessment phase. The calculations are done in the *R language* (R version 3.5.3), in which a dedicated algorithm was developed.

According to the presented scheme (Fig. 1), in the preparation phase, a forecasting aim and a dependent variable y should be defined. Next, data should be collected – either from appropriate systems (e.g. Enterprise Resource Planning (ERP), Computerised Maintenance Management System (CMMS)) or any adequate database (DB_x), which can contain for instance data coming from the sensors mounted on the machines. Depending on the forecasting aim, the required dataset will differ. Subsequently, the collected data should be initially analyzed and processed. The data is initially divided into a training set (80%) and a test set (20%). In the second phase a parameter should be defined. This parameter on one hand represents the value of a variable which indicates from how many periods an average – in average-based forecasting methods – should be computed and on the other hand it defines how many loops the algorithm will implement. For example for the scope $2 \le a \le 3$, the algorithm will compute 2 loops – in the first one, for a=2, all the average-based forecasting methods will apply the average from the last 2 periods, whereas for a=3, in all the average-based forecasting methods the average will be calculated from the last 3 periods. In the next step the 9 analyzed forecasting methods are applied and corresponding forecasts (F_1-F_9) are computed. In the algorithm following methods are implemented:

- F_1: autoregressive-integrated moving average (ARIMA),
- F_2: simple exponential smoothing (SES),
- F_3: Holt model (Holt),
- F_4: trigonometric exponential smoothing (TES),
- F_5: simple moving average (SMA),
- F_6: exponential moving average (EMA),
- F_7: weighted moving average (WMA),
- F_8: zero-lag exponential moving average (ZLEMA),
- F_9: Syntetos-Boylan method (SBA).

Formulas describing each of the 9 analyzed methods are given in Table 2. To check components of all formulas please refer to sources

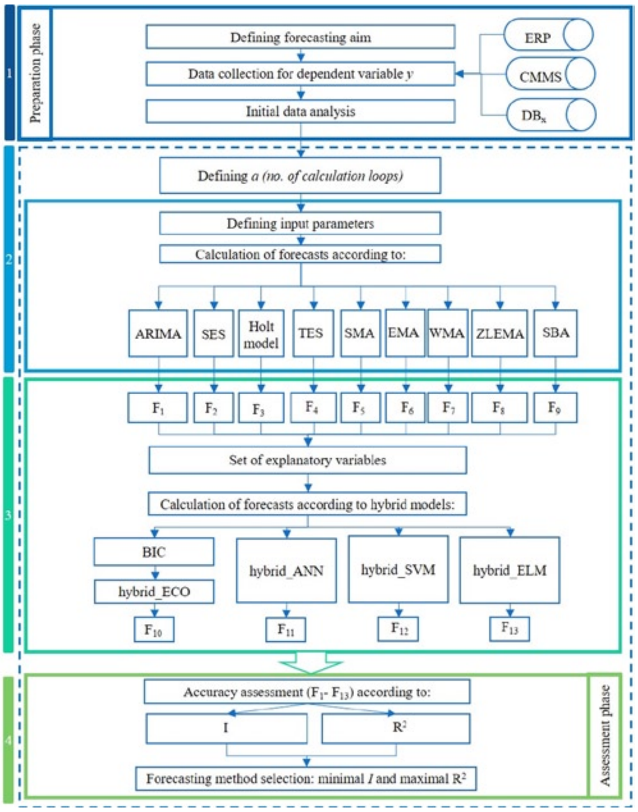

Fig. 1. Algorithm for the forecasting accuracy assessment and optimal method selection

given in the last column ($\hat{y}_t$ is a forecasted value of the variable y in the t period).

In the phase 3, after the forecasts according to 9 traditional methods are calculated, hybrid models are developed – one based on econometric modeling (hybrid_ECO) and three based on artificial intelligence – Hybrid ANN model (hybrid_ANN), Hybrid SVM model (hybrid_SVM) and Hybrid ELM model (hybrid_ELM). Explanatory variables set (EXS) is composed of forecasts coming from the 9 traditional methods (F_1-F_9). It represents an input to each of the proposed hybrid model.

Hybrid econometric model (hybrid_ECO) can be described by the following expression:

$$\hat{y}_t = \hat{\alpha}_0 + \hat{\alpha}_1 F_1 + \hat{\alpha}_2 F_2 + \cdots + \hat{\alpha}_m F_m \tag{10}$$

where: $\hat{\alpha}_i$ – parameters, F_i – explanatory variable composed of the forecasts. For constructing the hybrid_ECO model the Bayesian Schwarz information criterion (BIC) is used to select appropriate subset of explanatory variables from the EXS [1, 68]:

$$BIC = -2\log(L) + p\log(n) \tag{11}$$

where: p – number of model's parameters, L – the maximized value of the likelihood function of the model, n – sample size.

Hybrid ANN model (hybrid_ANN) is developed on the basis of neurons, where the output h_i of neuron i is given by the following formula [69]:

