The importance of prediction methods in industry 4.0 on the example of steel industry

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INTRODUCTION

With the technological advancement, the industry concept in the 21st century is referred to as Industry 4.0 (German: Industrie 4.0) – the equivalent of the fourth industrial revolution in connection with the use of automatic machines, autonomous robots and digital technology. Digital transformation is the most important trend in the global economy. Enterprises use IT technology and apply (more often) artificial intelligence. The essence of Industry 4.0 is to integrate the automation and robotization of production processes with systems and created networks and people. The basic structure of Industry 4.0 is made up of cyber-physical systems, the Internet of Things (IoT) and cloud computing. The realization of technology development is a smart factory in which cyber-physical systems (CPS) that control physical processes, create virtual (digital) copies of the real world and make decentralized decisions, and through the Internet of Things in real time communicate and cooperate with each other and with people, while through processing the internal and inter-operative services are offered and used (Bauernhansl et al., 2014; Gerbert et al., 2015; Schwab, 2016). The purpose of this new concept is higher (than before) efficiency and cost reduction, but also the speed of reaction to the ever-changing consumer needs and other dynamic phenomena in volatile markets. New business models are created on the market (Grabowska, 2016).

Companies that introduce new solutions to the fourth industrial revolution take over the market and customers, deepening their competitive edge. Industry sectors that are commencing changes at level 4.0 include the steel industry. In domestic conditions (territory coverage: Poland), the largest metallurgical enterprise – Arcelor Mittal Poland – introduces technological changes that will be building the foundations of intelligent production in the future. The potential production capacity of the company accounts for 70% of steel production in Poland (Gajdzik & Sroka, 2012). The company belongs to the largest global capital group in the field of steel production volume on the global market – the Arcelor Mittal Group. The Group produced 97.03 million tonnes (Mt) crude steel in 2017 (World Steel Association report: Top steelmakers in 2017). With relatively large investment opportunities, ArcelorMittal's staffing and research facilities can act as a pioneer in the trail. However, at the current stage of change it is difficult to find an example of a comprehensive approach to the industrial

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revolution, to implement Industry 4.0 solutions simultaneously at all levels of the business structure. Changes are introduced sequentially in various (selected) business segments (implementation of partial solutions). The scope of these changes is described in the first part of the work: *Steel production in Industry 4.0*. This part of the work was based on a study of literature and observation of changes in the steel sector in Poland. Observation was conducted by the author of this publication. Changes in production in the perspective of further development of Industry 4.0 in aspects of both mass and personalized require the use of predictive methods to production plan and control maintenance. Thanks to sensors, algorithms, advanced analytics and the ability to draw conclusions from information, producers can more effectively control production. Digital technologies connect machines, products and teams, creating new opportunities, including virtual simulations, advanced analysis, spatial printing, remote expertise and real-time collaboration. Technologies used in Industry 4.0 combine reality with virtuality. As a result, the real-time monitoring system removes employers into a virtual image (space). Current information is compiled with perspective information. The dual system of device operation analysis gives the possibility of controlling the production process in the extended horizon: virtual or extended reality (VR/AR) (Jasperneite, 2012; Sendler, 2013).

The production prediction is based on the regularities characterizing the forecasted phenomenon and the dependencies between the various components of production (cause-and-effect relationships, similarities in development, symptomatic relationships between the forecast phenomenon and other phenomena) (StatSoft, 2012, Dittmann, 2011).

In the perspective of the in the latest technological solutions in steel production that are expected to bring metallurgical enterprises to the level of 4.0, a prospective analysis of the production volume is necessary. In part of the work: *Forecasts of the world steel production* summarized the forecasts prepared by the author of this publication. This combination of steel production forecast (Table 1) can be a valuable research material for the short- or medium-term planning of steel production by steelmaking companies with global and international reach.

STEEL PRODUCTION IN INDUSTRY 4.0

The changes implemented in manufacturing enterprises (steelmaking companies) aspiring to the role of leaders in Industry 4.0 are an alternative to the traditional development of the enterprise. Enterprises of individual industry sectors are currently at various stages of investment work progress, which are to lead companies to achieve the level 4.0 (Saniuk et al., 2013). Investment projects are most often implemented in a selected manufacturing process for a specific product or group of products within core business (Kagermann, et al., 2013).

