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STEEL INDUSTRY 4.0 IN THE PERSPECTIVE OF FORECASTED QUANTITIES OF STEEL PRODUCTION IN THE WORLD

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Abstract: The development of new production systems during the fourth industrial revolution is called Industry 4.0. Production in industry 4.0 is carried out by industrial robots with intelligence computers using the Internet to control and communicate devices and man with devices and to integrate all processes inside and outside the enterprise within the supply chain using all possible technical solutions to connect the virtual world and the real world. Particular branches of industry in the world invest in new technology. New technology is implemented in the metallurgical industry, too. Managers in enterprises in the steel industry want to know how trends in steel production will be in the future. The key aim of this publication is to present forecasts of steel production quantities in the world until 2022.

Keywords: Industry 4.0, world steel production, forecasts of steel production.

1. Introduction

The steel industry is a very complex sector, with which the global economy as a whole is inextricably linked. Steel products are needed in many industries, such as in the automotive, construction and other industries. The steel industry consists of several large companies operating globally and with a significant share of production, as well as many small businesses operating on a lesser scale. The largest steel producers are consolidated into large international corporations (e.g. ArcelorMittal, created in 2006 as a result of the merger of Arcelor and Mittal Steel) (Gajdzik, and Sroka, 2012). The steel industry is subject to constant changes under the influence of market trends. Economic transformations in the post-socialist countries of Central and Eastern Europe significantly accelerated the changes introduced in the steel sector in such countries as: Poland, Romania, Slovakia, Croatia and others (Gajdzik, 2013). The rapidity of changes introduced in the steel industry in the second half of the last century was called restructuring, and its aim was to obtain and increase the competitiveness of the sector. Assuming that the steel industry restructuring processes in individual regions of the world

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concluded with the end of the last century, the steel industry in the XXI century has entered new possibilities of development, despite the fact that steel production is highly material and energy-consuming, and the raw materials needed to manufacture steel products are unevenly geographically distributed. The steelmaking technologies used in the industry have not fundamentally changed over the past few decades. The key converter technologies are the converter process (BOF − *Basic Oxygen Furnace*) and electric process (EAF − *Electric Arc Furnace*). The applied technologies are subject to innovation in order to adapt them especially to environmental protection requirements, as well as to increase productivity (Little, 1989). Steel enterprises (steel mills) invest in unconventional technologies that enable steel production without emissions (Birat, 2002; Garbarz, 2008). In addition to technological investments, according to industry reports (Deloitte, 2018, p. 22), innovation is more than half of innovation. The second decade of the XXI century has created a challenge for the steel sector in the context of new driving forces of the industrial revolution, such as IT and Internet infrastructure (IoT – Internet of Things), and its basic element is data (Big Data).

The aim of this publication is to present an overview of the capabilities of the steel industry in pursuit of industry 4.0, with an emphasis on the forecasted volume of steel production in the world until 2022. These forecasts are the result of own work and will form the basis for further long-term and medium-term analyses of the development of the steel industry. The work consists of two parts:

Section 1: Describes how steel enterprises adjust to industry 4.0.

Section 2: Sshows the main trends in steel production forecasts in the world.

The work ends with a conclusion of the final application based on the direction of forecast trends.

2. Steel enterprises in the perspective of industry 4.0

The fourth industrial revolution is focused on information and data processing (Big Data, Data Analysis). Industry 4.0 is the integration of cyber-physical systems in various objects and spatial systems, including in the field of cyber-physical production systems of various industries (CPPS − cyber-physical production systems) (Lasi, and Fettke, Feld, Hoffmann, 2014; Kunal Suri et al., 2017) as part of a coopetition network (Cygler, Gajdzik, and Sroka, 2014). New cooperation systems integrate people with digitally controlled machines that widely use the Internet and information technologies. Information in the XXI century is to be used at any time and from any place.

The new possibilities brought by the industry 4.0 translate into increased productivity and higher production economy, as well as an increase of individualised products produced in short production series. The implementation of changes in production enterprises is carried out at strategic and operational levels. Initiating changes falls within the domain of top management. The decision to proceed with changes requires modification of a company's mission and vision of development. In enterprises at industry level 4.0 (at the beginning of their evolution), new management positions are created (e.g. industry director 4.0, main CPPS technology, data analysis director), along with new teams (e.g. data analysis team, preventive maintenance team (UR)). The existing organisational structures are subject to radical, and over time, the mapping of work organisation in the form of real organisational structures will not be necessary. The existing structure will be lined with a network of virtual circuits a "smart" or "clever", "cute", "elastic". Enterprises, by adapting the organisation of production to industry-specific 4.0 solutions, usually first select a certain part of production (important for the implementation of business) and adapt it to the requirements of the cyber-physical system (this solution is referred to as an island of cyber-physical production). The basis for industry 4.0 is the achievement by enterprises of significant or full automation of production and robotisation activities. Investments in advanced technologies are a long-term activity, which means that after the completion of some investments, further ones are implemented (Report, PWC, 2018).