Table 2. Formulas of the forecasting methods

Method	Formula	No./ Source	
ARIMA	$\hat{y}_t = c + \Phi_1 y'_{t-1} + \cdots + \Phi_p y'_{t-p} + \Theta_0\varepsilon_t + \Theta_1\varepsilon_{t-1} + \cdots + \Theta_q\varepsilon_{t-q}$	(1)	[33]
SES	$\hat{y}_t = \alpha y_{t-1} + (1-\alpha)\,\hat{y}_{t-1}$	(2)	[33]
Holt	$\hat{y}_t = F_{t-1} + S_{t-1}, \quad F_t = \alpha y_t + (1-\alpha)(F_{t-1} + S_{t-1})$ $S_t = \beta(F_t - F_{t-1}) + (1-\beta)S_{t-1}$	(3)	[33]
TES	$\hat{y}_t = l_{t-1} + \varphi b_{t-1} + \sum_{i=1}^{T} s^{(i)}_{t-m_i} + d_t\,,\ l_t = l_{t-1} + \varphi b_{t-1} + \alpha d_t\,,\ b_t = (1-\varphi)b + \varphi b_{t-1} + \beta d_t\,,\ s^{(i)}_t = s^{(i)}_{t-m_i} + \gamma_i d_t$ $d_t = \sum_{i=1}^{p}\rho_i d_{t-1} + \sum_{i=1}^{q}\theta_i\varepsilon_{t-1} + \varepsilon_t$	(4)	[20]
SMA	$\hat{y}_t = \frac{1}{m}\sum_{j=-k}^{k} y_{t+j}$	(5)	[33]
EMA	$\hat{y}_t = \frac{y_{t-1} + (1-\alpha)y_{t-2} + (1-\alpha)^2 y_{t-3} + \ldots + (1-\alpha)^n y_{t-(n+1)}}{1 + (1-\alpha) + (1-\alpha)^2 + (1-\alpha)^3 + \ldots + (1-\alpha)^n}$	(6)	[59]
WMA	$\hat{y}_t = \sum_{j=-k}^{k} a_j y_{t+j}$	(7)	[33]
ZLEMA	$\hat{y}_t = \frac{2}{(n+1)}\left(2y_{t-1} - y_{lag}\right) + \left(1 - \frac{2}{(n+1)}\right) \times \hat{y}_{t-1}$	(8)	[89]
SBA	$\hat{y}_t = \left(1 - \frac{\alpha}{2}\right)\frac{Z_{t-1}}{P_{t-1}}, Z_t = \alpha X_t + (1-\alpha)Z_{t-1}$ $P_t = \alpha G_t + (1-\alpha)P_{t-1}$	(9)	[18]

$$h_i = \sigma\left(\sum_{j=1}^{N} W_{ij} x_i + T_i^{hidden}\right) \quad (12)$$

where: σ() – the transfer function, N – the number of input neurons; W_{ij} – the weights; x_j – inputs to the input neurons, T_i^{hidden} – the threshold of the hidden neurons. More details on ANN development can be found in [21].

Hybrid SVM model (hybrid_SVM) is based on the functional dependence of the dependent variable y on a set of explanatory variables x. The relationship between the explanatory variables and $\hat{y}_t$ is given by a deterministic function f and the addition of some noise [90]:

$$\hat{y}_t = f(x) + noise \quad (13)$$

where x is a set of explanatory variables ($x=F_1, F_2, \ldots, F_{12}$). The functional form for f which can correctly predict new cases can be achieved by training the SVM model on a sample set – a process involving the sequential optimization of an error function (for details see [90]). Radial basis function (RBF) will be the kernel type K used in the Hybrid SVM model [90]:

$$K(X_i, X_j) = \exp(-\gamma |X_i - X_j|^2) \quad (14)$$

where $K(X_i, X_j) = \phi(X_i) \cdot \phi(X_j)$, ϕ – transformation.

Hybrid extreme learning machine model is based on the algorithm which can be summarized as follows [32]: "given a training set $\aleph = \{(x_i, t_i) | x_i \in \boldsymbol{R}^n, t_i \in \boldsymbol{R}^m, i = \ldots, N\}$, activation function $g(x)$, and hidden node number $\tilde{N}$,

Step 1: Randomly assign input weight w_i and bias b_i, i=1, …, $\tilde{N}$.
Step 2: Calculate the hidden layer output matrix **H**.
Step 3: Calculate the output weight β

$$\beta = H \; T \quad (15)$$

where $\boldsymbol{T} = [t_1, \ldots, t_N]^T$".

After the hybrid models are developed, the last step of the research methodology can be applied – accuracy assessment of estimated forecasts for each analyzed method.

The third phase is finished when 4 forecasts (F_{10} - F_{13}) from hybrid models are computed. The last, fourth phase, is the assessment phase. The algorithm allows to compute five types of forecasts accuracy measures, namely: mean error (ME), mean absolute error (MAE), root mean squared error (RMSE), relative forecast error *ex post* (I) and coefficient of determination (R^2), yet in the proposed methodology, the selection of the most accurate forecasting method is based on the value of I. Therefore, the best model is the one with the lowest I. Relative forecast error *ex post* I is given by the formula:

$$I = \sqrt{\frac{\sum_{t=1}^{m} (y_t - \hat{y}_t)^2}{\sum_{t=1}^{m} y_t^2}} \quad (16)$$

In case of models with equal I, as the most accurate will be considered the one with the highest coefficient of determination R^2, which can be defined as follows:

$$R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_t - \bar{y})^2}{\sum_{i=1}^{n} (y_t - \bar{y})^2} \quad (17)$$

According to the presented approach, the calculations are over when the algorithm computes all the accuracy measures in all loops for the 13 considered methods (9 traditional and 4 hybrid) and – according to the above-mentioned rule – indicates the most effective method for the given forecasting aim. The proposed algorithm developed in *R language* is very flexible – it can be easily adjusted by adding other forecasting methods or – if necessary – more accuracy measures. It can serve as a supporting tool in the decision-making process of manufacturing companies trying to select the most appropriate forecasting method. It can also be considered as an approach supporting the transformation process of Industry 4.0 implementation in industrial factories. According to Bożejko et al., nowadays, in the ERP systems supporting the management, "particularly important are numerically efficient methods and algorithms for solving the new optimization problems derived from real manufacturing systems which constitute "intelligent engines" for these support systems" [11]. What is more, they are considered as critical for the production efficiency of large manufacturing companies. The proposed algorithm can be integrated into such support systems.

The further research discussed in this paper will be carried out according to the methodology presented in this chapter. It will be applied to 3 case studies and the calculations will be performed on real data from the manufacturing companies. In order to exemplify manufacturing areas, which will be considered in the practical part of this paper, the model of the manufacturing system was developed (Fig. 2).