Enterprises from various industry sectors implement pilot projects (start-up programs). Such programs are a form of gradual changes in production. Enterprises adopt a two-pronged production strategy, implementing and improving traditional production and investing in digital technological solutions that are to lead to the creation of autonomous cyber-physical production systems – CPPS. Such a way of development of companies allows them to produce and sell on the one hand as it has been so far (not every production profile requires installation of robots), and on the other hand they can monitor, modify and service real-time production equipment.

Stock market investors more and more often pay attention not to material resources (factories, machines) but to innovation, technology and knowledge. There are industries on the market where the scope of implemented changes on the way to smart production is larger (wider) than in other industries, eg automotive sector. In industries belonging to heavy industry: mining and metallurgy, innovations are more traditional.

ArcelorMittal Poland invests in advanced technologies and in computer software production and related processes. Investment works are carried out on individual devices, obtaining computer control of their work (exemplary devices: blast furnace, converters, plastic processing equipment) and on selected metallurgical products obtained using the latest technological advancements, eg modeling of 3D products. Thanks to sensors, algorithms, advanced analytics and the ability to draw conclusions from information, production companies can more effectively eliminate bottlenecks in production. Data from devices are gathered in one place – data center. The existing IT and computer systems implemented in metallurgical enterprises, eg ERP, SAP are expanded and adapted to the requirements of intelligent production control (software customization). Examples of investments carried out at ArcelorMittal Poland in recent years: modernization of a blast furnace in Cracow, refurbishment of heaters, a new blast furnace cooling system, hybrid filters in the sintering belt sintering system in Dąbrowa Górnicza (the first such installation in Poland). These investments are solutions outside the Industry 4.0, but significantly reducing the impact of steel production on the environment (lower water and coke consumption, reduction of emissions) (Special Report, 2018).

Investment implementations are part of the area of change known as "zero waste" and Lean Manufacturing (Grabowska, 2018; Furman et all., 2017) and higher efficiency in production (Gajdzik & Galwik, 2017). In the last 30 years, steel production in Poland has changed radically, obsolete and uneconomical steel production technologies have been withdrawn, the level of work automation has increased and manual labor has been reduced (Gajdzik, 2013).

Currently, metallurgical enterprises (international capital groups) are seeing deeper automation and stronger integration of infrastructure and data. The process of digitization and computerization is primarily implemented in the area of production harmonization. Industry 4.0 also enters the sectors related to steel production. The industry in a particular way conditioned in the implementation of Industry 4.0 solutions is welding - welding robotics of individual elements in enterprises. Modern technology are used in industry branches (sectors) that are associated with rather less complicated production, such as: steel constructions, agricultural machinery, metal fences. In addition to production, changes are introduced in logistics – modern warehouses of steel products, equipped with automatic devices for registering and servicing orders – steel structure warehouse in Dąbrowa Górnicza belonging to Thyssen Energo Stal (Gajdzik, 2019; Kramarz, 2012).

An important area of change is also building new customer relationship. ArcelorMittal has launched the *Steel Advisor for Industry* platform. The platform is an online guide and helps customers find the right metallurgical product depending on the target application. Transformations in production have an impact on the labor market. Automation, robotization of works and artificial intelligence that is used in machines, robots and software is able to replace a human being. Industry 4.0 requires different

competencies of employees in various areas of the organization. Currently, there is a growing demand for: automation and robotics engineers (Report PWC).
ArcelorMittal Poland has started recruitment for positions for the servicing of automated production lines, looking for engineers 4.0 (footnote). The existing organizational structures are radically changed by the creation and/or expansion of IT departments and the establishment of data analysis teams, as well as by cyber-physical production systems. Managers for Industry 4.0 are located at the top management level in this organization.
Summing up, at the current stage of development of metallurgical enterprises in Poland (taking into account the strong influence of foreign capital, which owns the largest steel mills), the automation of production processes is carried out, by using more and more modern machines, which does not exhaust the essence of Industry 4.0, but these are changes that lead to Industry 4.0. Metallurgical enterprises at the current stage of development, combine and integrate processes and devices with each other, deepening automation and robotization resulting from the previous industrial revolution (3.0) and using cloud computing technology to control production, as well as 3D printing for product design and presentation of market offers (Report PWC). By 2020, the metallurgical industry is planning an annual increase in investment by 4% in the aforementioned work area (weighted average of 5%) (Report, PWC). Investments in IT infrastructure will be developed systematically. Sensors will be installed on individual production machines, as well as solutions allowing to connect production devices to the network and business platforms (Sroka et al., 2014). New technology creates the intelligent production process with new products (Sitko, 2015) and increases the quality of standards of its. The problem of quality of products is discussed by scientists (Sitko et al., 2018; Gajdzik & Sitko, 2014; Gajdzik & Sitko, 2016).