Industry 4.0 is a challenge for individual industries and sectors of the economy. In the steel industry, the digitisation of business functions (digitisation) and technological processes and marketing, as well as administrative and management innovations, intensified at the end of the previous century, which determine the competitiveness of individual enterprises. Based on industry reports (Deloitte, 2017, p. 22), the following structure of innovation in the steel industry can be adopted: more than 50% are process innovations, approx. 30% are product innovations, and about 10% are marketing and administrative innovations. Important areas of innovation include: staff development, advanced manufacturing technology, research and development (R & D), digitisation of business functions, marketing research and analysis, licenses, patents. The areas of advanced manufacturing technology in the steel industry are: energy-saving production technologies, alternative energy sources, electronic document management, full automation of processes, advanced computer production support systems: ERP, CRM, SAP and others, Big Data, computer integration of processes, Internet of Things, cyber-physical systems and technological lines. The largest investments in recent years in the steel sector have been made in: Electronic Documents Management (EDM), advanced computer systems (supporting manufacturing processes), e.g. ERP and technologies that reduce energy consumption while diversifying it. The steel sector invests in advanced manufacturing technologies. However, the implementation of changes in the timing of individual regions of the world can be shifted by up to two decades. It is conventionally assumed that the development of cyber-physical production systems will take place in 2020-2030. The implementation of innovations at the 4.0 industry level by steel enterprises is conditioned by their financial capabilities and the current level of automation of manufacturing processes, as well as the degree of electronic (computer) handling of individual functions. It is much easier to implement innovations in large metallurgical enterprises belonging to international capital groups than it is to smaller enterprises (a result of the experience curve, financial capital, market share, etc.). Based on the research published by industry and consulting organisations on the adaptation of changes in the steel sector at the level of industry 4.0, it can be concluded that this process has been initiated, especially in regions where steel thought has a strong competitive position. Although steel production technologies have not changed for many years, the steel industry has carried out significant work to optimise production at various stages of business development, and above all, it strives to improve energy efficiency (energy intensity has been reduced by approx. half over the last 40 years) and to reduce the emissions of production pollutants. Examples of investments in the steel sector are: 3D printers used in steelworks, e.g. in the Severstal Group for the production of casting models (Cherepovets steel plant) (Deloitte, 2018), robotic storage and service centres (Thyssen EnergoStal), steel products with high added value, e.g. personalised steel structures and others obtained as part of the improved metalworking technology. The model of building personalised steel products is based on large (key) customers, which include: construction companies, fuel and energy recipients, transport companies, machine building industry. The SME segment, which also acquires metal products, is a secondary area. In the steel industry, there are currently several regional research initiatives around the world, such as the AISI Technology Roadmap programme in the US (http://steeltrp.com/), the Ultra-Low Carbon Steel Dioxide (ULCOS) project in Europe (http://www.ulcos.org), POSCO CO 2 Breakthrough Framework in Korea (http://www.posco.com/) and the COURSE50 programme in Japan (http://www.jisf.or.jp/).

3. Forecasts of steel production in the world

Investments in new technologies depend on the demand for steel products. In the perspective of the next few years, a 0.5% annual growth in steel production in the world is expected, with an increase in global consumption by 1.3% (Deloitte, 2018). Global steel production has been growing since the 1970s, from 595 million tonnes (Mt) in 1970 to 1,690 million tonnes (Mt) in 2017 (Worldsteel 2010, 2017, 2018). Geographically, steel production is concentrated in Asia (over 65% of world production volume). Since 2004, global steel production has exceeded 1,000 million tonnes (Mt) of steel produced during the year. Figure 1 shows steel production in the world in the years 2000-2017.