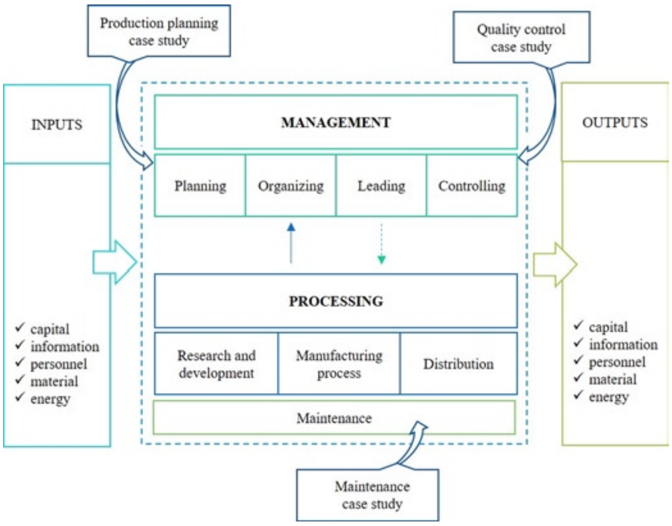

Fig. 2. Manufacturing system model

According to Caggiano a manufacturing (production) system can be defined as "an organization in the manufacturing industry for the creation of production. In the mechanical and electrical engineering industries, a manufacturing system, in general, has an integrated group of functions, e.g., the sales, design, production, and shipping functions"[14]. The case studies presented in the next chapter address three areas of the manufacturing system – production planning, maintenance and quality control. They are schematically presented in Fig. 2.

4. Performance assessment of the hybrid models – real data analysis

4.1. Forecasting in manufacturing systems – case studies

As presented in the Introduction, forecasting in manufacturing systems plays a very important role. In this chapter three case studies referring to particular areas of the manufacturing system will be addressed – production planning, maintenance, and quality control. The Author's intention was to apply the hybrid models to datasets coming not only from different areas of the production system, but also from different manufacturing sectors, therefore to verify the proposed models 3 different companies were selected and addressed. The idea behind this approach was to check if the developed algorithms are versatile and comprehensive enough to meet forecasting challenges from various industries.

4.1.1. Production planning case study

The first case study is related to the forecasting of a product demand in a furniture factory. The details of the research concerning this case can be found in [66]. The main problem in the addressed company, which sells its products mainly via Internet, was to develop a new manufacturing system that would allow to increase effectiveness and production volume, reduce delivery time to 48 hours (in the online sales channel) and to compute more accurate sales forecasts, which, in turn, would result in more efficient production planning. Development of the manufacturing system answering all these challenges was a demanding and a complex task. While constructing the concept of the expected system, several research questions were raised, namely: (1) how the sales level can be predicted, if the company did not have a sufficient and reliable database; (2) how in such circumstances a set of explanatory variables can be prepared, (3) how to control the manufacturing process if the demand was very diversified – series production and individual, customized orders; (4) how to develop production strategy for various product types; and last but not least, (5) how to verify, if the proposed system was immune to disturbances. The answers to these questions were addressed in [66]. In this paper however, only selected aspects will be tackled – particularly – how to select the right forecasting method and how to assure the most accurate forecasts to given datasets. Due to the reason that "future demand plays a very important role in production planning and inventory management, fairly accurate forecasts are needed" [26]. What is more, "in the customization processes, it is important to keep the manufacturing system reliable, therefore, a prognostic method is essential" [73]. For the purpose of this study 5 datasets were investigated – the basic information about them contains Table 3. Moreover, for each product a box plot (Fig. 3) and a histogram (Fig. 4) were developed.

Table 3. Production planning case study – summary of the datasets

No.	Product	Unit	n	Demand type	Expected result: Forecasted value of variable *y*
1	Product A	piece	23	monthly	Expected monthly demand for product A (e.g. 10 pieces)
2	Product B	piece	23	monthly	Expected monthly demand for product B (e.g. 20 pieces)
3	Product C	piece	23	monthly	Expected monthly demand for product C (e.g. 30 pieces)
4	Product D	piece	23	monthly	Expected monthly demand for product D (e.g. 15 pieces)
5	Product E	piece	23	monthly	Expected monthly demand for product E (e.g. 5 pieces)

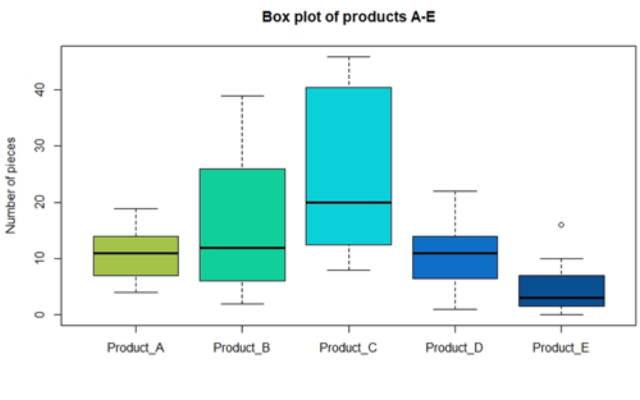

Fig. 3. Box plots of products A-E

In order to verify the accuracy of the proposed in this paper hybrid forecasting models and compare their effectiveness with other methods, 5 types of products were investigated (Products A-E). Due

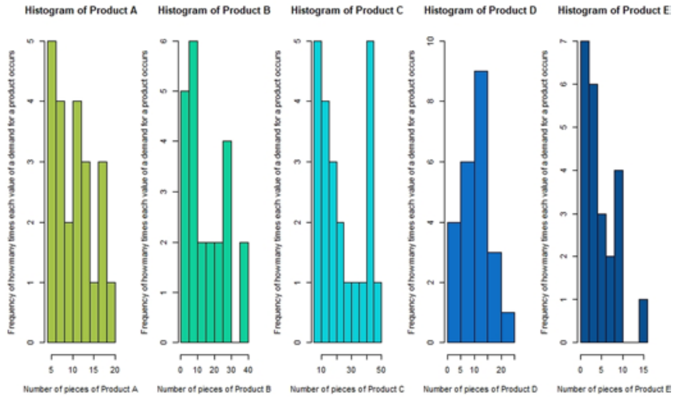

Fig. 4. Histograms of products A-E

to unsatisfactory precisions of daily forecasts of demand for selected types of furniture (caused by a shortage of available historical data in the investigated company), the analysis was carried-out in aggregated, monthly terms.

