"Financial modeling trends for production companies in the context of Industry 4.0"

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NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
55	2	0

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FINANCIAL MODELING TRENDS FOR PRODUCTION COMPANIES IN THE CONTEXT OF INDUSTRY 4.0

Abstract

Over the years, technological progress has accelerated highly, and the speed, flexibility, human error reduction, and the ability to manage the process in real time have become more critical and required production companies to adapt production and business models according to the needs. The demand for real-time decision support systems adapted to these raising business needs is continuously growing. Nevertheless, businesses usually face challenges in identifying new indicators, data sources, and appropriate financial modeling methods to analyze them. This paper aims to define and summarize the main financial/economic forecasting methods for production companies in the context of Industry 4.0. Main findings show forecasting accuracy of up to 96% when combining economic and demand information, optimal forecasting period from 10 months to five years, more frequent use of soft indicators in forecasting, the relationship between company's size and production planning. Four groups of indicators used in financial modeling, such as (I) production-related, (II) customers' and demand-oriented, (III) industry-specific, and (IV) media information indicators, were separated. The analysis forms a suggestion for decision-makers to pay more attention to the forecasting object identification, indicators' selection peculiarities, data collection possibilities, and the choice of appropriate methods of financial modeling.

Keywords	Industry 4.0, financial modeling, production management, artificial intelligence
JEL Classification	C53, E27, M11, O14

INTRODUCTION

Phrases such as cyber-physical systems (CPS), Internet of Things (IoT), information and communication technologies (ICTs), Big Data, cloud computing, artificial intelligence (AI), machine-to-machine (M2M), digitalization, robotization, automation, and other synonyms are linked to industrial progress. The world has already passed through three industrial revolutions since the 18th century (Li, 2017; Ghobakhloo, 2018; Nascimento et al., 2018). The fourth industrial revolution, which was named Industry 4.0, has led to radical changes in industrial processes. The concept of Industry 4.0, introduced in 2011 in Germany, can be defined as an autonomous network, connection and modern integration among systems, employees and partners, intelligent machines, production processes, humans' actions, virtual components, data, information flow, and real-time management (Hozdić, 2015; Sikorski et al., 2017, Agostini & Filippini, 2019; Basl, 2017; Sanders et al., 2016). Technological advance has increased significantly, and speed, flexibility, humans' errors reduction, efficiency, and possibility to manage processes in the real time became essential in the production industry. Caused by a changing environment, industrial companies are required to react fast to changes and adapt production and business models according to the needs.

Technological advancement, which allows planning, analyzing, and optimizing the enormous amount of production data in real time differs Industry 4.0 from previous industrial revolutions. Dynamic self-optimization and synchronization of all processes in the whole supply chain are some of the reasons smart factories integrate intelligent programmable machines (Sanders et al., 2016). Supply chain processes such as inventory, usage history, transport, logistics, production speed, and components expiration time are tracked and controlled by using simulation (Wan et al., 2015). Future actions and demand forecasts are predicted by simulation processes to avoid errors (Calatayud, 2017). An opportunity to set up specific product costs, keep minimal resources, assess risks and impacts of environmental changes, choose an appropriate supplier considering different costs and margins occurs due to process simulation (Wan et al., 2015). The capacity of suppliers is instantly analyzed by extended networks, allowing them contact directly through secure cloud channels (Wan et al., 2015). An autonomous production supply chain is considered to be more flexible and agile (Calatayud, 2017; Calatayud et al., 2019).

Time, counted and analyzed by the processes that companies make and turn into monetary form, provides a very straightforward meaning for the phrase "time is money". Nevertheless, this requires colossal preparation. This paper provides summarized information of indicators and financial forecasting models suggested for production forecasting. Main findings show that production line's operation consists of 90% of working and 10% of failures' time as the optimal time to repair is up to 40 minutes; forecasting accuracy is 96%, when combining economic and demand information; optimal forecasting period is from 10 months to 5 years; there is a relationship between company size and production planning (correlation 0,27-0,46). Moreover, the paper invites decision-makers to clearly identify forecasting objects, appropriate indicators, methods, and data collection capabilities in financial modeling in Industry 4.0.

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1. LITERATURE REVIEW

The era of Industry 4.0 is characterized by smart solutions. Some systems are created to be more intelligent so that they could communicate with a human. A look, touch, word or gesture will soon make machines work (Valdez et al., 2015). Robots and artificial intelligence integrated into systems logically suggest autonomy. Production process and huge data arrays will soon be continuously monitored by plenty of different algorithms in real time, with the possibility to make autonomous decisions to predict and prevent errors or risks (Calatayud et al., 2019). Those machines are called artificial intelligence. Artificial intelligence has no definition yet. Still, it is related to information systems that are based on biological systems and focus on four human intelligence elements – learning, reasoning, problem-solving, and perception (Simon, 2019). Artificial intelligence-based models are more accurate, adaptable, generalized, and require fewer data assumptions (Farooq & Qamar, 2019). Artificial intelligence solutions instead of human intervention will probably be used more by production companies in Industry 4.0 (Bassi, 2017; Sony & Naik, 2019; Melnyk et al., 2019a, 2019b).