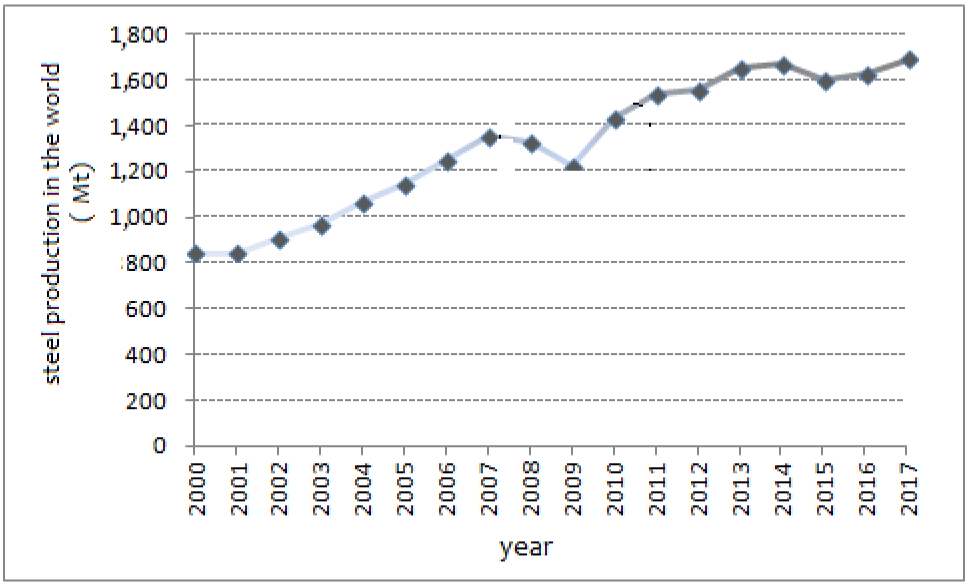

Figure 1. Steel production in the world in 2000-2017 (reports: Worldsteel 2010, Worldsteel 2017, Worldsteel 2018).

The annual volume of steel production in the world (in millions of tonnes) for the period 2000-2017 was used to determine forecasts for the period 2018-2022. The methodology of forecasting consisted in applying both classic methods of forecasting extrapolation of linear and nonlinear trends of the studied phenomenon, as well as adaptive methods, advanced exponential-autoregressive models and forecasting by the creeping trend method using harmonic weights. In particular adaptive methods, the following methods were used: the naïve method in the additive and multiplicative approach, the method of the moving average straight line for the time series shaped around the average value (constant) for various starting points (*k*), the weighted moving average method for the time series around the average value (constant) for different starting points (*k*) and different weights (w_i), the moving average straight method for the time series around the development trend for different starting points (*k*), methods the weighted average moving around the development trend for different starting points (*k*) and different weights (w_i), the simple exponential smoother smoothing model for different starting points in the α optimisation due to the value of forecast errors: Ψ and RMSE, a single exponential smoothing model for various start points in the α optimisation due to the value of forecast errors: Ψ and RMSE (formulas 1-2), the exponential-autoregressive model (for different: *k* and l and different values: β i δ) while optimising α due to the value of forecast errors: Ψ and RMSE, the Holt linear model with the additive and multiplicative trend (for different starting mechanisms $S_1 = 0$, $S_1 = y_2 - y_1$, $S_1 = y_2 / y_1$, $S_1 = 1$) due to the minimum value Ψ and RMSE, the Holt linear model with the extinction effect of the additive or multiplicative trend for different boot mechanisms and due to the minimum value of forecast errors, Brown's double exponential smoothing model for the linear model, the triple exponential smoothing model for the square model. The results of forecasting using the aforementioned models are summarised in Table 1.

Used formulas:

$$RMSE = \sqrt{\frac{1}{n-m}\sum_{t=m+1}^{n}(y_t - y_t^*)^2} \qquad (1)$$

$$\Psi = \frac{1}{n-m}\sum_{t=m+1}^{n}\frac{\left|y_t - y_t^*\right|}{y_t} \qquad (2)$$

In formulas 1 & 2, y_t is an empirical value, i.e. realisation of variable y in a t period of time ($t \in \overline{1,T}$); y_t^* is the forecast value; n is the number of elements of the time series; m is the number of initial time moments t, for which an expired forecast has not been carried out or is being treated as a part of necessary start-up mechanism.

The optimisation of the point forecast value was based on the search for the minimum value of one of the above-mentioned errors, treated as the optimisation criterion.