4.1.2. Maintenance case study

The second case study is related to the forecasting of spare parts and consumable materials demand in a copper mine. The details of the research concerning this case can be found in [16, 64, 65]. This study is related to the aspects of preventive maintenance, which can be defined as: "maintenance executed at predetermined intervals or according to prescribed criteria, aiming to reduce the probability of failure or the probability that an item will only fulfill its functions to a limited extent (degradation of functioning)", where an item is "any part, component, devise, subsystem, functional unit, equipment, or system that can be individually considered. Failure is regarded as the termination of the ability of an item to perform an action as required" [71]. Predictive maintenance "helps to avoid downtimes due to unexpected failures during the production process" [22]. When investigating different sectors of economy, it can be observed that in particular enterprises from underground mining are characterized by very high failure rates of machines [43]. The main reasons for that are the very specific working environment characterized by high temperatures, high humidity and poor road conditions. What is more, mining machines are almost constantly in motion. Besides, the complexity of these machines and the high loads to which they are subjected impose very strict requirements on their reliability and maintenance [12, 27]. Mining processes are unstable and cost-intensive, which makes that controlling them very difficult [82]. Hence the aspect of accurate spare parts demand forecasting is essential because it directly influences the availability of machines and their maintenance processes. "When a critical part is requested and not available in stock, the company is not able to perform the maintenance operation in time. This could jeopardize a client's productivity, causing time delays and high costs" [78]. It is also worth mentioning that according to Chen et al. "in practice, the forecast and inventory planning of service parts depend on accurate predictions of product failure rates" [15].

For the purpose of this paper real data from the underground copper mine were used. The data were gathered within the research project "Adaptation and Implementation of Lean Methodology in Copper Mines" co-financed by the Polish National Centre for Research and Development. To assess the forecasting accuracy of the proposed in this study hybrid models in maintenance area 4 datasets were selected, namely: demand for brake pump, actuator, hydraulic oil and diesel

Table 4. Maintenance case study – summary of the datasets

No.	Spare part/ consumable material	Unit	n	Demand type	Expected result: Forecasted value of variable y
1	Brake pump	piece	47	weekly	Expected weekly demand for brake pump (e.g. 5 pieces)
2	Actuator	piece	52	weekly	Expected weekly demand for actuator (e.g. 3 pieces)
3	Hydraulic oil	litre	248	weekly	Expected weekly demand for hydraulic oil (e.g. 500 litres)
4	Diesel oil	litre	313	weekly	Expected weekly demand for diesel oil (e.g. 5000 litres)

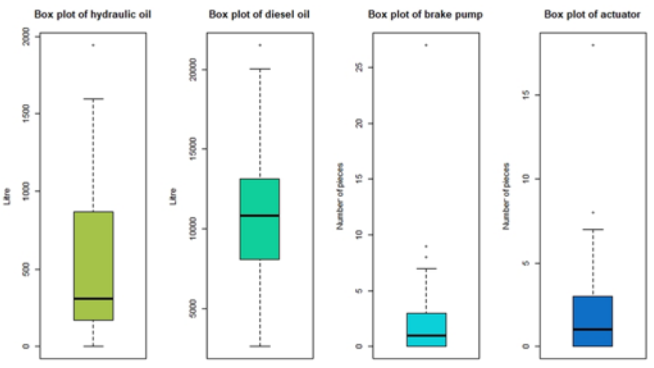

Fig. 5. Box plots of investigated spare parts and consumable materials

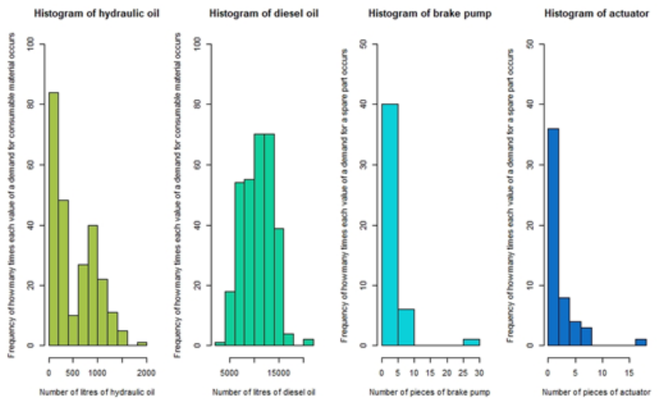

Fig. 6. Histograms of investigated spare parts and consumable materials

Table 5. Quality control case study – summary of the datasets

No.	Dependent variable:	Unit	n	Level of defects	Expected result: Forecasted value of variable *y*
1	level of defects	%	21	monthly	Expected monthly level of defects (e.g. 2%)
2	level of defects	%	22	monthly	Expected monthly level of defects (e.g. 4%)

oil. The basic information about the investigated cases is presented in Table 4, Fig. 5 (box plots) and Fig. 6 (histograms).

Spare parts demand is very hard to predict – it is characterized by the large degree of uncertainty and by unpredictable fluctuations. This type of demand is often classified as lumpy, which can be defined as "a demand with great differences between each period's requirements and with a great number of periods with zero requests" [23] or as intermittent, which means that this demand "is characterised by variable demand sizes coupled with irregular demand arrivals, with many observations having zero demand"[57]. An in-depth literature review on the spare parts demand forecasting can be found in works by Bacchetti and Saccani, who discuss spare parts classification and demand forecasting for stock control [7], Van Horenbeek et al., who present a review on joint maintenance and inventory optimization systems [79], Rego and Mesquita, who have developed a literature review on spare parts inventory control [61], and De Gooijer and Hyndman, who have investigated and described 25 years of time series forecasting [19]. An accurate forecasting of spare parts demand is very challenging – usually obtained predictions are characterized by large errors. Therefore, forecasting in maintenance area is especially hard, yet at the same time very important. It is worth mentioning that the management of spare parts is considered to be of the most neglected areas of management whereas its meaning cannot be overemphasized [24, 65].