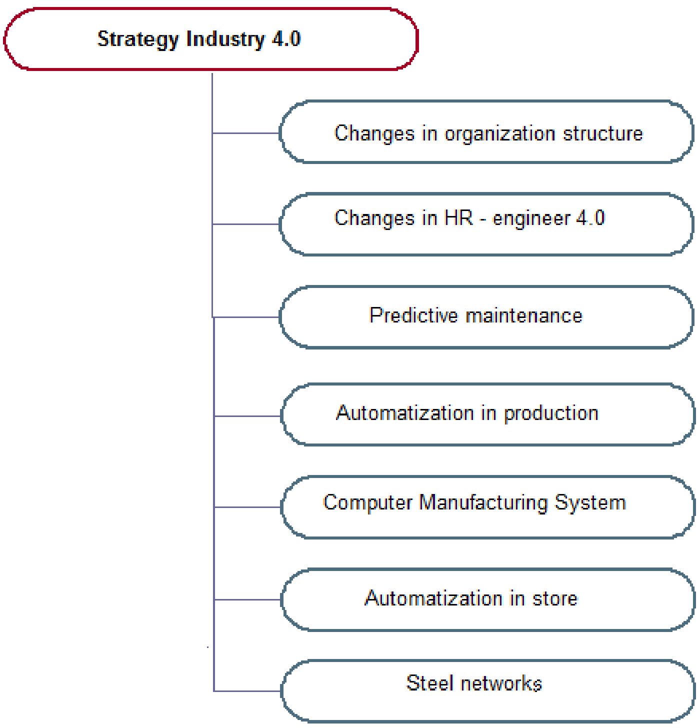

Fig. 1 Fields of changes in an steel enterprise in I 4.0

PREDICTION OF STEEL PRODUCTION IN INDUSTRY 4.0

Forecasts are built on the basis of empirical data in order to obtain production in the future. At the stage of initiating changes in steel production under the pressure of the economy 4.0, the prediction (forecast) of steel production is used in the planning phase of production processes. Steel production forecasts provide information for planning machine load, material demand, determining the range of products and the number of employees. Thanks to production forecasts, technologists can, for example, test and optimize machine settings, harmonize production before starting it physically, shortening material ordering time, etc. Production forecasts are used to simulate production (simulations can use real-time data to reflect the physical world in a virtual model). Information on the course of steel production in metallurgical enterprises (the example of ArcelorMittal Poland) is organized into a vertical pyramid of automation, in which sensors and field devices with limited intelligence and automation controllers supply the superior control system of the production process. In the future, the sector will, like other industry sectors, strive to incorporate steel production technologies into the network (including the protection of critical industrial systems and production lines). Metallurgical enterprises from the data used on the Intranet of the company, while maintaining the principles of cyber security, will create a business platform and block chain.

Forecasts of the world steel production

In this part of the work, steel production forecasts (table1) have been compiled. The sources of empirical data are World Steel Association reports (Steel Statistical Yearbook). The forecasting methodology was implemented sequentially (Dittmann, 2016 pp. 25-33; Green, 2003; Snarska, 2005; Zeliaś, 1997) and included: 1. Formulating the research goal – scientific goal – popularizing built forecasts in the scientific community, 2. Indicating factors that influence the forecasted phenomenon – the global steel market situation (core factor), 3. Collection statistical processing and analysis of forecast data – current steel production trend with random fluctuations caused by the global economic crisis in 2008-2010, 4. Selection of forecasting methods – classic trend models and adaptive trend models (single-equation models), 5. Design of forecasts in the layout: total steel production, BOF steel production, EAF steel production, 6. Assessment of the acceptability of the forecast, 7. Presentation of the obtained forecasts in scientific publications (in accordance with the adopted research goal), 8. Assessment of the accuracy of the forecast - opinions of experts from the steel industry, intuitive assessments, AHP method. This publication summarizes the obtained forecasts in the system: total production and according to technological processes. This structure of forecasts will allow managers to make production decisions, including in the area of introducing technological changes. In Poland, due to the high costs of environmental protection, management considers the decision to replace BOF technology by EAF. However, another problem arises because energy costs in the steel sector in Poland are much higher than in neighboring EU countries, eg Germany (even by approx. 60%).