Digital twins – systems gathering all the processes of a company that allow one to faster and easier monitor, analyze and forecast production companies' activities are only one proof of the previous statement. Technological devices and IT networks are used by such systems and require comprehensive information from human knowledge to be capable of learning different methods of data processing to provide the most effective and valuable solution in every decision-making situation. More indicators and techniques to teach artificial intelligence devices and smart technologies to evaluate companies' activities that will lead to financial efficiency are required in the Industry 4.0 era.

Not many studies that involve all the keywords and their combinations of Industry 4.0, financial forecasting, and production planning in the same articles were found, even considering the fact that all those technologies were being implemented in many processes for a relatively long time. The classics to forecast sales and demand of production is still suggested by some authors (Osadchiy et al., 2013; Doszyń, 2019; Blackburn et al., 2014; Amornpetchkul et al., 2015; Lee et al., 2012) but by using different methods or indicators.

Four main features of current economic environment – volatility (of circumstances and information), uncertainty (of predictability), complexity (of factors involved and their relationships), and ambiguity (of interpretation) – are distinguished by Blackburn et al. (2014). Environmental changes, Big Data (described by 5 Vs – Volume, Variety, Velocity, Veracity, and Value (Reis & Kenett, 2018)) and increased data collecting possibilities lead to improvement of existing production forecasting models and techniques with new factors involved. Since information is the "new natural resource" of Industry 4.0 (Reis & Kenett, 2018), any possible form of data (oral, graphic, visual, acoustic, written, etc.) is an irreplaceable recourse in any company's performance. The importance of identifying information and its sources necessary for forecasting and selecting the best method is increasing (Danese & Kalchschmidt, 2011). The improvement in performance is expected by using unexpected and complex surrounding information and different its combinations. Taking that into account, the most important things to determine before forecasting are: (I) forecasting object and starting point, (II) affecting indicators, (III) data collecting possibilities and data sufficiency, and (IV) forecasting model selection.

Companies were led to improve their supply chains in many different aspects by information technology (IT) advancement. Information sharing that promotes performance transparency and allows reducing related costs is one of them. Companies' relationships with partners, suppliers, and customers were improved by IT with increasing importance of sharing appropriate information with different interest groups (Cannella et al., 2015). Financial and production-related information (order rate variance ratio, safety stock on the order rate, the variance of inventory in continuous time, inventory variance cost, order variance cost, inventory rate, stock out the size, number of stock-outs, order cost, lead time, demand variability, capacity constraints, sharing of inventory status information, inventory variance ratio, capacity, product quality and etc.) sharing impact on production simulation was analyzed by Cannella et al. (2015). A decentralized linear supply chain model where authors used (I) order rate variance ratio (which detects demand variability in the supply chain), (II) inventory variance ratio (in-

forms about the strength of forces that affect the demand), (III) backlog (captures data of all partners' performance and is used in terms of customer service level), and (IV) average fill rate (assesses the number of delivered goods) indicators was presented, and decreasing inventory instability in all supply chain levels was found (Cannella et al., 2015). Inventory costs, profitability indicators, supply chain costs, and customer service level-related indicators are noted as important to evaluate business performance (Vereecke et al., 2018). The greater maturity of demand planning processes for larger companies versus smaller ones is supported by correlation results (Vereecke et al., 2018).

The ability to process considerable amounts of data in a short time, provided by technological advancement and Big Data progress, has led to Blackburn et al.'s (2014) suggestion to assess companies beyond customers' demand behavior and predict industry changes in the economic context to avoid risks. Seven major groups of indicators essential in forecasting by considering customers' behavior peculiarities were emphasized: (I) national, international, and companies' regular events (holidays, annual events, closures that might be specific to some industries), (II) inter-industrial macroeconomic data (especially the trends between customers' and suppliers' industries) and consumption-related political changes, (III) industrial value chain and product components, (IV) industry-specific indicators and affecting trends, (V) regulation changes (customs, tariffs, legislation and etc.), (VI) companies' internal data related to future development (new markets, products, mergers, etc.), and (VII) selection of leading indicators that usually changes before the changes in the economy (Blackburn et al., 2014). Customers' concentration is considered important to increase companies' technological innovation in industrial processes because the higher the concentration of customers, the less diversity of purchases and customers' resources, for that customer concentration was suggested to measure by using five top customers of companies' sales divided by total sales (Shen et al., 2018).

Exponential smoothing with covariates model was used by Blackburn et al. (2014) to analyze demand forecasting based on company's data and economic information, which allows modeling and

forecasting economic and industry-related data by including historical and environmental data. (I) Internal variables (products' demand, general demand in different levels, companies' financial indicators), (II) external economic indicators (branch and macro-economic indicators), and (III) public data (available on the internet) were separated (Blackburn et al., 2014). The performance of exponential smoothing with covariates model has been better than models that use only statistical historical demand data and allowed reliably forecast business performance up to 12 months (Blackburn et al., 2014). The trends of accuracy of longer forecasting periods are revealed. Reliable forecasting accuracy of 96% over the one-year period was shown by Blackburn et al. (2014) when incorporating economic information in demand forecasting, periods of 10-12 months by Ulbricht et al. (2016) and up to 5 years by McLemore (2018) were also obtained.