4.1.3. Quality control case study

The third case study addressed in this paper was focused on the forecasting of defects. The data which was used in order to assess the forecasting accuracy of the proposed in this paper hybrid models, came from an industrial company which manufactured ceramic insulators. In this example the main challenge was to develop an efficient solution supporting process control in production of ceramic insulators to ensure the desired product quality. The details of this study can be found in [40]. The goal of this research was to find a correlation between grain-size distribution of aluminum oxide and the number of quality defects. It was assumed that it was possible to control addition of raw aluminum oxide (and its graining) to obtain its desired grain-size composition in the mass and thus to reduce to acceptable level the number of insulators' defects, namely: (1) cracks (on bodies, on sheds, on face surfaces and in holes), (2) twists and (3) disturbed structure. In this research 2 datasets from 2 different periods were investigated – their summary is presented in Table 5. What is more, for each dataset a box plot (Fig. 7) and a histogram (Fig. 8) were developed.

In this case study the forecasted variable y is an expected monthly level of defects. The challenge in this case was to create effective models (model A based on the first data set, model B based on the second data set) enabling accurate forecasting of the level of defects. For the purpose of this study the explanatory variables were ignored and only dependent variable was investigated. It is expected that the analyzed level of defects should be easily forecasted and controlled. It should be underlined that the precise defects forecasting is one of the pillars of the effective quality control.

4.2. Accuracy assessment of the hybrid models

According to the research methodology presented in the previous chapter, computations were carried out in *R language*. The scope of *a* parameter was set from 2 to 7, which means that the algorithm computed 6 loops for each dataset. In total 11 datasets were investigated – 5 products A-E from production planning case study, 4 datasets from maintenance case study (brake pump, actuator, hydraulic oil, diesel oil) and 2 datasets from quality control case study. The accuracy as-

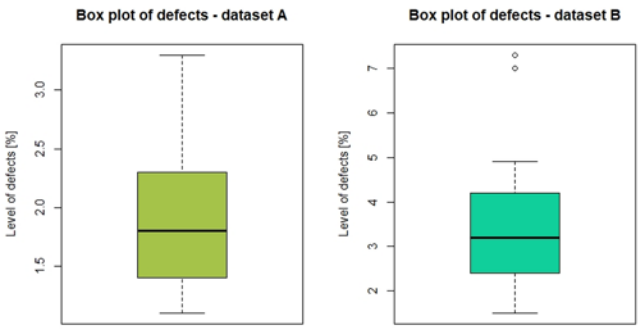

Fig. 7. Box plots presenting levels of defects [%] – datasets A and B

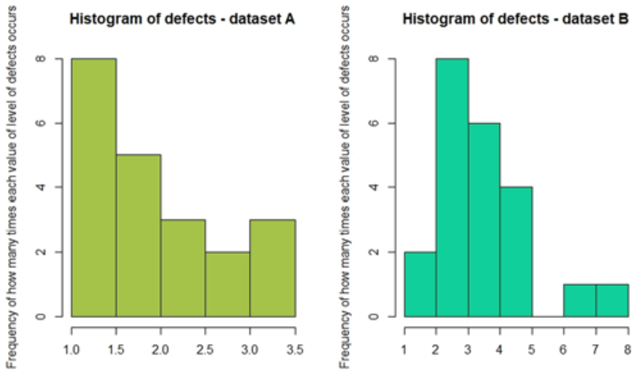

Fig. 8. Histograms presenting levels of defects – datasets A and B

*Table 6. Relative forecast error **ex post** for production planning case study*

Method	Production planning				
	Product A	Product B	Product C	Product D	Product E
	a=4	a=2	a=5	a=6	a=7
ARIMA	0,374	0,271	0,399	0,353	0,421
SES	0,504	0,281	0,445	0,379	0,458
Holt	0,433	0,282	0,445	0,365	0,422
TES	0,343	0,270	0,437	0,338	0,311
SMA	0,385	0,258	0,466	0,360	0,535
EMA	0,414	0,272	0,436	0,369	0,490
WMA	0,408	0,262	0,440	0,352	0,472
ZLEMA	0,486	0,322	0,443	0,377	0,419
SBA	0,608	0,611	0,489	0,443	0,600
hybrid_ECO	**0,118**	0,226	0,292	0,242	**0,155**
hybrid_ANN	0,446	**0,161**	**0,142**	**0,167**	0,316
hybrid_SVM	0,289	0,206	0,258	0,271	0,276
hybrid_ELM	0,216	0,193	0,303	0,219	0,165

*Table 7. Relative forecast error **ex post** for maintenance case study*

Method	Maintanance			
	Brake pump	Actuator	Hydraulic oil	Diesel oil
	a=6	a=7	a=2	a=6
ARIMA	0,887	0,819	0,282	0,183
SES	1,160	1,052	0,315	0,211
Holt	1,061	0,971	0,298	0,207
TES	0,825	0,821	0,282	0,182
SMA	0,949	0,886	0,302	0,201
EMA	0,965	0,878	0,301	0,194
WMA	0,971	0,892	0,306	0,199
ZLEMA	1,099	0,994	0,407	0,222
SBA	0,900	1,301	0,539	0,197
hybrid_ECO	0,815	0,768	0,284	0,180
hybrid_ANN	**0,260**	**0,550**	**0,263**	**0,157**
hybrid_SVM	0,635	0,638	0,266	0,174
hybrid_ELM	0,731	0,744	0,280	0,180

sessment was performed in two steps – at first analysis based on relative forecast error *ex post I* was done, and secondly analysis based on coefficient of determination R^2.