Table 1
Forecasts of the world steel production

No.	Method	Total (Mt)	BOF (Mt)	EAF (Mt)
1	Additive naïve method (point forecast)	1690.479	1206.963	471.778
2	Multiplicative naïve method with increasing tendency	a) 1756.430 b)1824.955 c)1896.152 d)1970.128 e) 2046.128	1214.192 1221.464 1228.780 1236.140 1243.544	532.838 601.789 679.670 767.629 866.972
3	Simple moving average for time series with constant k-point value (*k* = 2)	1658.742 1674.610 1666.676 1670.643 1668.659	1203.370 1205.167 1204.268 1204.717 1204.493	444.749 458.263 451.506 454.885 453.195
4	Simple moving average for time series with constant k-point value (*k* = 3)	1638.470 1651.984 1660.311 1654.183 1662.220	1203.480 1203.407 1204.616 1203.834 1203.952	426.149 438.549 445.492 436.730 440.257
5a	Weighted moving average for time series with constant k-point value (*k* = 2) and weighs *(w_1=0.40; w_2=0.60)*	1665.089 1675.245 1671.183 1672.808 1672.158	1204.089 1205.238 1204.778 1204.962 1204.889	450.154 458.804 455.344 456.728 456.174
5b	Weighted moving average for time series with constant k-point value (*k* = 2) and weighs *(w_1=0.30; w_2=0.70)*	1671.437 1677.149 1675.435 1675.950 1675.795	1204.807 1205.454 1205.260 1205.318 1205.301	455.560 460.426 458.966 459.404 459.273
6	Weighted moving average for time series with constant k-point value (*k* = 3) and weighs *(for columns no. 4 and 5: w_1=0.10; w_2=0.20; w_2=0.70; for column no. 3: w_1=0.10; w_2=0.30; w_2=0.60)*	1662.181 1667.153 1667.994 1667.160 1667.410	1205.199 1205.010 1205.243 1205.192 1205.184	452.683 453.006 454.819 454.242 454.234
7	Simple moving average for increasing time series with k-point *k = 2*	1736.756 1791.631 1842.207 1894.933 1946.584	1208.595 1213.004 1216.025 1219.740 1223.108	513.192 560.929 605.504 651.661 697.026
8	Simple moving average for increasing time series with k-point *k = 3*	1698.254 1731.697 1766.594 1791.966 1823.203	1199.509 1198.112 1197.558 1194.422 1192.727	485.620 516.844 551.219 577.699 608.392
9a	Weighted moving average for increasing time series with k-point *k = 3* and weights *(for columns no. 4 and 5: w_1=0.15; w_2=0.25; w_2=0.60; for column no. 3: w_1=0.20; w_2=0.30; w_2=0.50)*	1717.094 1755.260 1795.023 1831.677 1869.565	1206.450 1207.351 1208.841 1209.883 1211.016	505.211 543.100 582.301 620.309 658.597
9b	Weighted moving average for increasing time series with k-point *k = 3* and weights *(for column no. 3: w_1=0.10; w_2=0.30; w_2=0.60; for column no. 4: w_1=0.10; w_2=0.20; w_2=0.70; for column no. 5: w_1=0.50; w_2=0.30; w_2=0.20)*	1730.365 1776.246 1822.088 1867.347 1912.843	1208.646 1210.870 1213.481 1215.922 1218.376	470.570 500.931 533.670 548.722 576.735
10a	Simple single exponential smoothing (Brown's model), $\alpha_{opt.}$ for min. value *Ψ	1727.833 1756.928 1779.589 1797.239 1810.987	1210.222 1212.031 1213.459 1214.585 1215.473	466.125 460.777 458.367 457.281 456.792