Table 1.
Forecasts of steel production in the world until 2022

No	**Prognostic method/model**		**total**	**Forecast error *ex post***		**Additional information about models**
			Mt	Ψ	*RMSE*	
1.	Additive naïve method (forecast for 2018)		1,690.479	0.0558	87.482	-
2.	Multiplicative naïve method with increasing tendency	2018 2019 2020 2021 2022	1,756.430 1,824.955 1,896.152 1,970.128 2,046.128	0.0550	106.746	
3.	Simple moving average for time series with constant (average) *k*-point value *k = 2*	2018 2019 2020 2021 2022	1,658.742 1,674.610 1,666.676 1,670.643 1,668.659	0.0762	112.358	*k* = 2
4.	Simple moving average for time series with constant (average) *k*-point value *k = 3*	2018 2019 2020 2021 2022	1,638.470 1,651.984 1,660.311 1,654.183 1,666.120	0.0905	134.326	*k* = 3
5a.	Weighted moving average for time series with constant *k*-point value (k = 2) and weights w_i (w_1 = 0.40 and w_2 = 0.60)	2018 2019 2020 2021 2022	1,665.089 1,675.245 1,671.183 1,672.808 1,672.158	0.0721	106.820	k = 2 w_1 = 0.40 w_2 = 0.60
5b.	Weighted moving average for time series with constant *k*-point value (k = 2) and weights w_i (w_1 = 0.30 and w_2 = 0.70)	2018 2019 2020 2021 2022	1,671.437 1,677.149 1,675.435 1,675.950 1,675.795	0.0683	101.756	k = 2 w_1 = 0.30 w_2 = 0.70
6.	Weighted moving average for time series with constant *k*-point value (k = 3) and weights w_i (w_1 = 0.10; w_2 = 0.30 and w_3 = 0.60)	2018 2019 2020 2021 2022	1,662.181 1,667.153 1,667.994 1,667.160 1,667.410	0.0747	110.947	k = 3 w_1 = 0.10 w_2 = 0.30 w_3 = 0.60

Cont. table 1.

7.	Simple moving average for increasing time series with *k*-point *k = 2*	2018 2019 2020 2021 2022	1,736.756 1,791.631 1,842.207 1,894.933 1,946.584	0.0548	104.878	$k = 2$
8.	Simple moving average for increasing time series with *k*-point *k = 3*	2018 2019 2020 2021 2022	1,698.254 1,731.697 1,766.594 1,791.966 1,823.203	0.0510	94.109	$k = 3$
9a.	Simple moving average with weights ($w_1 = 0.20$; $w_2 = 0.30$ and $w_3 = 0.50$) for increasing time series with k-point $k = 3$	2018 2019 2020 2021 2022	1,717.094 1,755.260 1,795.023 1,831.677 1,869.565	0.0495	96.161	$k = 3$ $w_1 = 0.20$ $w_2 = 0.30$ $w_3 = 0.50$
9b.	Simple moving average with weights ($w_1 = 0.10$; $w_2 = 0.30$ and $w_3 = 0.60$) for increasing time series with k-point $k = 3$	2018 2019 2020 2021 2022	1,730.365 1,776.246 1,822.088 1,867.347 1,912.843	0.0505	100.327	$k = 3$ $w_1 = 0.10$ $w_2 = 0.30$ $w_3 = 0.60$
10a.	Simple exponential smoothing (Brown's model) for start point: $y^*_{t=1} = y_1$ and α opt. for Ψ	2018 2019 2020 2021 2022	1,689.835 1,689.835 1,689.835 1,689.835 1,689.835	0.0529	85.288	Ψ for $\alpha_{opt} = 0.9899$
10b.	Simple exponential smoothing (Brown's model) for start point: $y^*_{t=1} = y_1$ and α opt. for RMSE	2018 2019 2020 2021 2022	1,687.800 1,687.800 1,687.800 1,687.800 1,687.800	0.0537	86.187	RMSE for α_{opt} = 0.9585
11a.	Simple exponential smoothing (Brown's model) for start point: $y^*_{t=1}$ = averange (y_1:y_6) and α opt. for Ψ	2018 2019 2020 2021 2022	1,690.466 1,690.466 1,690.466 1,690.466 1,690.466	0.0603	89.285	Ψ for $\alpha_{opt} = 0.9998$
11b.	Simple exponential smoothing (Brown's model) for start point: $y^*_{t=1}$ = averange (y_1:y_6) and α opt. for RMSE	2018 2019 2020 2021 2022	1,690.473 1,690.473 1,690.473 1,690.473 1,690.473	0.0603	89.283	RMSE for α_{opt} = 0.9999
12a.	Single exponential smoothing (Brown's model) for: α opt. for Ψ	2018 2019 2020 2021 2022	1,727.833 1,756.928 1,779.589 1,797.239 1,810.987	0.0498	89.610	Ψ for $\alpha_{opt} = 0.7789$
12b.	Single exponential smoothing (Brown's model) for: α opt. for RMSE	2018 2019 2020 2021 2022	1,707.836 1,718.729 1,725.565 1,729.855 1,732.547	0.0531	85.354	RMSE for α_{opt} = 0.2716
$13_{a1.}$	Exponential autoregressive model for: $k = 3$ and $l = 2$, and with α opt. for Ψ	2018 2019 2020 2021 2022	1,702.327 1,737.649 1,737.980 1,770.564 1,775.161	0.0607	102.857	$k = 3$ and $l = 2$ with $\beta_1 = 0.7$ $\beta_2 = 0.2$ $\beta_3 = 0.1$ $\delta_1 = 0.2$ $\delta_2 = 0.8$ Ψ for $\alpha_{opt} = 0.7912$

Cont. table 1.