For each case study a dedicated table was prepared covering values of relative forecast error *ex post I* calculated for every analyzed method. Table 6 contains obtained results for production planning case study – particular columns represent products A-E and corresponding values of *a* parameter for which the highest accuracy was obtained (the lowest value of *I* for the most accurate method). In rows all 13 investigated methods are listed. The lowest value of *I* for the most accurate method for each product is marked in bold.

Analysis of obtained results in Table 6 shows that in case of 3 products out of 5 the most accurate method is hybrid_ANN. For the products A and E the lowest *I* were obtained by Hybrid forecasting econometric model (hybrid_ECO). In general it can be said that for production planning the forecasts from the most efficient hybrid models are very accurate – relative forecast errors *ex post* vary from 11,8% to 16,7%.

Table 7 presents computation results for the maintenance case study. There were 4 types of datasets analyzed – 2 representing spare parts (brake pump, actuator) and 2 representing consumable materials (hydraulic oil, diesel oil).

The values of a parameter for which the highest accuracy was obtained for particular cases are following: a=6 for brake

Table 8. Relative forecast error ex post for quality control case study

Method	Quality control	
	No. of defects A	No. of defects B
	a=4	a=3
ARIMA	0,300	0,333
SES	0,288	0,314
Holt	0,300	0,308
TES	0,292	0,265
SMA	0,327	0,319
EMA	0,292	0,299
WMA	0,300	0,309
ZLEMA	0,323	0,326
SBA	0,334	0,367
hybrid_ECO	0,242	0,168
hybrid_ANN	**0,146**	**0,151**
hybrid_SVM	0,217	0,260
hybrid_ELM	0,251	0,223

pump, a=7 for actuator, a=2 for hydraulic oil and a=6 for diesel oil. In maintenance case study the lowest values of relative forecast errors ex post were obtained by hybrid_ANN models, which delivered the most accurate forecasts. Analogous to the production planning and the maintenance case studies, the calculations were performed in terms of the quality control example. The obtained results are presented in Table 8. In this research only 2 cases were investigated – level of defects based on 2 datasets (A and B).

For both analyzed datasets, the most accurate method of forecasting level of defects turned out to be Hybrid forecasting ANN model (I = 14,6% for dataset A, I = 15,1% for dataset B). Other investigated methods were less accurate.

In order to assess the accuracy of the analyzed forecasting methods in terms of particular manufacturing system's areas, an average relative forecast error *ex post* was computed in percentage terms for each case study separately. Table 9 contains the obtained results. The average I values were divided into three groups:

- accurate forecasts: $I \leq 25\%$ (results marked **in bold**);
- moderately accurate forecasts: $25\% < I < 50\%$ (results marked in light grey);
- not accurate forecasts: $I \geq 50\%$ (results marked in dark grey).

*Table 9. Comparison of the forecasting methods accuracy based on **I***

Method	Average relative forecast error ex post		
	Production planning	Maintanance	Quality control
ARIMA	36%	54%	32%
SES	41%	68%	30%
Holt	39%	63%	30%
TES	34%	53%	28%
SMA	40%	58%	32%
EMA	40%	58%	30%
WMA	39%	59%	30%
ZLEMA	41%	68%	32%
SBA	55%	73%	35%
hybrid_ECO	**21%**	51%	**21%**
hybrid_ANN	**25%**	31%	**15%**
hybrid_SVM	26%	43%	**24%**
hybrid_ELM	**22%**	48%	**24%**

An analysis of obtained results leads to several conclusions. First of all it can be noticed that only in 2 manufacturing areas accurate forecasts were obtained – in production planning and in quality control. In case of maintenance all methods provided either moderately accurate forecasts (for the proposed artificial intelligence based hybrid models: $31\% \leq I \leq 48\%$) or not accurate forecasts at all (all the other 10 investigated methods). In production planning only Hybrid forecasting econometric model (average I = 21%), Hybrid forecasting ANN model (average I = 25%) and Hybrid forecasting ELM model (average I = 22%) provided satisfactory results – the obtained I was not higher than 25%. Among conventional forecasting methods SBA turned out to be not accurate, whereas the other methods can be classified as moderately accurate. In quality control all the four proposed hybrid models (hybrid_ECO, hybrid_ANN, hybrid_SVM, hybrid_ELM) provided accurate forecasts (average I did not exceed 24%). Other analyzed methods – ARIMA, SES, Holt, TES, SMA, EMA, WMA, ZLEMA, SBA – occurred to generate moderately accurate forecasts.

In order to assess the accuracy of the four proposed hybrid models in comparison to 9 other researched forecasting methods an average I was computed (in percentage terms) and presented in Fig. 9.

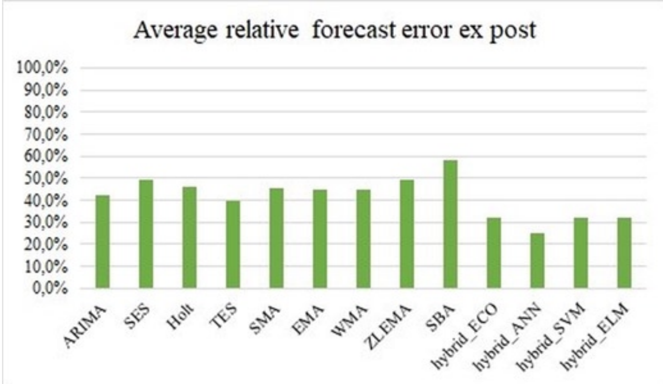

Fig. 9. Average relative forecast error ex post for analyzed methods

The average I was computed from 11 investigated datasets for each method separately. Obtained results show that the proposed in this paper hybrid models deliver much more precise forecasts in comparison to other researched methods. The accuracy of estimated forecasts from hybrid models is significantly higher. An analysis of efficiency of other methods leads to a conclusion that for investigated cases they seem to be not effective.

