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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; Sandler, 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 al., 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).

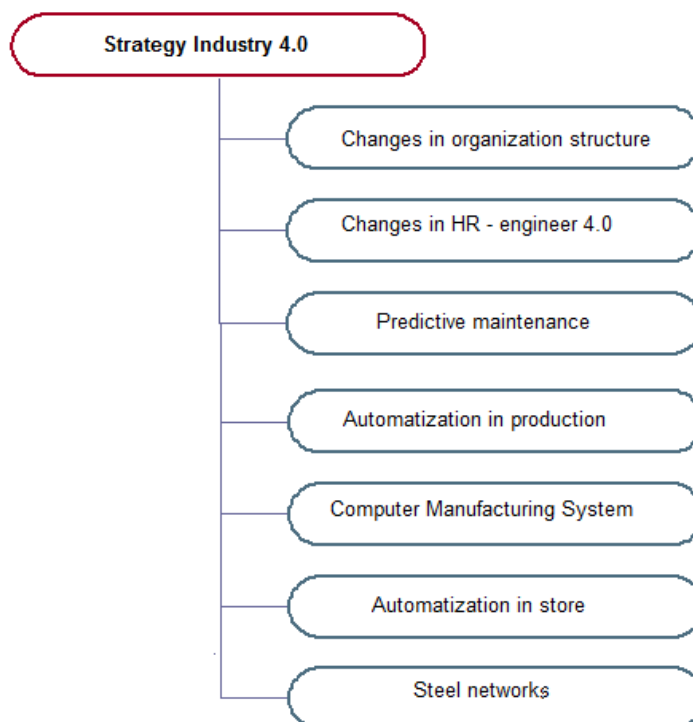


Fig. 1 Fields of changes in an steel enterprise in I 4.0

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), α_{opt} for min. value *RMSE	1707.836	1209.308	465.195
		1718.729	1210.531	459.094
		1725.565	1211.414	456.395
		1729.855	1212.050	455.201
11a1	Exponential autoregressive model for k-point ($k = 3$) and l-point ($l = 2$) and α_{opt} for min. value * Ψ ; $\beta_1=0.7$; $\beta_2=0.2$; $\beta_3=0.1$; $\delta_1=0.2$; $\delta_2=0.8$	1732.547	1212.509	454.673
		1702.327	1210.701	468.087
		1737.649	1214.230	445.203
		1737.980	1217.296	437.374
11a2	Exponential autoregressive model for k-point ($k = 3$) and l-point ($l = 2$) and α_{opt} for min. value *RMSE; $\beta_1=0.7$; $\beta_2=0.2$; $\beta_3=0.1$; $\delta_1=0.2$; $\delta_2=0.8$	1770.564	1219.736	434.773
		1775.161	1221.858	435.332
		1689.463	1210.153	467.173
		1707.054	1211.143	443.875
12b1	Exponential autoregressive model for k-point ($k = 3$) and l-point ($l = 2$) and α_{opt} for min. value * Ψ ; column no. 3: $\beta_1=0.7$; $\beta_2=0.2$; $\beta_3=0.1$; $\delta_1=0.8$; $\delta_2=0.2$; columns no. 4-5: $\beta_1=0.5$; $\beta_2=0.3$; $\beta_3=0.2$; $\delta_1=0.8$; $\delta_2=0.2$	1688.045	1212.428	436.084
		1707.281	1213.233	433.611
		1732.610	1211.453	472.756
		1804.755	1214.759	454.299
12b2	Exponential autoregressive model for k-point ($k = 3$) and l-point ($l = 2$) and α_{opt} for min. value *RMSE; column no. 3: $\beta_1=0.7$; $\beta_2=0.2$; $\beta_3=0.1$; $\delta_1=0.8$; $\delta_2=0.2$; columns no. 4-5: $\beta_1=0.5$; $\beta_2=0.3$; $\beta_3=0.2$; $\delta_1=0.8$; $\delta_2=0.2$	1885.117	1217.630	441.318
		2005.275	1219.561	435.408
		1710.050	1211.264	471.343
		1735.307	1212.262	451.945
13a1	Exponential autoregressive model for k-point ($k = 2$) and l-point ($l = 2$) and α_{opt} for min. value * Ψ ; $\beta_1=0.7$; $\beta_2=0.3$; $\delta_1=0.8$; $\delta_2=0.2$	1749.405	1213.434	438.917
		1781.783	1213.918	433.316
		1809.211	1214.524	435.084
		1731.419	1209.972	467.374
13a2	Exponential autoregressive model for k-point ($k = 2$) and l-point ($l = 2$) and α_{opt} for min. value *RMSE; $\beta_1=0.7$; $\beta_2=0.3$; $\delta_1=0.8$; $\delta_2=0.2$	1758.892	1213.900	446.222
		1782.800	1216.613	436.869
		1806.388	1219.041	437.219
		1827.015	1221.162	437.366
14b1	Exponential autoregressive model for k-point ($k = 2$) and l-point ($l = 2$) and α_{opt} for min. value * Ψ ; $\beta_1=0.3$; $\beta_2=0.7$; $\delta_1=0.2$; $\delta_2=0.8$	1707.118	1209.149	466.208
		1697.032	1211.400	444.573
		1691.535	1212.509	435.260
		1693.322	1213.520	435.719
14b2	Exponential autoregressive model for k-point ($k = 2$) and l-point ($l = 2$) and α_{opt} for min. value *RMSE; $\beta_1=0.3$; $\beta_2=0.7$; $\delta_1=0.2$; $\delta_2=0.8$	1694.511	1214.290	435.912
		1701.872	1210.145	475.232
		1725.536	1214.459	468.157
		1718.794	1216.418	447.300
15a1	Holt's linear trend model with additive trend for start point $S_1 = y_2 - y_1$ and α_{opt} for min. value * Ψ	1729.058	1218.327	448.348
		1733.333	1219.891	448.253
		1694.918	1209.829	467.115
		1708.717	1212.328	454.894
15a2	Holt's linear trend model with additive trend for start point: $S_1 = y_2 - y_1$ and α_{opt} for min. value *RMSE	1691.944	1212.562	432.388