$13_{a2.}$	Exponential autoregressive model for: $k = 3$ and $l = 2$, and with α opt. for RMSE	2018 2019 2020 2021 2022	1,689.463 1,707.054 1,688.045 1,707.281 1,698.021	0.0616	99.585	$k = 3$ and $l = 2$, and with $\beta_1 = 0.7$ $\beta_2 = 0.2$ $\beta_3 = 0.1$ $\delta_1 = 0.2$ $\delta_2 = 0.8$ RMSE for $\alpha_{opt} = 0.6944$
$13_{b1.}$	Exponential autoregressive model for different β or δ (according to model 13a), and with α opt. for Ψ	2018 2019 2020 2021 2022	1,732.610 1,804.755 1,885.117 2,005.275 2,156.854	0.0493	94.304	$\beta_1 = 0.7$ $\beta_2 = 0.2$ $\beta_3 = 0.1$ $\delta_1 = 0.8$ $\delta_2 = 0.2$ Ψ for $\alpha_{opt} = 0.8812$
$13_{b2.}$	Exponential autoregressive model for different β or δ (according to model 13a), and with α opt. for RMSE	2018 2019 2020 2021 2022	1,710.050 1,735.307 1,749.405 1,781.783 1,809.211	0.0517	87.435	$\beta_1 = 0.7$ $\beta_2 = 0.2$ $\beta_3 = 0.1$ $\delta_1 = 0.8$ $\delta_2 = 0.2$ RMSE for $\alpha_{opt} = 0.6944$
$14_{a1.}$	Exponential autoregressive model for: $k = 2$ and $l = 2$, and with α opt. for Ψ	2018 2019 2020 2021 2022	1,731.419 1,758.892 1,782.800 1,806.388 1,827.015	0.0494	94.167	$k = 2$ and $l = 2$, and with $\beta_1 = 0.7$ $\beta_2 = 0.3$ $\delta_1 = 0.8$ $\delta_2 = 0.2$ Ψ for $\alpha_{opt} = 0.8839$
$14_{a2.}$	Exponential autoregressive model for: $k = 2$ and $l = 2$, and with α opt. for RMSE	2018 2019 2020 2021 2022	1,707.118 1,697.032 1,691.535 1,693.322 1,694.511	0.0528	86.823	$k = 2$ and $l = 2$, and with $\beta_1 = 0.7$ $\beta_2 = 0.3$ $\delta_1 = 0.8$ $\delta_2 = 0.2$ RMSE for $\alpha_{opt} = 0.6903$
$14_{b1.}$	Exponential autoregressive model for: $k = 2$ and $l = 2$, and with α opt. for Ψ and for different β or δ (according to model 14a)	2018 2019 2020 2021 2022	1,701.872 1,725.536 1,718.794 1,729.058 1,733.333	0.0616	99.749	$k = 2$ and $l = 2$, and with $\beta_1 = 0.3$ $\beta_2 = 0.7$ $\delta_1 = 0.2$ $\delta_2 = 0.8$ Ψ for $\alpha_{opt} = 0.7839$
$14_{b.2.}$	Exponential autoregressive model for: $k = 2$ and $l = 2$, and with α opt. for RMSE, and for different β or δ (according to model 14a)	2018 2019 2020 2021 2022	1,694.918 1,708.717 1,691.944 1,696.505 1,697.197	0.0624	98.359	$k = 2$ and $l = 2$, and with $\beta_1 = 0.3$ $\beta_2 = 0.7$ $\delta_1 = 0.2$ $\delta_2 = 0.8$ RMSE for $\alpha_{opt} = 0.7144$
$15_{a1.}$	Holt's linear trend model with additive trend for start movement: $S_1 = y_2 - y_1$, and with α opt. and β opt. for Ψ	2018 2019 2020 2021 2022	1,731.578 1,772.771 1,813.963 1,855.156 1,896.348	0.0464	90.392	Ψ for $\alpha_{opt} = 0.9983$ Ψ for $_{\beta opt.} = 0.6027$
$15_{a2.}$	Holt's linear trend model with additive trend for start move: $S_1 = y_2 - y_1$, and with α opt. and β opt. for RMSE	2018 2019 2020 2021 2022	1,727.270 1,764.484 1,801.697 1,838.910 1,876.123	0.0502	80.156	RMSE: α = 0.9856 β = 0.1092
$16_{a1.}$	Holt's linear trend model with additive trend for $S_1 = 0$, and with α opt. and β opt. for Ψ	2018 2019 2020 2021 2022	1,731.569 1,772.744 1,813.919 1,855.094 1,896.268	0.0467	90.432	Ψ: α = 0.9985 β = 0.6023
$16_{a2.}$	Holt's linear trend model with additive trend for $S_1 = 0$, and with α opt. and β opt. for RMSE	2018 2019 2020 2021 2022	1,727.819 1,765.165 1,802.510 1,839.856 1877,202	0.0505	80.459	RMSE: α = 0.9998 β = 0.1190

Cont. table 1.