Indicators that are specific for production industry and isolate fluctuation in production processes, such as production cost and cost per unit, productivity (or value-added), prices of raw materials and packaging, production mix (amount of different finished products per specific time), changes in direct and indirect costs parameters, production line speed and operational excellence indicators (operational energy consumption, direct labor used, raw material loss, packaging material loss, maintenance labor extra time, maintenance spare parts), were used by Gólcher-Barguil et al. (2019). An automated Manufacturing Execution System (MES), which is based on Big Data and cloud computing and helps to collect real-time data in production lines, was briefly presented by Zou et al. (2018). The system is programmed according to production plans and reduces staff involvement in the production process, improves resource utilization, reduces production capacity loss, allows controlling and monitoring status of the production line, and related processes also helps ensure product quality (Zou et al., 2018). Failure analysis, is considered as one of the best ways to evaluate company performance. The analysis of limoncello production line reliability have suggested counting a number of failures, time-between-failures, and time-to-repair of specific production line segments (Tsarouhas & Arvanitoyannis, 2012). The loss of income that the company has not received

because of the possibly stopped production process are reflected by such indicators. The price of production unit, time spent to make production unit and time the production line process was interrupted, also including costs of fixing the problem, are used to evaluate the loss of income. The effectiveness of production line operation time and a time lag of 40 minutes long, which is important for a company to maintain 90% of production line's profitability, was found (Tsarouhas & Arvanitoyannis, 2012). To fix production lines' failures within less than 1 hour is a condition necessary to keep production line's profitability. Otherwise, the maximum efficiency of a company would not be reached. 10% of failures are a substantial amount of time wasted and income not received for production that were not produced. The high importance of this issue is especially evident in huge production companies with continuous production processes and high volumes of production units being made. However, possible failures must always be taken into account when forecasting production and financial data. Production costs were separated into a variable (raw materials, waste treatment, utilities (for extensive volume processes) and fixed costs (capital depreciation, labor (operation and supervisory), utilities (for small volume processes), companies' maintenance, suppliers, companies' support (R&D personnel for troubleshooting) site services (security, infrastructure)) (Aldarrat et al., 2018). Analyses show that internal indicators are used firstly but macroeconomic indicators have a huge impact on the assessment of companies' activities.

Profitability indicators such as return on equity, return on net operating assets, return on assets, return on sales, growth in sales, which are specific to the industry sector and are suitable for industry-specific and economy-wide forecasting models to implement, were analyzed by Schröder and Yim (2017); the authors revealed that profitability forecasting in single-segment firms and some business segments is affected by the industry, but multiple-segment firms are not affected. The investigation "whether incorporating economically motivated prior information yields more accurate forecasts of industry costs of equity" was made by McLemore (2018). Capital Asset Pricing Model and Bayesian hierarchical models were used to evaluate risk-free rate, market re-

turns, returns of industry portfolios indicators. Optimal forecast horizon from 1 to 5 years and reduction in industry costs on equity forecasting errors by long-run mean or hybrid estimates were found (McLemore, 2018).

Despite different kinds of indicators and methods used, the basic idea of intelligent forecasting is to model and forecast real-time data by the time it is published or updated. Nevertheless, different indicators' publication time, frequency, and appropriate indicators' selection are the arising problems. A bridge model and a factory-based model were used in forecasting the industrial production index (IPI) in Italy (Girardi et al., 2016). IPI is defined as a high-frequency manufacturing indicator that is extremely important to the whole business cycle fluctuations and in forecasting short-term periods of GDP (Bulligan et al., 2010; Boero & Lampis, 2016). IPI is used by the European Commission to group European industries in terms of demand-based products (Eurostat, 2008) and to evaluate "changes in value added at factor cost of industry" (Eurostat, 2019a). IPI is counted by total industry's output and input that is used for these outputs, for example, gross production values (deflated), volumes of production, turnover (deflated), work, raw material, and energy inputs (Eurostat, 2019a). However, extra time until the index is published is necessary, so the usefulness of IPI in forecasting decreases (Bulligan et al., 2010). Similar issues are visible with other composite indicators. The model that could provide significant benefit in forecasting euro area quarterly GDP by using business surveys indicator PMI (Purchasing Managers' Index), proposed by Markit Economics, and ESI (Economic Sentiment Indicator) was presented (Camacho & Garcia-Serrado, 2014). According to Eurostat (2019b), ESI consists of several indicators: (I) Industrial confidence indicator, (II) Services confidence indicator, (III) Consumer confidence indicator, (IV) Construction confidence indicator, and (V) Retail trade confidence indicator. PMI's variables are as follows: in manufacturing – output, new orders, employment, input costs, output prices, backlogs of work, export orders, the number of purchases, suppliers' delivery times, stocks of purchases, stocks of finished goods, future outputs; in services – business activity, incoming new business, input costs, prices charged, business outstanding, business expec-

