

## BUSINESS PROCESS MANAGEMENT: FORECASTING THE MARKET FOR DECARBONIZATION AND RELATED PRODUCTS USING THE LCA METHOD

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### Summary

The aim of this work is to manage business processes based on the forecasting of the decarbonization market and related products. The methods used in this study include general scientific methods (analysis and synthesis, induction and deduction), theoretical research methods (abstraction, theoretical modeling. The importance of by-products in the metallurgical industry is demonstrated, including dust and sludge, hot rolling scale, iron ore, fine fractions of agglomerate, pitch, and sulfur. Based on the dynamic trend of retrospective data on steel production from the World Steel Association for the period 2003-2022, trends were analyzed and forecast indicators were developed. LCA inventory data (using OpenLCA software), calculated using the Environmental Footprint method (Mid-point indicator) considering a projected steel volume of 2,231 thousand tons, assessed environmental impacts. The results indicated the greatest impact on environmental indicators. The forecasted capacity of potential decarbonization markets and related products was determined. The most significant segments of the global steel market for by-products will be: sludge, tails, stockpiled

**Key words:** by-products, life cycle, Brown's model, circular economy, metallurgical production.

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## 1. Introduction

Predictive business process management is essential for supply chain management, especially in the metal mining industry, which faces significant fluctuations in supply and demand. In this context, exponential smoothing methods have gained prominence due to their inherent simplicity and high accuracy. Time series methods are fundamental methods for forecasting any process and phenomenon. The purpose of this paper is to demonstrate the effectiveness of Brown's model in forecasting world steel production. By analyzing dynamic data and applying smoothing techniques, we can create forecasts that provide a clearer picture of production trends. In addition, this study incorporates life cycle assessment (LCA) to evaluate the environmental impacts of steel production processes. LCA provides a comprehensive framework for assessing the environmental impacts associated with the various stages of product production

## 2. Materials and methods

### 2.1 Brown's double smoothing model

Exponential smoothing methods are very popular in supply chain management (Fliedner, 1999) and business analytics (Dekker, M. and etc, 2004) due to their simplicity, transparency and accuracy (Gardner, 1985). They are based on the assumption that observed

time series can be additively or multiplicatively decomposed into levels, trends and seasonal patterns. These models are widely used in various empirical applications to filter out random variations in observed series and to identify underlying trends and seasonal fluctuations. Apart from their long tradition, they are nowadays one of the most recommended tools for time series forecasting. Despite their advanced age, they have shown surprisingly good forecasting performance compared to more sophisticated approaches (*Makridakis & Hibon, 2000*). Also, the literature on exponential smoothing has grown rapidly in the last few years (*Smyl, Liu and etc, Rendon-Sanchez & de Menezes*).

In this article, it is shown that the exponential smoothing method may give more accurate steel market forecasting results compared to the state-of-the-art methods. This fills a gap in the existing literature on the use of exponential smoothing methods for the purpose of forecasting the dynamics of steel production dynamics of the steel product of the metallurgical industry.

Brown's model consists of the following equations:

Smoothing data

$$a_t = \alpha y_t + (1 - \alpha)(a_{t-1} + b_{t-1}) \quad (1)$$

Smoothing the trend

$$b_t = \alpha(a_t - a_{t-1}) + (1 - \alpha)b_{t-1} \quad (2)$$

Forecast for the period

$$t + k : y_{t+k} = a_t + b_t k \quad (3)$$

where  $a_t$  — smoothed value of the forecast indicator for the period  $t$ ;  $b_t$  - trend increment estimation, showing the possible increase or decrease of values in one period;  $\alpha$  – smoothing

parameter ( $0 \leq \alpha \leq 1$ ). Parameter  $\alpha$  can be determined by the following formula:  $\alpha = \frac{2}{n-1}$ ;

$k$  – the number of time periods for which the forecast is made.

The smoothing parameter  $\alpha$  is chosen subjectively or by minimising the forecast error. Larger values of the parameter will result in a faster response to changes. The larger the parameter, the more the data are smoothed.

In order to use the equations to obtain a forecast, it is necessary, to define the initial conditions. Firstly, the initial condition for smoothed data can be set equal to the first observation, with the initial condition for trend being zero. Second, the initial condition for the smoothed data may be defined as the average of the first  $k$  observations. Then the initial condition for the trend can be estimated by the slope of the line formed by these  $k$  points.

The main indicators of Brown's model, which characterise it: trend equation, forecast value of the volume of world steel production, forecast abbreviation, evaluation criterion of model adequacy (Student's criterion), lower and upper boundary of the forecast

## 2.2 Method of product life cycle assessment

Life Cycle Assessment (LCA) is based on the ISO 14040-14044 standards, which describes four steps in its development: purpose and scope definition, inventory analysis, impact assessment and interpretation (ISO. ISO 14044:2006. 2006). The life cycle includes stages such as raw material extraction, production, product components and the product itself, use and recycling or final disposal. It is important to note that it is not necessary to prepare an LCA with all life cycle stages; it can be adapted to the needs of the project. A life cycle inventory analysis is a compilation of all environmentally relevant inputs and outputs of a system that are derived or adapted from primary and secondary data. All inputs and outputs are quantified according to functional units. The impact assessment phase involves the use of characterisation models that include emission and resource use factors that are used to convert environmentally relevant input and output data into life cycle environmental impact indicator results. The use of LCA has proven to be very useful in the characterisation of steel product production by different methods (EAF, BOF).