		1696.505	1213.409	435.464
		1697.197	1214.022	435.762
		1731.578	1210.538	474.231
16a1	Holt's linear trend model with additive trend for start point: $S_1 = 0$ and α_{opt} for min. value * Ψ	1772.771	1214.134	476.695
		1813.963	1217.730	479.159
		1855.156	1221.325	481.623
		1896.348	1224.921	484.087
15a2	Holt's linear trend model with additive trend for start point: $S_1 = y_2 - y_1$ and α_{opt} for min. value *RMSE	1727.270	1229.149	474.516
		1764.484	1251.331	479.063
		1801.697	1273.513	483.610
		1838.910	1295.695	488.158
16a1	Holt's linear trend model with additive trend for start point: $S_1 = 0$ and α_{opt} for min. value * Ψ	1876.123	1317.878	492.705
		1731.569	1230.218	473.630
		1772.744	1221.245	475.493
		1813.919	1212.272	477.356
16a1	Holt's linear trend model with additive trend for start point: $S_1 = 0$ and α_{opt} for min. value * Ψ	1855.094	1203.299	479.219
		1896.268	1194.326	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	1224.821	471.395
		1765.165	1242.675	475.453
		1802.510	1260.530	479.511
		1839.856	1278.385	483.570
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	1877.202	1296.239	487.628
		1721.978	1225.999	474.486
		1754.418	1245.332	477.221
		1787.470	1264.970	479.972
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	1821.144	1284.918	482.738
		1855.453	1305.181	485.520
		1735.098	1245.615	476.685
		1780.900	1285.497	482.409
18 _{a1}	Holt's linear trend model with multiplicative trend for start point: $S_1 = 1$ and $\alpha_{opt.}$ for min. value * Ψ	1827.911	1326.657	488.202
		1876.163	1369.134	494.064
		1925.688	1412.972	499.997
		1728.517	1241.151	473.717
18 _{a2}	Holt's linear trend model with multiplicative trend for start point: $S_1 = 1$ and $\alpha_{opt.}$ for min. value *RMSE	1767.612	1276.302	475.674
		1807.535	1312.448	477.640
		1848.360	1349.618	479.613
		1890.106	1387.840	481.595
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. value Ψ	1735.570	1246.615	472.925
		1781.866	1287.561	477.865
		1829.397	1329.853	482.856
		1878.196	1373.533	487.898
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	1928.296	1418.649	492.994
		1721.800	1210.588	493.651
		1712.477	1214.214	489.518
		1712.465	1217.838	482.553
20 _{a1}	Holt's linear trend model with additive damped trend for start point: $S_1 = 0$ and $\alpha_{opt.}$ for min. value * Ψ	1705.616	1221.461	477.581
		1699.809	1225.082	474.693
		1726.022	1216.221	471.688
		1761.071	1223.964	471.688
20 _{a2}	Holt's linear trend model with additive damped trend for start point: $S_1 = 0$ and $\alpha_{opt.}$ for min. value *RMSE	1795.627	1230.363	471.688
		1829.695	1235.587	471.688
		1863.281	1239.786	471.688
		1721.800	1210.243	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	1721.477	1213.115	471.684
		1713.465	1215.603	471.684
		1705.616	1217.743	471.684
		1699.809	1219.517	471.684
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	1722.856	1213.062	471.684
		1754.690	1217.829	471.684
		1785.365	1221.462	471.684
		1814.924	1224.156	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	1843.385	1226.073	471.684
		1717.175	1206.971	473.094
		1744.691	1206.981	474.425
		1772.648	1206.991	475.760
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	1801.054	1207.007	477.098
		1829.914	1207.012	478.440
		1731.007	1212.224	476.102
		1772.776	1217.506	480.477
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	1815.553	1222.812	484.892
		1859.361	1228.141	489.347
		1904.227	1233.493	493.843
		1731.007	1212.224	476.102