The second part of the accuracy assessment was based on R^2. The analysis was performed analogous to the above presented. For each case study a dedicated table was prepared with values of coefficient of determination computed for every analyzed method. Table 10 contains obtained results for production planning case study – particular columns represent products A-E and corresponding values of *a* parameter for which the highest accuracy was obtained (the highest value of R^2 for the most accurate method). In rows all 13 investigated methods are listed. The highest value of R^2 for the most accurate method for each product is marked in bold.

Analysis of obtained results shows that in case of 3 products out of 5 the most accurate method is Hybrid forecasting artificial neural network – R^2 in percentage terms is equal respectively for product B 93,0%, for product C 88,2%, for product D 77,1%. For product A and E the highest R^2 was obtained by hybrid_ECO models (R^2 = 91,3%, R^2 = 92,7%). These results confirm the conclusion derived from

Table 10. Coefficient of determination for production planning case study

Method	Production planning				
	Product A	Product B	Product C	Product D	Product E
	a=4	a=2	a=5	a=6	a=7
ARIMA	0,278	0,837	0,110	0,005	0,520
SES	0,024	0,820	0,119	0,002	0,447
Holt	0,087	0,823	0,118	0,006	0,486
TES	0,306	0,824	0,106	0,072	0,740
SMA	0,207	0,852	0,045	0,018	0,410
EMA	0,125	0,819	0,075	0,008	0,496
WMA	0,143	0,844	0,086	0,009	0,488
ZLEMA	0,042	0,737	0,185	0,016	0,537
SBA	0,232	0,452	0,014	0,002	0,498
hybrid_ECO	**0,913**	0,852	0,484	0,373	**0,927**
hybrid_ANN	0,406	**0,930**	**0,882**	**0,771**	0,710
hybrid_SVM	0,555	0,885	0,633	0,272	0,836
hybrid_ELM	0,710	0,892	0,446	0,487	0,917

I analysis – it can be stated that for production planning the forecasts from hybrid models are accurate – in case of all investigated products R^2 exceeded 77%.

Table 11 presents computation results for maintenance case study, in which 4 types of datasets were analyzed.

Table 11. Coefficient of determination for maintenance case study

Method	Maintanance			
	Brake pump	Actuator	Hydraulic oil	Diesel oil
	a=6	a=7	a=2	a=6
ARIMA	0,231	0,561	0,794	0,549
SES	0,001	0,000	0,753	0,461
Holt	0,007	0,001	0,776	0,463
TES	0,156	0,020	0,794	0,562
SMA	0,039	0,001	0,768	0,469
EMA	0,021	0,000	0,770	0,502
WMA	0,022	0,000	0,764	0,482
ZLEMA	0,010	0,003	0,639	0,417
SBA	0,011	0,022	0,618	0,489
hybrid_ECO	0,156	0,121	0,788	0,562
hybrid_ANN	**0,914**	0,573	**0,820**	**0,668**
hybrid_SVM	0,639	**0,743**	0,817	0,592
hybrid_ELM	0,321	0,175	0,796	0,567

In maintenance case study the highest values of R^2 were again obtained by hybrid models – in 3 out of 4 cases Hybrid forecasting ANN model delivered the most accurate forecasts – R^2 in percentage terms reached respectively: 91,4% for brake pump, 82,0% for hydraulic oil, and 66,8% for diesel oil. In the case of the actuator the hybrid_SVM model turned out to be the most effective forecasting method (R^2 = 74,3%).

Next, the calculations for quality control example were applied. The obtained results are presented in Table 12. As mentioned before, in this research only 2 cases were investigated – level of defects based on dataset A and level of defects based on dataset B.

Table 12. Coefficient of determination for quality control case study

Method	Quality control	
	No. of defects A	No. of defects B
	a=4	a=3
ARIMA	0,337	0,343
SES	0,342	0,379
Holt	0,283	0,384
TES	0,292	0,637
SMA	0,168	0,401
EMA	0,280	0,493
WMA	0,262	0,415
ZLEMA	0,354	0,418
SBA	0,155	0,540
hybrid_ECO	0,455	0,814
hybrid_ANN	**0,808**	**0,851**
hybrid_SVM	0,579	0,678
hybrid_ELM	0,416	0,674

The obtained values of R^2 confirm the results based on *I* analysis – for both datasets the most accurate method of forecasting level of defects turned out to be Hybrid forecasting ANN model (R^2 = 80,8% for dataset A and R^2 = 85,1% for dataset B).

Assessment of the accuracy of the analyzed forecasting methods in terms of particular manufacturing system's areas, was based on average R^2 (in percentage terms) calculated for each case study separately. Table 13 contains the obtained results. The average R^2 values were divided into three groups:

- accurate forecasts: R^2 >70% (results marked **in bold**);
- moderately accurate forecasts: 61% ≤ R^2 ≤ 70% (results marked in light grey);
- not accurate forecasts: R^2 ≤ 60% (results marked in dark grey).

*Table 13. Comparison of the forecasting methods accuracy based on average **R^2***

Method	Average coefficient of determination		
	Production planning	Maintanance	Quality control
ARIMA	35%	53%	34%
SES	28%	30%	36%
Holt	30%	31%	33%
TES	41%	38%	46%
SMA	31%	32%	28%
EMA	30%	32%	39%
WMA	31%	32%	34%
ZLEMA	30%	27%	39%
SBA	24%	29%	35%
hybrid_ECO	**71%**	41%	63%
hybrid_ANN	**74%**	**74%**	**83%**
hybrid_SVM	64%	70%	63%
hybrid_ELM	69%	46%	54%

An analysis of average R^2 values shows that accurate forecasts were obtained in each analyzed manufacturing system area: in production planning (hybrid_ECO: R^2 = 71%, hybrid_ANN: R^2 = 74%), in maintenance (hybrid_ANN: R^2 = 74%) and in quality control (hybrid_ANN: R^2 = 83%). In case of maintenance example – apart from hybrid_ANN and hybrid_SVM (moderately accurate forecasts) all the other 11 investigated methods provided not accurate forecasts. In production planning hybrid_SVM and hybrid_ELM delivered moderately accurate forecasts, whereas all the other methods can be assessed as not accurate. In quality control, apart from hybrid_ANN, which turned out to provide accurate forecasts, two methods can be classified as moderately accurate (hybrid_ECO and hybrid_SVM), whereas other investigated methods – ARIMA, SES, Holt, TES, SMA, EMA, WMA, ZLEMA, SBA – brought not satisfactory results. On the basis of these results it can be concluded that hybrid models can be more efficient forecasting tools in the areas of production planning and quality control, than in maintenance, where the accurateness of the proposed hybrid methods is lower.