tations (Markit Economics, 2017). Bridge model is characterized by fewer indicators and more space for interpretation possibilities, unlike the factory-based model that assesses a huge amount of data and has limited economic interpretation possibility (Girardi et al., 2016). Nonlinear data, like seasonality, is a frequent forecasting problem. An analysis was made of the leading indicators of cross-industry relations between seasonally unadjusted 24-month series of industrial production volume in three European countries: Germany, United Kingdom, and France, by implementing singular spectrum analysis (SSA) and multivariate SSA (MSSA) models (Silva et al., 2018). Models are known for filtering capabilities in any time series, the possibility to enrich analysis by using SSA, and to choose the window length and the number of eigenvalues in the MSSA model (Silva et al., 2018). Algorithms that improved an SSA model with the loss function and made the model more universal to any forecasting issue were presented (Hassani et al., 2015). SSA was outperformed by MSSA in the study of Silva et al. (2018), but there is no single model suitable for every element or forecast of the chosen country's performance. The significance of financial indicators in forecasting output growth was noted by using extension of the Stock and Watson single-index dynamic factor model that combines different frequency: (I) hard indicators (that show economic activity – GDP, unemployment rate, industrial production, export), (II) soft indicators (based on opinion surveys – consumer and service confidence from the perspective of households and industry confidence from manufacturing perspective), and (III) financial indicators (total credit to households and the term spread), and the model is suggested for short-term analysis as it allows more accurate forecast than standard autoregression models (Camacho & Garcia-Serrado, 2014).

All the previous singular were related to financial, production, or economic indicators. But the Industry 4.0 and Big Data period is perfectly reflected by monthly German industrial production forecasting by using media information (Ulbricht et al., 2016). Private consumption, stock market volumes, stock prices, growth rates of the GDP, business cycle turning points and other financial and economic indicators were forecasted, as well as real-time media information (counted specific named

words) that is being kept in global cloud computing technologies (Ulbricht et al., 2016). This sentiment analysis of opinion-leading media is based on the expectations of production companies' managers or analysts (Ulbricht et al., 2016). The usefulness of media indicators on the results of the 10-12-month forecast period was noted, as well as the relationship with future changes in production industry, which is in line with announcements of monetary policy (Ulbricht et al., 2016). Sentiment analysis in forecast of sales based on online social media data was also used (Lau et al., 2017).

Continuing the idea of using media data in forecasting, publicly available, online, free of charge and constantly updated Google Trends data was suggested to use (Woo & Owen, 2018; Boone et al., 2017), as well as the social media's data (Cui et al., 2018). Google Trends data in forecasting private consumption in the USA based on news-related information was used (Woo & Owen, 2018). Consumer behavior (for example, in pre-purchasing) is evaluated differently by Google Trends than surveys' data, which show their attitudes and, according to the research, forecasting models are significantly improved by both news and consumption-related search data in Google Trends (Woo & Owen, 2018). The relationship between media news and consumer sentiment, having in mind that specific words, like recession or layoff, search frequencies should negatively affect consumption, were noted (Woo & Owen, 2018). ARIMA model and Google Trends data were used to analyze if the volumes of specific media platforms have an impact on sales, and the searches were assumed as a possible intent to buy (Boone et al., 2017). The importance of choosing an appropriate search term was carefully emphasized because even unrelated searches seemed to have an impact on customers' buying decisions and sales forecasting explanatory results (Boone et al., 2017). The ability to improve production forecasts by using several ML linear and nonlinear models (Linear regression, Lasso regression, Forward selection, SVM (Support vector machine) with the linear and radial kernel, Gradient boosting model (GBM), Random forests) by including and excluding media data (users' provided information on social networks, like Facebook) was studied (Cui et al., 2018). Better forecasting results by using media information were performed by nonlinear models with the possibility to select

features (Cui et al., 2018). Additional information supplementing survey-based consumer sentiment indicators is provided by Google Trends augmented models. Information on possible trends in consuming and forecasting models provided by data obtained from Google Trends are highly improved by news about the changes and combination between the news and data (Woo & Owen, 2018). Unfortunately, limited data availability is noted as an issue of Google Trends (data since 2008 – the Great recession period that continued following recovery period, noted with uncharacteristic data) (Woo & Owen, 2018)

Although media data is considered essential for supplementing forecasting, in most cases, the importance of including as much sufficient historical and present data as possible to make research more accurate and reliable in terms of data quantity is emphasized, instead of data quality. The importance of qualitative data utilization to assess industry performance by investigating the chemistry industry was proposed by Reis and Kenett (2018), with the method used – *InfoQ*, which might be adapted to other industrial companies. The value of information in the company by using analytical expression (1) below, where "the level of Utility, *U*, achieved by applying the analytical method of to the dataset *X*, given the activity goal *g*" was assessed (Reis & Kenett, 2018).

$$InfoQ(f, X, g) = U\{f(X|g)\}. \qquad (1)$$

InfoQ data structure and characteristics such as (1) structured (data arrays, time series, cross-sectional and network) data or unstructured (text, images, sound, vibration), (2) tensor nature ((zero-order (process sensors), first-order (spectra)), (3) noise (missing or bad data – e. g. shutdowns), (4) single- or multi-block (existing groups and integrities of variables that should be maintained), (5) static or time-delayed structure (lagged correlation pattern), (6) observational (occurrence data) or casual (data collected following the design of experiments plan) were presented (Reis & Kenett, 2018). Multi-block methods and Bayesian networks to assess and optimize industrial processes are suggested to use due to an increase in complexity of industrial processes and the amount of historical and present data that is possible to collect (Reis & Kenett, 2018).