Table 1 (continued)
Forecasts of the world steel production

No.	Method	Total (Mt)	BOF (Mt)	EAF (Mt)
10b	Simple single exponential smoothing (Brown's model), $\alpha_{opt.}$ for min. value *RMSE	1707.836 1718.729 1725.565 1729.855 1732.547	1209.308 1210.531 1211.414 1212.050 1212.509	465.195 459.094 456.395 455.201 454.673
11_{a1}	Exponential autoregressive model for k-point ($k = 3$) and l-point (l = 2) and $\alpha_{opt.}$ for min. value *Ψ; β_1=0.7; β_2=0.2; β_3=0.1; δ_1=0.2; δ_2=0.8	1702.327 1737.649 1737.980 1770.564 1775.161	1210.701 1214.230 1217.296 1219.736 1221.858	468.087 445.203 437.374 434.773 435.332
11_{a2}	Exponential autoregressive model for k-point ($k = 3$) and l-point (l = 2) and $\alpha_{opt.}$ for min. value *RMSE; β_1=0.7; β_2=0.2; β_3=0.1; δ_1=0.2; δ_2=0.8	1689.463 1707.054 1688.045 1707.281 1698.021	1210.153 1211.143 1212.428 1213.233 1213.916	467.173 443.875 436.084 433.611 434.246
12_{b1}	Exponential autoregressive model for k-point ($k = 3$) and l-point (l = 2) and $\alpha_{opt.}$ for min. value *Ψ; column no. 3: β_1=0.7; β_2=0.2; β_3=0.1; δ_1=0.8; δ_2=0.2; columns no. 4-5: β_1=0.5; β_2=0.3; β_3=0.2; δ_1=0.8; δ_2=0.2	1732.610 1804.755 1885.117 2005.275 2156.854	1211.453 1214.759 1217.630 1219.561 1221.257	472.756 454.299 441.318 435.408 436.924
12_{b2}	Exponential autoregressive model for k-point ($k = 3$) and l-point (l = 2) and $\alpha_{opt.}$ for min. value *RMSE; column no. 3: β_1=0.7; β_2=0.2; β_3=0.1; δ_1=0.8; δ_2=0.2; columns no. 4-5: β_1=0.5; β_2=0.3; β_3=0.2; δ_1=0.8; δ_2=0.2	1710.050 1735.307 1749.405 1781.783 1809.211	1211.264 1212.262 1213.434 1213.918 1214.524	471.343 451.945 438.917 433.316 435.084
13_{a1}	Exponential autoregressive model for k-point ($k = 2$) and l-point (l = 2) and $\alpha_{opt.}$ for min. value *Ψ; β_1=0.7; β_2=0.3; δ_1=0.8; δ_2=0.2	1731.419 1758.892 1782.800 1806.388 1827.015	1209.972 1213.900 1216.613 1219.041 1221.162	467.374 446.222 436.869 437.219 437.366
13_{a2}	Exponential autoregressive model for k-point ($k = 2$) and l-point (l = 2) and $\alpha_{opt.}$ for min. value *RMSE; β_1=0.7; β_2=0.3; δ_1=0.8; δ_2=0.2	1707.118 1697.032 1691.535 1693.322 1694.511	1209.149 1211.400 1212.509 1213.520 1214.290	466.208 444.573 435.260 435.719 435.912
14_{b1}	Exponential autoregressive model for k-point ($k = 2$) and l-point (l = 2) and $\alpha_{opt.}$ for min. value *Ψ; β_1=0.3; β_2=0.7; δ_1=0.2; δ_2=0.8	1701.872 1725.536 1718.794 1729.058 1733.333	1210.145 1214.459 1216.418 1218.327 1219.891	475.232 468.157 447.300 448.348 448.253
14_{b2}	Exponential autoregressive model for k-point ($k = 2$) and l-point (l = 2) and $\alpha_{opt.}$ for min. value *RMSE; β_1=0.3; β_2=0.7; δ_1=0.2; δ_2=0.8	1694.918 1708.717 1691.944 1696.505 1697.197	1209.829 1212.328 1212.562 1213.409 1214.022	467.115 454.894 432.388 435.464 435.762
15_{a1}	Holt's linear trend model with additive trend for start point $S_1 = y_2$-y_1 and $\alpha_{opt.}$ for min. value *Ψ	1731.578 1772.771 1813.963 1855.156 1896.348	1210.538 1214.134 1217.730 1221.325 1224.921	474.231 476.695 479.159 481.623 484.087
15_{a2}	Holt's linear trend model with additive trend for start point: $S_1 = y_2$-y_1 and $\alpha_{opt.}$ for min. value *RMSE	1727.270 1764.484 1801.697 1838.910 1876.123	1229.149 1251.331 1273.513 1295.695 1317.878	474.516 479.063 483.610 488.158 492.705
16_{a1}	Holt's linear trend model with additive trend for start point: S_1 = 0 and $\alpha_{opt.}$ for min. value *Ψ	1731.569 1772.744 1813.919 1855.094 1896.268	1230.218 1221.245 1212.272 1203.299 1194.326	473.630 475.493 477.356 479.219 481.082