In order to assess the accuracy of the four proposed hybrid models in comparison to 9 other researched forecasting methods an average R^2 was computed (in percentage terms). The average R^2 was calculated from 11 investigated datasets for each method separately (Fig. 10).

The obtained values of average R^2 show that the proposed hybrid models provide significantly more accurate forecasts in comparison to the other 9 researched methods. The average R^2 in percentage terms in case of hybrid_ECO equals 59%, in case of hybrid_ANN 76%, in case of hybrid_SVM 66% and in case of hybrid_ELM 58%, whereas

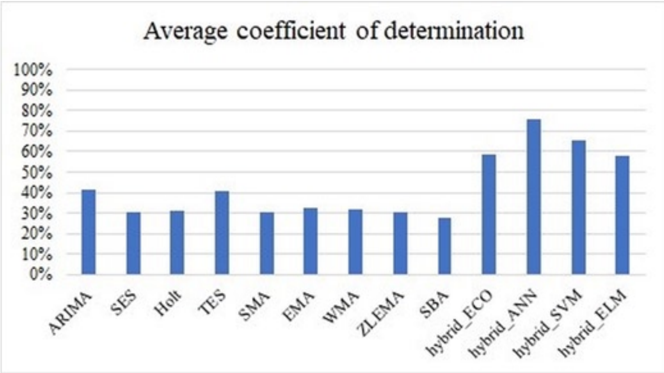

Fig. 10. Average coefficient of determination for analyzed methods

for the other methods R^2 reached only 41% (ARIMA, TES) or less. The least efficient turned out to be conventional time series forecasting methods, namely: SES, Holt, SMA, EMA, WMA, ZLEMA and SBA – R^2 did not reach 34%.

5. Conclusions

The main aim of the paper was to propose the new artificial intelligence-based hybrid forecasting models and assess their accuracy in comparison to traditional techniques. The analysis was performed based on the assumption that the access to explanatory (independent) variables was not possible – lack of corresponding data. The results of the study were satisfactory – the analysis of the forecasting accuracy of the new hybrid models (hybrid_ECO, hybrid_ANN, hybrid_SVM, hybrid_ELM) showed that they are more precise than other investigated methods, namely: ARIMA, SES, Holt, TES, SMA, EMA, WMA, ZLEMA and SBA. Obtained values of the relative forecast errors *ex post I* and the coefficients of determination R^2 proved that hybrid models proposed in this paper are significantly more accurate than the rest of the methods. Moreover, the study fills in the literature gap on application of hybrid forecasting in manufacturing systems. According to the presented research methodology, the proposed models were verified on real data from the three areas of the manufacturing system – production planning, maintenance and quality control. The investigated case studies showed that the proposed hybrid models can serve as efficient forecasting tools in manufacturing companies. The obtained forecasting results were especially satisfactory in terms of production planning and quality control. The accuracy of predictions in maintenance was acceptable, yet less efficient than in two other investigated areas of the manufacturing system. Bearing in mind, however, that the analyzed demand was lumpy and intermittent, the obtained results were sufficient. In general conventional time series forecasting methods were ineffective in the researched areas of the manufacturing system.

Results of the literature review showed also that although an increasing number of scientific papers is focusing on the development of the hybrid forecasting models, the majority of them is combining only a few methods (usually two or three). The distinguishing feature of the proposed hybrid models is that each of them combines in total 10 methods. This approach also helps to solve a common problem in manufacturing companies which is related to the limited access to appropriate data. The preparation of the right set of potential explanatory variables is sometimes impossible due to the lack of available, reliable, complete and comparable statistical data. Due to this reason the companies cannot use the forecasting methods based on the independent variables. The proposed hybrid models solve this problem.

What is more, in the paper, the algorithm for the forecasting accuracy assessment and optimal method selection was introduced. It can serve not only as an efficient and costless tool for advanced manufacturing companies willing to select the right forecasting method for their particular needs, but also as an approach supporting implementation of Industry 4.0 technologies and transformation towards smart factories. It is an important and required solution as still many manufacturing companies are facing the challenge of transformation from the so-called 3rd to the 4th industrial revolution.

The presented case studies showed that the accurate forecasts can efficiently support production planning, quality control and maintenance management, through: (1) controlling the product quality parameters, (2) making a manufacturing process more flexible, (3) reducing failures and (4) elimination of root causes of defects. In consequence, thanks to improved forecasts, the manufacturing companies can reduce their inventory, increase inventory turns and improve order indicators, which brings significant savings and leads to lower costs, increased revenues and thus influences profitability.

The future research will focus on the further development of the algorithm for the forecasting accuracy assessment and optimal method selection – it is planned to add more prediction methods. The proposed hybrid models will be tested on more real datasets from a wider range of manufacturing applications. It is also planned to optimize the models parameters, so that the obtained forecasts are as accurate as possible. Further works include also studies on the implementation of the algorithm to a comprehensive information system which will be an extension of integrated systems currently used in companies (e.g. the Enterprise Resources Planning) or as a part of the company integrated management system. What is more, it is planned to develop the integration capabilities to form a connection with a range of sensors and monitoring equipment so as to collect more accurate machine/device data directly to the algorithm.

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