Machine learning methods' abundance includes Bayesian models that, with different combinations, are used in many studies. For example, for forecasting data quality analysis (Reis & Kenett, 2018), prior economic information impact on forecasting accuracy (McLemore, 2018), macroeconomic environment predictors' forecasting (Prüser, 2019), inflation (van der Maas, 2014), or financial crises prediction (Chen et al., 2011). Bayesian models are characterized by the possibility to select built-in variables, use nonlinear data with the case of indicators' interaction, and see not only the noise but the pattern of the problem analyzed and to assess uncertainty (Prüser, 2019). Models were noted as flexible, allowing one to see changes in the relationship between the measures and the set of predictors, and are suitable for using real-time data (van der Maas, 2014). One can also analyze high-frequent data (Contino & Gerlach, 2017). Much richer forecasting information was provided by many variables used in Bayesian model because, if there are many macroeconomic indicators but a small number of observations, a wide range of indicators could enrich macroeconomic information base and the conclusions made are more accurate (Prüser, 2019). Bayesian models were also used to forecast value-at-risk as they allow evaluating the uncertainty of parameters, receiving a proper conclusion for finite samples, and are efficient in handling complex information and limitations (Chen et al., 2011). Economic activity, real GDP and GDP deflator, industrial production, unemployment rate, real personal consumption expenditure (PCE) and PCE deflator, consumer price index, effective federal funds rate, and treasury constant maturity rate were forecasted by Prüser (2019). The results of Bayesian tree in most cases outperformed AR and Lasso (Prüser, 2019).

In terms of the ability to collect plenty of different data, the importance of using real-time data to forecast the performance of companies has grown. Nevertheless, the difference between real-time data forecasting results and the latest available data results was found (Heinisch & Scheufele, 2018). Seasonally adjusted Germany's indicators provided by surveys (IFO, ZEW, ESI, and PMI), hard financial indicators (industrial production, orders), and other financial indicators (German stock index DAX, short-term interest rate, the spread between short-term and long-term interest rates) were analyzed (Heinisch & Scheufele, 2018). Benchmark revisions that affect mean time series shifts, the greater volatility of the latest available data and more difficult forecasting in comparison to real-time data have caused the forecasting differences following by lower results of real-time data GDP growth forecast when compared to the latest available data. Moreover, hard data-based forecasts might be improved by surveys used in real-time data forecasting (Heinisch & Scheufele, 2018). Hard data is considered to have strong forecasting power (Banbura et al., 2013), and an analysis augmented with surveys and orders of industrial production, in combination with hard industrial production indicators, was noticed to improve the results (Heinisch & Scheufele, 2018). Only the slight inaccuracy seen in the real-time data forecasts compared to the latest available data suggests that the latest available data can be used if existing data cannot be collected. The main findings of the literature review are summarized in Figure A1 (Appendix A).

Better sources and more information necessary for performance modeling in larger companies are considered, as well as more constant production demand and better profitability than smaller companies (as mentioned the benefit of using production line). The assessment of larger companies' activity is facilitated by better possibilities to implement artificial intelligence solutions. Predictions and decisions on investment in technologies or production demand trends have become available for decision makers by longer forecasting periods obtained. The differences between models analyzed are revealed mostly due to the amount and the number of different kinds of variables used. Forecasting accuracy results are significantly improved by the combination of soft, hard, media, and macroeconomic indicators, and sentiment analysis. Models that use more indicators and include soft indicators are more accurate.

2. GENERALIZATION OF THE MAIN STATEMENTS

Analyzing huge amounts of data that includes different kinds of information (economic, environmental, customer and user information, etc.) and different types of data (visual, sounds, text, etc.) that can be processed and useful in

modeling company performance are revealed in financial forecasting, planning, and modeling in the Industry 4.0 period. The importance of using as many indicators as possible to obtain accurate forecast results and reliable interpretations is emphasized. The search for the information necessary to forecast financial performance in the most unexpected sources is provided by technological progress, artificial intelligence, cloud computing, machine learning, and Big Data. The forecast accuracy and significance of soft data usefulness has been increased by extended use of media data and sentiment analysis. Production demand, consumption, changes in the economic, social, and political environment, the opinion of interest groups – all this is predicted by incorporating survey data that influence decision-making related to financial modeling, and which can affect the activities of companies.

To have the most recent forecasts, real-time data is used. The most recent data can be used instead of real-time data. Unfortunately, there was a slight inaccurateness in using real-time data when combined with recently available data. It was noted that this difference is due to differences in data sources and data collection periods. In addition, the quality and sufficient amount of data used in forecasting are essential. Finding leading indicators affecting the specific industry is substantial. For the most accurate forecast, it is proposed to use forecasting models that include hard, soft, internal, external, micro-, and macro-economic indicators, as well as composite indicators that affect company performance. Models that assess nonlinear data and have specific indicators built in are more accurate than traditional linear data-based financial forecasting models.

To sum up, below are the points that should be noted by decision-makers in terms of financial modeling in production companies in the Industry 4.0 period, following the aforementioned financial modeling sequence. (I) The forecasting object (production, customers, business expansion possibilities) must be identified. The analysis beyond the forecasting object itself, thinking of the whole context, not only one company is essential. (II) Indicators that reflect the object the best should be identified. Indicator selection using as many indicators of good quality, current and historical, different types of indicators (soft, hard, visual, etc.) from every source possible (companies' internal and external, macroeconomic, media data, etc.), having in mind the whole information surrounding, not only one segment is important. (III) The sufficiency of relevant indicators' (do they isolate production fluctuation, measure customer concentration, estimate failure statistics, etc.) and data collection possibilities should be assessed. (IV) An appropriate forecasting model selection based on its possibility to process huge amount of data, high variety of indicators, soft information, to provide long enough forecast or to leave wide space for result interpretation is essential. Models that combine various good quality indicators and historical data are considered more accurate.