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 $\alpha_{opt.}$ for min. value* Ψ	1727.874	1209.653	471.700
		1766.196	1212.350	472.856
		1805.369	1215.054	474.015
		1845.411	1217.764	475.177
22 _{a2}	Holt's linear trend model with multiplicative damped trend for start point: $S_1 = 1$ and $\alpha_{opt.}$ for min. value *RMSE	1886.340	1220.480	476.342
		1731.697	1208.708	473.880
		1774.184	1210.455	477.195
		1871.714	1212.205	480.534
23 _{a1}	Holt's quadratic trend model with additive formula for point start: $S_1 = y_2 - y_1$ and $\alpha_{opt.}$ for min. value* Ψ	1862.311	1213.957	483.896
		1908.003	1215.712	487.281
		1862.290	1210.250	440.563
		1915.889	1209.632	443.369
23 _{a2}	Holt's quadratic trend model with additive formula for point start: $S_1 = y_2 - y_1$ and $\alpha_{opt.}$ for min. value *RMSE	1965.536	1205.106	449.546
		2023.232	1196.673	459.094
		2076.976	1184.332	472.014
		1806.171	1235.728	441.989
24 _{a1}	Holt's quadratic trend model with additive formula for point start: $S_1 = 0$ and $\alpha_{opt.}$ for min. value* Ψ	1856.092	1263.626	444.883
		1906.009	1290.661	449.850
		1955.921	1316.833	456.890
		2005.828	1342.142	466.002
24 _{a2}	Holt's quadratic trend model with additive formula for point start: $S_1 = 0$ and $\alpha_{opt.}$ for min. value *RMSE	1906.375	1209.082	451.938
		1966.167	1207.651	456.386
		2025.940	1202.666	461.005
		2085.693	1194.127	465.945
25 _{a1}	Brown's double exponential smoothing (linear) and $\alpha_{opt.}$ for min. value* Ψ	2145.427	1182.035	471.057
		1834.603	1232.951	446.885
		1889.946	1255.747	450.565
		1945.358	1275.352	454.691
25 _{a2}	Brown's double exponential smoothing (linear) and $\alpha_{opt.}$ for min. value *RMSE	2000.838	1291.768	459.263
		2056.386	1304.995	464.280
		1706.754	1253.150	453.604
		1732.993	1272.900	460.093
26 _{a1}	Brown's triple exponential smoothing (quadratic) and $\alpha_{opt.}$ for min. value* Ψ	1759.231	1292.649	466.582
		1785.470	1312.650	473.071
		1811.709	1332.149	479.560
		1706.917	1209.897	453.117
26 _{a2}	Brown's triple exponential smoothing (quadratic) and $\alpha_{opt.}$ for min. value *RMSE	1733.236	1213.054	459.457
		1759.555	1216.211	465.797
		1785.875	1219.368	472.137
		1812.194	1222.525	478.478
27 _{a1}	Advanced exponential autoregressive model and $\alpha_{opt.}$ for min. value* Ψ	1695.716	1193.375	452.873
		1709.094	1178.536	459.014
		1722.472	1163.697	465.155
		1735.850	1148.858	471.295
27 _{a2}	Brown's triple exponential smoothing (quadratic) and $\alpha_{opt.}$ for min. value *RMSE	1749.229	1134.019	477.436
		1706.909	1201.397	452.805
		1720.830	1184.734	458.221
		1734.056	1168.071	463.636
27 _{a3}	Advanced exponential autoregressive model and $\alpha_{opt.}$ for min. value* Ψ	1747.630	1151.408	469.051
		1761.203	1134.746	474.467
		1733.301	1210.716	459.461
		1776.133	1214.531	475.009
27 _{a4}	Advanced exponential autoregressive model and $\alpha_{opt.}$ for min. value* Ψ	1818.965	1218.345	490.557
		1861.797	1222.159	506.104
		1904.630	1225.974	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	1210.751	457.382
		1755.847	1215.609	472.135
		1796.368	1220.466	486.887
		1836.890	1225.324	501.640
		1877.411	1230.182	516.392
28.	Creep trend and harmonic weights method	1723.048	1232.629	479.450
		1755.618	1258.295	487.122
		1788.187	1283.960	494.794
		1820.187	1309.626	502.465
		1853.326	1335.292	510.137
29.	Linear model	1829.988	1354.003	472.974
		1884.130	1401.010	482.144
		1938.272	1448.017	491.314
		1992.414	1495.024	500.484
		2046.556	1542.031	509.655
30.	Logarithmic model	1831.222	1355.019	474.321
		1885.104	1401.797	483.449
		1938.960	1448.553	492.573
		1992.789	1495.286	501.693
		2046.591	1541.995	510.808