17 a1.	Holt's linear trend model with multiplicative trend for $S_1 = y_2/y_1$, and with *α* opt. and β opt. for Ψ	2018 2019 2020 2021 2022	1,721.978 1,754.418 1,787.470 1,821.144 1,855.453	0.0507	81.649	Ψ: α = 0.9899 β = 0.0316
17 a2.	Holt's linear trend model with multiplicative trend for $S_1 = y_2/y_1$, and with *α* opt. and β opt. for RMSE	2018 2019 2020 2021 2022	1,735.098 1,780.900 1,827.911 1,876.163 1,925.688	0.0507	80.721	RMSE: α = 0.9998 β = 0.0628
18 a1.	Holt's linear trend model with multiplicative trend for $S_1 = 1$, and with *α* opt. and β opt. for Ψ	2018 2019 2020 2021 2022	1,728.517 1,767.612 1,807.535 1,848.360 1,890.106	0.0464	89.520	Ψ: α = 0.9984 β = 0.4930
18 a2.	Holt's linear trend model with multiplicative trend for $S_1 = 1$, and with *α* opt. and β opt. for RMSE	2018 2019 2020 2021 2022	1,735.570 1,781.866 1,829.397 1,878.196 1,928.296	0.0515	81.282	RMSE: α = 0,9999 β = 0,0712
19 a1.	Holt's linear trend model with additive damped trend for $S_1 = y_2 - y_1$ and with: *α* opt., β opt and. φ opt. for Ψ	2018 2019 2020 2021 2022	1,721.800 1,712.477 1,712.465 1,705.616 1,699.809	0.0468	84.388	Ψ: α = 0.9999 β = 0.9999 φ = 0.4949
19a2.	Holt's linear trend model with additive damped trend for $S_1 = y_2 - y_1$, and with: *α* opt., β opt and. φ opt. for RMSE	2018 2019 2020 2021 2022	1,726.022 1,761.071 1,795.627 1,829.695 1,863.281	0.0468	80.119	RMSE: α = 0.9793 β = 0.0001 φ = 0.4156
20 a1.	Holt's linear trend model with additive damped trend for $S_1 = 0$, and with: *α* opt., β opt and. φ opt. for Ψ	2018 2019 2020 2021 2022	1,721.800 1,721.477 1,713.465 1,705.616 1,699.809	0.0469	84.309	Ψ: α = 0.9999 β = 0.9999 φ = 0.4949
20a2.	Holt's linear trend model with additive damped trend for $S_1 = 0$, and with: *α* opt., β opt and. φ opt. for RMSE	2018 2019 2020 2021 2022	1,722.856 1,754.690 1,785.365 1,814.924 1,843.385	0.0504	80.545	RMSE: α = 0.9899 β = 0.1307 φ = 0.9820
21a1.	Holt's linear trend model with multiplicative damped trend for $S_1 = y_2/y_1$, and with: *α* opt., β opt and. φ opt. for Ψ	2018 2019 2020 2021 2022	1,717.175 1,744.691 1,772.648 1,801.054 1,829.914	0.0510	82.104	Ψ: α = 0.9899 β = 0.0316 φ = 0.9998
21a2.	Holt's linear trend model with multiplicative damped trend for $S_1 = y_2/y_1$, and with: *α* opt., β opt and. φ opt. for RMSE	2018 2019 2020 2021 2022	1,731.007 1,772.776 1,815.553 1,859.361 1,904.227	0.0501	80.928	RMSE: α = 0.9899 β = 0.0628 φ = 0.9998
22a1.	Holt's linear trend model with multiplicative damped trend for $S_1 = 1$, and with: *α* opt.; β opt and. φ opt. for Ψ	2018 2019 2020 2021 2022	1,727.874 1,766.196 1,805.369 1,845.411 1,886.340	0.0465	89.458	Ψ: α = 0.9982 β = 0.4935 φ = 0.9998

Cont. table 1.