Unfortunately, despite the power of Big Data and intelligent machines, there are limitations to predicting production. First, the ability to collect relevant data is due to the timing of the publication of different indicators (for example, companies' financial statements, where the basic financial indicators are provided, appear in the first quarter of the year, economic (or branch) ratios that include companies' financial data are released after the financial statements are processed). Secondly, there are different types and amounts of data, nonlinear or seasonal data processing. Thirdly, the forecast accuracy is due to the successful selection of the most appropriate forecasting model and depends on the increase in the variety of indicators. Soft data and sentiment analysis results are difficult to process. Machine learning or artificial intelligence techniques that are suitable for data processing and implementation require huge financial investment and user knowledge.

3. DISCUSSION

It is proposed to use many different indicators in forecasting processes. Four groups of indicators can be separated by the objects of forecasting: (I) production-related, (II) customers and demand-oriented, (III) industry-specific, and

(IV) media information indicators (see Figure A2 in Appendix A). The indicators referred to the first (I) group are proposed to be used in production forecasting, since they show the performance of production lines, storage volumes of raw materials and finished product, companies' capacities associated with maintenance, resources consumption, and failures in production processes. Capacity, production cost, and maintenance are among the most frequently mentioned. Production processes are controlled and monitored by each of the production-related indicators within each forecasting period. Those indicators are directly or indirectly related to companies' income.

The second (II) group is focused on forecasting customer demand and analyzing customer and demand behavior indicators in forecasting processes. Indicators of customer concentration, political, legal, environmental change-related indicators that have a significant impact on product demand and customers' decision to buy a specific product are suggested to be analyzed. The examples of customs and tariffs for imported goods and materials that might fluctuate based on the product but differ in other countries could be mentioned. Customer decisions of buying product or not related to production unit selling price is highly affected by even a slight change in customs. Better forecasting results were obtained when indicators that assess peculiarities of customer demand behavior were incorporated.

The importance of analyzing industry-specific indicators was emphasized. Those indicators were summarized in the third (III) group. The difference between industry-specific indicators (and most likely their values) based on the sector in which a company operates is evident. Specific branch and macroeconomic indicators, price indices, profitability (ROE, ROA, RNOA, ROS, GSL), or sentiment analysis-based indicators – PMI, ESI, IFO, ZEW that supplement forecasts are the most important indicators proposed to be incorporated in forecasting models. The ability of making benchmark analysis and evaluating company performance in the context of sectors is the benefit gained. Industry-specific indicators were mostly applied to forecast national-level data. Nevertheless, the im-

portance of those indicators in forecasting and modeling the performance of companies was highly noticed.

Media information – the most valuable data in the Industry 4.0 period – was summarized in the fourth (IV) group. The possibility to use publicly available media data include a survey-based sentiment analysis supplemented with expectations of top-level managers of production companies and analysts about future innovations in production, demand, and other possible changes-related activities of companies has gained the highest importance in today's production planning. Search volumes for specific words on the internet are assumed to be customers' intent to buy. Consumption risk is also predicted using media data. In this case, the importance of quality of information used increases and it is recommended to set the level of information utility.

The literature analyzes many different models that differ in the data used, the number of indicators that can be incorporated, or a time period that can be modeled. Four groups of production forecasting models have been identified, similar to those in Figure A2, and are suitable for modeling company-level indicators, customer and demand behavior, industrial performance, and media information-related indicators. The possibility of augmentation with more indicators and with different kinds of indicators in the model are noticed to provide more accurate results. Information on soft indicators has not been widely analyzed before the Industry 4.0 period. Bayesian models, which manage to process soft data, are most often used in forecasting. Different modifications of AR and other models are also used. Different forecast accuracy, different amount of indicator processing or forecasting result interpretation capabilities are determined by selecting appropriate indicators and forecasting methods. Trends in the digitalization of company processes are revealed, as well as the need to analyze an increasing number of variables at a time and reach maximum accurateness possible, which contributes to the search by companies for intelligent alternatives to production financial modeling, which were summarized in this paper.

CONCLUSION

Many new trends in production forecasting arose in Industry 4.0 era comparatively to previous industrial revolutions. Four groups of forecasting indicators: production-related, customer and demand-oriented, industry-specific, and media information indicators, were classified. Indicators are highly connected with each other within the groups and among the groups. All kinds of indicators, from production line performance-related and demand-related to economic indices, profitability ratios, and public data available online, are used. It is noted that forecasting and modeling results become more accurate when different kinds of indicators (e. g. media data, hard indicators, and sentiment analysis) are included in the forecasting process. Soft indicators have substantial power in supplementing analysis based on hard data.

Many different forecasting models and techniques are applied. Bayesian models are among the most frequently used. They are characterized by different modifications and a user-friendly environment because of the possibility to include many different kinds of indicators in forecasting. Media data and sentiment analysis of opinion-leading media usage by emphasizing data quality, forecast accuracy, and longer forecast periods are all revealed in Industry 4.0 modeling trends.