Table 1 (continued)
Forecasts of the world steel production

No.	Method	Total (Mt)	BOF (Mt)	EAF (Mt)
16_{a2}	Holt’s linear trend model with additive trend for start point: $S_1 = 0$ and $\alpha_{opt.}$ for min. value *RMSE	1727.819 1765.165 1802.510 1839.856 1877.202	1224.821 1242.675 1260.530 1278.385 1296.239	471.395 475.453 479.511 483.570 487.628
17_{a1}	Holt’s linear trend model with multiplicative trend for start point $S_1 = y_2/y_1$ and $\alpha_{opt.}$ for min. value *Ψ	1721.978 1754.418 1787.470 1821.144 1855.453	1225.999 1245.332 1264.970 1284.918 1305.181	474.486 477.221 479.972 482.738 485.520
17_{a2}	Holt’s linear trend model with multiplicative trend for start point: $S_1 = y_2/y_1$ and $\alpha_{opt.}$ for min. value *RMSE	1735.098 1780.900 1827.911 1876.163 1925.688	1245.615 1285.497 1326.657 1369.134 1412.972	476.685 482.409 488.202 494.064 499.997
18_{a1}	Holt’s linear trend model with multiplicative trend for start point: $S_1 = 1$ and $\alpha_{opt.}$ for min. value *Ψ	1728.517 1767.612 1807.535 1848.360 1890.106	1241.151 1276.302 1312.448 1349.618 1387.840	473.717 475.674 477.640 479.613 481.595
18_{a2}	Holt’s linear trend model with multiplicative trend for start point: $S_1 = 1$ and $\alpha_{opt.}$ for min. value *RMSE	1735.570 1781.866 1829.397 1878.196 1928.296	1246.615 1287.561 1329.853 1373.533 1418.649	472.925 477.865 482.856 487.898 492.994
19_{a1}	Holt's linear trend model with additive damped trend for start point: $S_1 = y_2 - y_1$ and $\alpha_{opt.}$ for min. valueΨ	1721.800 1712.477 1712.465 1705.616 1699.809	1210.588 1214.214 1217.838 1221.461 1225.082	493.651 489.518 482.553 477.581 474.693
19_{a2}	Holt's linear trend model with additive damped trend for start point: $S_1 = y_2 - y_1$ and $\alpha_{opt.}$ for min. value *RMSE	1726.022 1761.071 1795.627 1829.695 1863.281	1216.221 1223.964 1230.363 1235.587 1239.786	471.688 471.688 471.688 471.688 471.688
20_{a1}	Holt's linear trend model with additive damped trend for start point: $S_1 = 0$ and $\alpha_{opt.}$ for min. value*Ψ	1721.800 1721.477 1713.465 1705.616 1699.809	1210.243 1213.115 1215.603 1217.743 1219.517	471.684 471.684 471.684 471.684 471.684
20_{a2}	Holt's linear trend model with additive damped trend for start point: $S_1 = 0$ and $\alpha_{opt.}$ for min. value *RMSE	1722.856 1754.690 1785.365 1814.924 1843.385	1213.062 1217.829 1221.462 1224.156 1226.073	471.684 471.684 471.684 471.684 471.684
21_{a1}	Holt's linear trend model with multiplicative damped trend for start point: $S_1 = y_2/y_1$ and $\alpha_{opt.}$ for min. value*Ψ	1717.175 1744.691 1772.648 1801.054 1829.914	1206.971 1206.981 1206.991 1207.007 1207.012	473.094 474.425 475.760 477.098 478.440
21_{a2}	Holt's linear trend model with multiplicative damped trend for start point: $S_1 = y_2/y_1$ and $\alpha_{opt.}$ for min. value*RMSE	1731.007 1772.776 1815.553 1859.361 1904.227	1212.224 1217.506 1222.812 1228.141 1233.493	476.102 480.477 484.892 489.347 493.843