$22_{a2.}$	Holt's linear trend model with multiplicative damped trend for $S_1 = 1$, and with: *α* opt., β opt and. φ opt. for RMSE	2018 2019 2020 2021 2022	1,731.697 1,774.184 1,871.714 1,862.311 1,908.003	0.0517	81.477	RMSE: α = 0.9899 β = 0.0712 φ = 0.9998
$23_{a1.}$	Holt's quadratic trend model with additive formula for $S_1 = y_2\text{-}y_1$, and with: *α* opt., β opt and. φ opt. for Ψ	2018 2019 2020 2021 2022	1,862.290 1,915.889 1,965.536 2,023.232 2,076.976	0.0393	70.727	Ψ: α = 0.0001 β = 0.2315 φ = 0.3017
$23_{a2.}$	Holt's quadratic trend model with additive formula for $S_1 = y_2\text{-}y_1$, and with: *α* opt., β opt and. φ opt. for RMSE	2018 2019 2020 2021 2022	1,806.171 1,856.092 1,906.009 1,955.921 2,005.828	0.0409	64.960	RMSE: α = 0.0001 β = 0.2600 φ = 0.3789
$24_{a1.}$	Holt's quadratic trend model with additive formula for $S_1 = 0$, and with: *α* opt., β opt and. φ opt. for Ψ	2018 2019 2020 2021 2022	1,906.375 1,966.167 2,025.940 2,085.693 2,145.427	0.0390	78.668	Ψ: α = 0.0001 β = 0.5397 φ = 0.9999
$24_{a2.}$	Holt's quadratic trend model with additive formula for $S_1 = 0$, and with: *α* opt., β opt and. φ opt. for RMSE	2018 2019 2020 2021 2022	1,834.603 1,889.946 1,945.358 2,000.838 2,056.386	0.0426	68.825	RMSE: α = 0.0001 β = 0.5200 φ = 0.9999
$25_{a1.}$	Brown's double exponential smoothing (linear), and with *α* opt. for Ψ	2018 2019 2020 2021 2022	1,706.754 1,732.993 1,759.231 1,785.470 1,811.709	0.0562	87.928	Ψ: α = 0.5006
$25_{a2.}$	Brown's double exponential smoothing (linear), and with *α* opt. for RMSE	2018 2019 2020 2021 2022	1,706.917 1,733.236 1,759.555 1,785.875 1,812.194	0.0564	87.931	RMSE: α = 0.4952
$26_{a1.}$	Brown's triple exponential smoothing (quadratic), and with *α* opt. for Ψ	2018 2019 2020 2021 2022	1,695.716 1,709.094 1,722.472 1,735.850 1,749.229	0.0525	96.930	Ψ: α = 0.4436
$26_{a2.}$	Brown's triple exponential smoothing (quadratic), and with *α* opt. for RMSE	2018 2019 2020 2021 2022	1,706.909 1,720.483 1,734.056 1,747.630 1,761.203	0.0560	93.750	RMSE: α = 0.3344
$27_{a1.}$	Advanced exponential autoregressive model, and with *α* opt. for Ψ	2018 2019 2020 2021 2022	1,733.301 1,776.133 1,818.965 1,861.797 1,904.630	0.0581	110.836	*k* = 3 and *l* = 2, and with $\beta_1 = 0.2$ $\beta_2 = 0.3$ $\beta_3 = 0.5$ $\delta_1 = 0.4$ $\delta_2 = 0.6$ Ψ αopt. = 0.9998
$27_{a2.}$	Advanced exponential autoregressive model, and with *α* opt. for RMSE	2018 2019 2020 2021 2022	1,717.326 1,755.847 1,796.368 1,836.890 1,877.411	0.0605	98.189	*k* = 3 and *l* = 2, and with $\beta_1 = 0.2$ $\beta_2 = 0.3$ $\beta_3 = 0.5$ $\delta_1 = 0.4$ $\delta_2 = 0.6$ RMSE αopt. = 0.7818

Cont. table 1.

28.	Creep trend and harmonic weights method	2018 2019 2020 2021 2022	1,723.048 1,755.618 1,788.187 1,820.187 1,853.326	0.0171	30.732	$k = 4$
29.	Linear model	2018 2019 2020 2021 2022	1,829.988 1,884.130 1,938.272 1,992.414 2,046.556	0.0471	69.933	$R^2 = 0.9417$
30.	Logarithmic model	2018 2019 2020 2021 2022	1,831.222 1,885.104 1,938.960 1,992.789 2,046.591	0.0471	69.779	$R^2 = 0.9419$

y = forecasted variable; y_t^* = expired forecast's value; S_t = smoothed evaluation of increasing time series in t moment of time; w_i = weight of i evaluation of smoothed value or incremental smoothing parameter for increasing time series; δ_l = weight of smoothed value's increment; k = smoothing constant; l = forecast's smoothing constant; t = time; w = weight attributed by the evaluator to the forecasted variable in t moment of time.