AUTHOR CONTRIBUTIONS

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ACKNOWLEDGMENT

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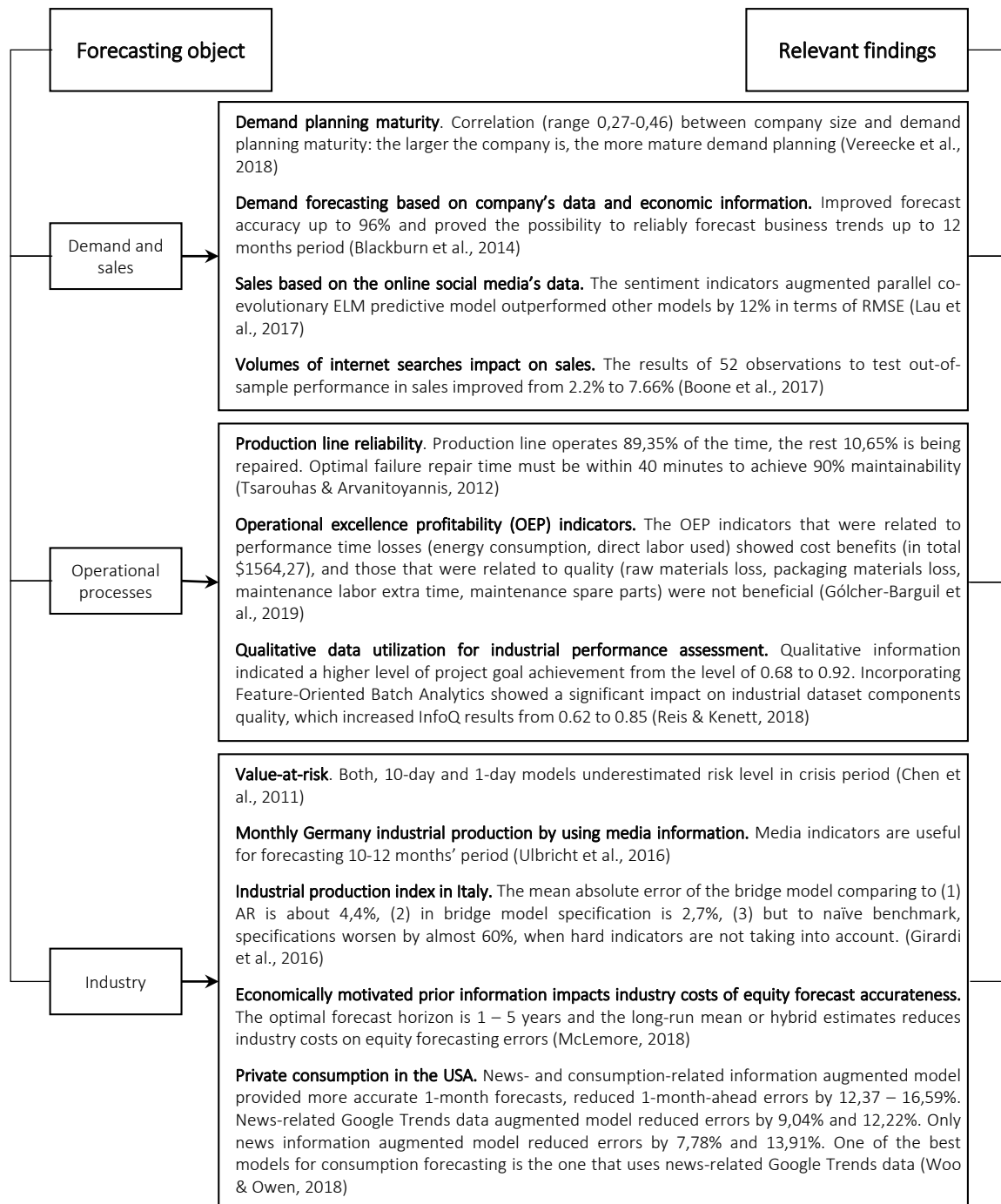
APPENDIX A

Forecasting object	Relevant findings

Demand and sales

Demand planning maturity. Correlation (range 0,27-0,46) between company size and demand planning maturity: the larger the company is, the more mature demand planning (Vereecke et al., 2018)

Demand forecasting based on company's data and economic information. Improved forecast accuracy up to 96% and proved the possibility to reliably forecast business trends up to 12 months period (Blackburn et al., 2014)

Sales based on the online social media's data. The sentiment indicators augmented parallel co-evolutionary ELM predictive model outperformed other models by 12% in terms of RMSE (Lau et al., 2017)

Volumes of internet searches impact on sales. The results of 52 observations to test out-of-sample performance in sales improved from 2.2% to 7.66% (Boone et al., 2017)

Operational processes

Production line reliability. Production line operates 89,35% of the time, the rest 10,65% is being repaired. Optimal failure repair time must be within 40 minutes to achieve 90% maintainability (Tsarouhas & Arvanitoyannis, 2012)

Operational excellence profitability (OEP) indicators. The OEP indicators that were related to performance time losses (energy consumption, direct labor used) showed cost benefits (in total $1564,27), and those that were related to quality (raw materials loss, packaging materials loss, maintenance labor extra time, maintenance spare parts) were not beneficial (Gólcher-Barguil et al., 2019)

Qualitative data utilization for industrial performance assessment. Qualitative information indicated a higher level of project goal achievement from the level of 0.68 to 0.92. Incorporating Feature-Oriented Batch Analytics showed a significant impact on industrial dataset components quality, which increased InfoQ results from 0.62 to 0.85 (Reis & Kenett, 2018)