Table 1 (continued)
Forecasts of the world steel production

No.	Method	Total (Mt)	BOF (Mt)	EAF (Mt)
22_{a1}	Holt's linear trend model with multiplicative damped trend for start point: S_1 = 1 and α opt. for min. value*Ψ	1727.874 1766.196 1805.369 1845.411 1886.340	1209.653 1212.350 1215.054 1217.764 1220.480	471.700 472.856 474.015 475.177 476.342
22_{a2}	Holt's linear trend model with multiplicative damped trend for start point: S_1 = 1 and α opt. for min. value *RMSE	1731.697 1774.184 1871.714 1862.311 1908.003	1208.708 1210.455 1212.205 1213.957 1215.712	473.880 477.195 480.534 483.896 487.281
23_{a1}	Holt's quadratic trend model with additive formula for point start: $S_1=y_2-y_1$ and α opt. for min. value*Ψ	1862.290 1915.889 1965.536 2023.232 2076.976	1210.250 1209.632 1205.106 1196.673 1184.332	440.563 443.369 449.546 459.094 472.014
23_{a2}	Holt's quadratic trend model with additive formula for point start: $S_1 = y_2-y_1$ and α opt. for min. value *RMSE	1806.171 1856.092 1906.009 1955.921 2005.828	1235.728 1263.626 1290.661 1316.833 1342.142	441.989 444.883 449.850 456.890 466.002
24_{a1}	Holt's quadratic trend model with additive formula for point start: S_1 = 0 and α opt. for min. value*Ψ	1906.375 1966.167 2025.940 2085.693 2145.427	1209.082 1207.651 1202.666 1194.127 1182.035	451.938 456.386 461.005 465.945 471.057
24_{a2}	Holt's quadratic trend model with additive formula for point start: S_1 = 0 and α opt. for min. value *RMSE	1834.603 1889.946 1945.358 2000.838 2056.386	1232.951 1255.747 1275.352 1291.768 1304.995	446.885 450.565 454.691 459.263 464.280
25_{a1}	Brown's double exponential smoothing (linear) and α opt. for min. value*Ψ	1706.754 1732.993 1759.231 1785.470 1811.709	1253.150 1272.900 1292.649 1312.650 1332.149	453.604 460.093 466.582 473.071 479.560
25_{a2}	Brown's double exponential smoothing (linear) and α opt. for min. value *RMSE	1706.917 1733.236 1759.555 1785.875 1812.194	1209.897 1213.054 1216.211 1219.368 1222.525	453.117 459.457 465.797 472.137 478.478
26_{a1}	Brown's triple exponential smoothing (quadratic) and α opt. for min. value*Ψ	1695.716 1709.094 1722.472 1735.850 1749.229	1193.375 1178.536 1163.697 1148.858 1134.019	452.873 459.014 465.155 471.295 477.436
26_{a2}	Brown's triple exponential smoothing (quadratic) and α opt. for min. value *RMSE	1706.909 1720.830 1734.056 1747.630 1761.203	1201.397 1184.734 1168.071 1151.408 1134.746	452.805 458.221 463.636 469.051 474.467
27_{a1}	Advanced exponential autoregressive model and α opt. for min. value*Ψ	1733.301 1776.133 1818.965 1861.797 1904.630	1210.716 1214.531 1218.345 1222.159 1225.974	459.461 475.009 490.557 506.104 521.652

Table 1 (continued)
Forecasts of the world steel production

No.	Method	Total (Mt)	BOF (Mt)	EAF (Mt)
27_{a2}	Advanced exponential autoregressive model and α opt. for min. value *RMSE	1717.326 1755.847 1796.368 1836.890 1877.411	1210.751 1215.609 1220.466 1225.324 1230.182	457.382 472.135 486.887 501.640 516.392
28.	Creep trend and harmonic weights method	1723.048 1755.618 1788.187 1820.187 1853.326	1232.629 1258.295 1283.960 1309.626 1335.292	479.450 487.122 494.794 502.465 510.137
29.	Linear model	1829.988 1884.130 1938.272 1992.414 2046.556	1354.003 1401.010 1448.017 1495.024 1542.031	472.974 482.144 491.314 500.484 509.655
30.	Logarithmic model	1831.222 1885.104 1938.960 1992.789 2046.591	1355.019 1401.797 1448.553 1495.286 1541.995	474.321 483.449 492.573 501.693 510.808

Information about forecast period: a) in 2018 year, b-e) in 2019-2022 for all columns in Table 1.
**Ψ and *RMSE – forecast errors.*
The best models (analysis of forecast errors and R2 for models no. 29-30) were presented on the Figure 2 (point: 3.2).
Source: (Gajdzik, 2018).

Analysis of trends of obtained forecasts for the world steel production

Analyzing the trends of obtained global steel production forecasts (Figure 2), a projected upward tendency is observed. In the optimistic scenario, it can be assumed that steel production in the world in 2022 will exceed 2000 million tonnes (Mt in Table 1). BOF's share (as before) is larger than EAF. The forecasted BOF steel production is growing faster than the predicted EAF steel production. In an optimistic scenario, it may exceed 1500 million tonnes (Mt in Table 1) in 2022.