Additional information: when the author carried out the forecast, the steel production in 2018 was not published in steel industry reports; thus, the author carried out the forecast for the year. When official data concerning steel production in 2018 will be published, the managers in enterprises in steel production can compare the real production with the forecast.

Source: own research (Gajdzik, 2019).

Based on the obtained forecasting models, a trend of increasing steel production in the world was found in 18 out of 30 obtained models (the remaining models are marked in grey in Table 1). Figure 2 presents the directions of changes in the forecasted quantities of steel production – an optimistic scenario.

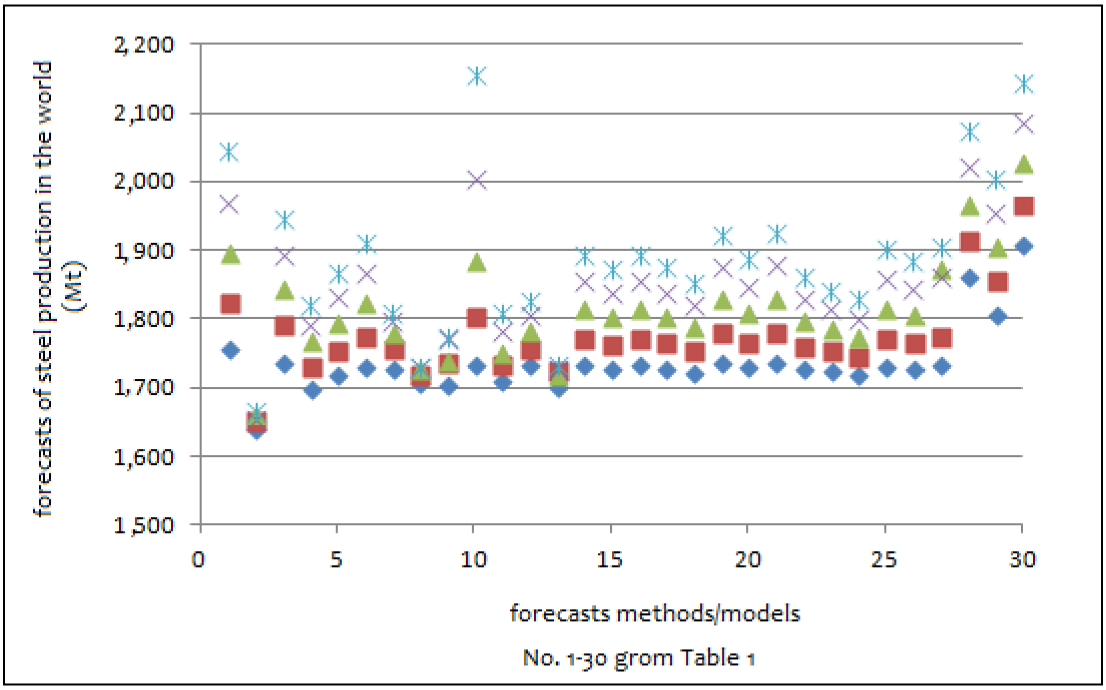

Figure 2. Forecasts of steel production in the world in 2018-2022 (own research on the basis of data from World Steel Association reports).

Therefore (with the optimistic scenarios for steel production in the world), it can be assumed that with the forecasted increase in steel production in the world, it is possible to develop industry 4.0 in the steel industry. Among the proposed models, the best fit was obtained via the creeping trend method, using forecasting with the harmonic weights method. The individual upward trends in changes in the forecasted volume of steel production in the world were divided according to three scenarios: a very optimistic, optimistic and moderately optimistic scenario. In the very optimistic scenario, the forecasted increase in steel production in relation to current production (steel production in 2017) is 20% in 2022, in the optimistic scenario, the increase is approx. 10%, and in moderately optimistic, there is an increase by 5%.

4. Summary

Prepared forecasting models form the basis for planning steel production in the perspective of industrial development 4.0. The obtained forecasts (for many models – table 1) are optimistic, which allows us to adopt a steel industry development strategy. Investments in cyber-physical production systems are expensive. Steel sector enterprises have to reckon with high investment expenditures to increase the scope of automation of continuous steel casting. Metallurgical enterprises invest more and more in robots and industrial manipulators. Industry 4.0 enters both steel mills and companies dealing in the distribution of steel products, which include modern service and distribution centres with fully automated warehouses for steel products.

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