Industry

Value-at-risk. Both, 10-day and 1-day models underestimated risk level in crisis period (Chen et al., 2011)

Monthly Germany industrial production by using media information. Media indicators are useful for forecasting 10-12 months' period (Ulbricht et al., 2016)

Industrial production index in Italy. The mean absolute error of the bridge model comparing to (1) AR is about 4,4%, (2) in bridge model specification is 2,7%, (3) but to naïve benchmark, specifications worsen by almost 60%, when hard indicators are not taking into account. (Girardi et al., 2016)

Economically motivated prior information impacts industry costs of equity forecast accurateness. The optimal forecast horizon is 1 – 5 years and the long-run mean or hybrid estimates reduces industry costs on equity forecasting errors (McLemore, 2018)

Private consumption in the USA. News- and consumption-related information augmented model provided more accurate 1-month forecasts, reduced 1-month-ahead errors by 12,37 – 16,59%. News-related Google Trends data augmented model reduced errors by 9,04% and 12,22%. Only news information augmented model reduced errors by 7,78% and 13,91%. One of the best models for consumption forecasting is the one that uses news-related Google Trends data (Woo & Owen, 2018)

Figure A1. The most relevant literature analysis findings
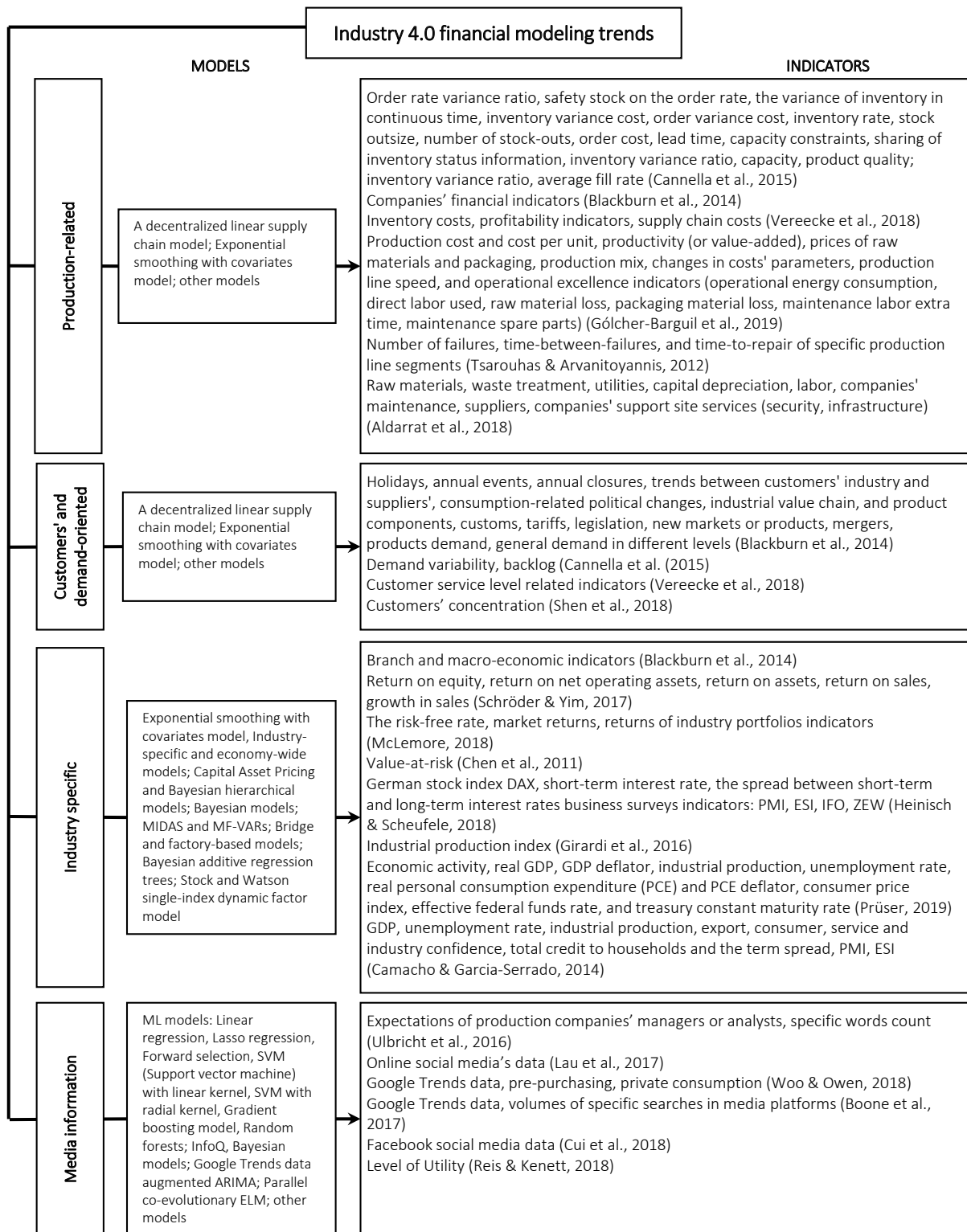
Figure A2. Industry 4.0 financial/economic forecasting models and indicators by analyzed authors