Information about forecast period: a) in 2018 year, b-e) in 2019-2022 for all columns in Table 1.

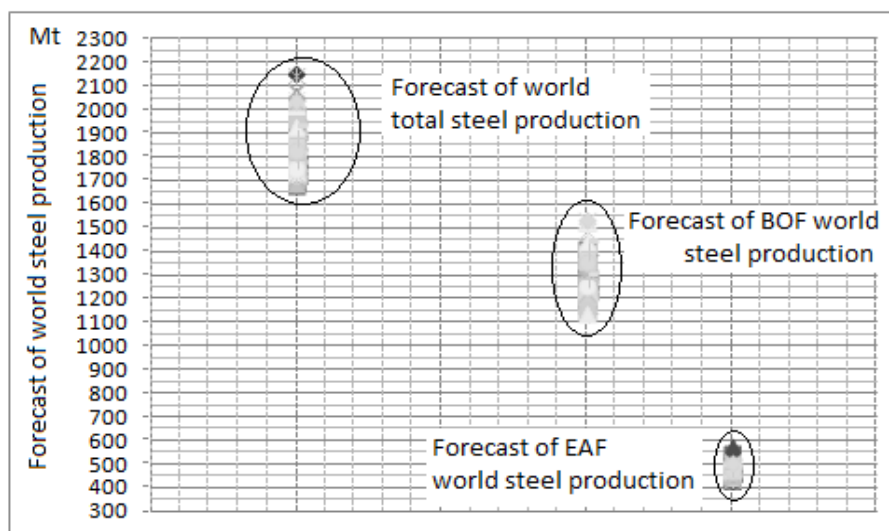
* Ψ and *RMSE – forecast errors.

The best models (analysis of forecast errors and R^2 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