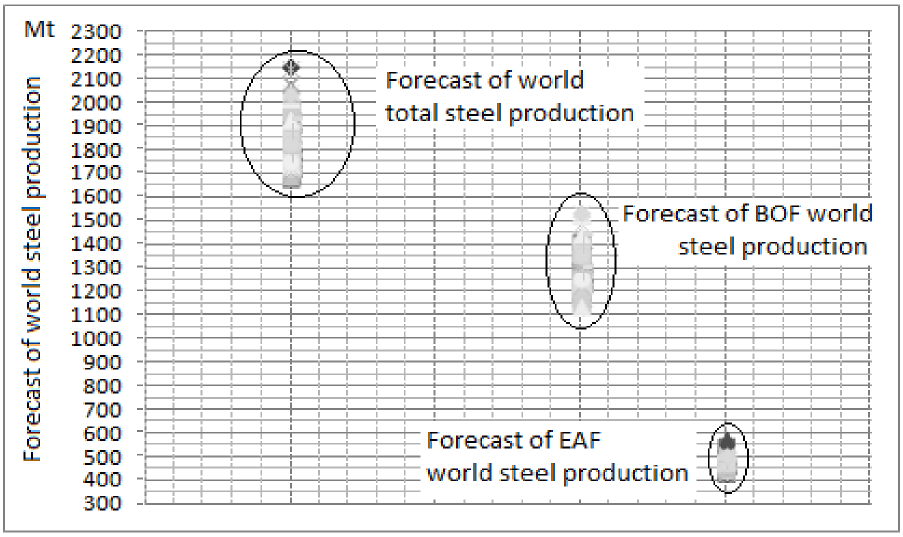

Fig. 2 Forecasts of world steel production

CONCLUSION

The implementation of technology required by Industry 4.0 in steel enterprises (metallurgical market) is implemented gradually, and current investments mainly concern on production automation. Recording production data, which has been extended in steel mills (along with the development of IT), facilitates the analysis of steel production using predictions. The projection of the forecasts presented in the publication (Gajdzik, 2018) indicated growing trends in the volume of steel production in the world, both in terms of forecasting which was total steel production and the following ranges: BOF steel production and EAF steel production.

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Abstract. This paper presents the importance of the prediction of steel production in industry 4.0 along with forecasts for steel production in the world until 2022. In the last two decades, the virtual world has been increasingly entering production. Today's manufacturing systems are becoming faster and more flexible – easily adaptable to new products. Steel is the basic structural material (base material) for many industrial sectors. Industries such as automotive, mechanical engineering, construction and transport use steel in their production processes. Prediction methods in cyber-physical production systems are gaining in importance. The task of prediction is to reduce risk in the decision-making process. In autonomous manufacturing systems in industry 4.0 the role of prediction is more active than passive. Forecasts have the following functions: warning, reaction, prevention, normative, etc. The growing number of customized solutions in industry 4.0 translates into new challenges in the production process. Manufacturers must respond to individual customer needs more quickly, be able to personalize products while reducing energy and resource costs (saving energy and resources can increase the product competitiveness). The modern market becomes increasingly unpredictable. Production prediction under such conditions should be carried out continuously, which is possible because there is more empirical data and access to data. Information from the ongoing monitoring of the company's production is directly transferred to the prospective evaluation. In view of the contemporary reciprocal use of automation, data processing, data exchange and manufacturing techniques, there is greater access to external data, e.g. on production in different target markets and with global, international, national, regional coverage. Companies can forecast in real time, and the forecasts obtained give the possibility to quickly change their production. Industry 4.0 (from the business objective point of view) aims to provide companies with concrete economic benefits – primarily by reducing manufacturing costs, standardizing and stabilizing quality, increasing productivity. Industry 4.0 aims to create a given autonomous smart factory system in which machines, factory components and services communicate and cooperate with each other, producing a personalized product. The aim of this paper is to present new challenges in the production processes in relation to steel production, as well as to prepare and present forecasts of (quantitative) steel production of territorial, global and temporary range until 2022, taking into account the applied production technologies (BOF and EAF). For forecasting purposes, classic trend models and adaptive trend models were used. This methodology was used to build separate forecasts for: total steel production, BOF steel and EAF steel. Empirical data is world steel production in 2000-2017 (annual production volume in Mt).

Keywords: steel production, Industry 4.0, prediction, forecasts