LCA is a standardised methodology for quantifying and analysing the full life cycle of products, technologies, systems and services, which can provide decision support for identifying preferred options in terms of environmental impacts across a wide range of impact types. Thus, LCA modelling tools process and edit large amounts of process, material, and product data (*Makepa and etc, 2023*).

There are a number of different LCA software: SimaPro software (Dutch company Pré-Consultants) Versions: SimaPro 7.3.3 and SimaPro 8.0.3; GaBi is an LCA modelling software from the German company Thinkstep; OpenLCA (openLCA is a free and open source software for sustainability and life cycle assessment) (*Sangma and etc, 2023*).

The openLCA 2.0 software was used to conduct LCA in this study. This software is a comprehensive open source tool for sustainability modelling and LCA developed by Green-Delta. It allows modelling and analysing the life cycle of a product or service in a clear and methodical manner, adhering to the ISO 14040 series of recommendations. OpenLCA software also enables LCA studies using a database from its library (*Makepa and etc, 2023*).

Worldsteel database was used in this study. This study contains global and regional LCI data for 16 steel products ranging from hot rolled coils to sheets, rebar, sections and coated steel.

The study was conducted in accordance with the worldsteel LCI methodological report and ISO 14040 and 14044 standards and represents the most comprehensive and accurate LCI dataset for steel products produced worldwide.

## 3. Results and Discussion

The durability of steel allows many products to be reused after the end of their service life (the second level of the circular economy), the extension of the product's service life allows to avoid the need for transportation and remelting of steel, as well as the creation of new products (*Belodedenko and etc, 2023*). Over the last century, reprocessing of steel has saved 33 billion tons. of iron ore and 16 billion tons. coal (*World Steel, 2023*). By-products (coke, converter, blast furnace) are used as energy for technological purposes (*Sui and etc, 2023*), which can reduce the operating cost by 8-10% (*Arastoa and etc, 2013*). Smelting steel scrap from products after the end of their service life is the third level of the circular economy in steelmaking. About 650 million tons of scrap is consumed annually for steel production, which makes it possible to avoid emissions of about 975 million tons. CO<sub>2</sub> per year and reduces the use of basic material resources (*World Steel. Blog, 2018*). Steel industry by-products have many uses within the industry, in other industries and in society as a whole. The following is a general list of applications for steel

industry by-products: blast furnace slag as a clinker substitute in the cement industry (*Jiang and etc, 2020*); steelmaking slag as aggregates in road construction (*Jiang and etc, 2020; Sukmak and etc, 2023*) and soil improvement (*Fisher & Barron, 2022*); dust and sludge as internal and external applications for iron oxides and alloying elements (*Sui and etc, 2023*); petrochemicals from coke production – tar, ammonia, phenol, sulphuric acid and naphthalene for the chemical industry; mill emulsions and waste oil – reducing agent in blast furnaces or used at coke plants.

A number of by-products with a high iron content are generated throughout the steelmaking process. These include dust and sludge from wet and dry decelerating equipment, mill scale from the hot strip mill, as well as iron ore and sinter fines. Tar is a by-product of coking and is used as a material for sealing materials in the construction sector, as well as for the production of paints and synthetic dyes. Tar can be further processed and used in consumer products such as soap and shampoo to treat dandruff and skin diseases (psoriasis) (*Ma and etc., 2021*). Sulphur is used to vulcanise rubber and produce sulphuric acid, and is also used in insecticides and fertilisers (*Ma and etc., 2014*).

Table 1

**Co – products of the circular economy concept**

Product	Process	Composition of substances
Cement (Sample S-NS-90)	Mechanical and hydration properties of low clinker cement containing high volume superfine blast furnace slag	<p>OPC – 10%; SFBFS – 89%; NS – 1%</p> <p>OPC – ordinary portland cement</p> <p>OPC (21.99% – SiO<sub>2</sub> 5.92% – Al<sub>2</sub>O<sub>3</sub> 3.26% – Al<sub>2</sub>O<sub>3</sub> 58.64% – CaO 1.98% – MgO 0.74% – K<sub>2</sub>O 0.27% – Na<sub>2</sub>O 2.6% – SO<sub>3</sub> 3.5% – LOI)</p> <p>SFBFS – substituting part of cement clinker with superfine blast furnace slag</p> <p>(34.39% – SiO<sub>2</sub> 13.78% – Al<sub>2</sub>O<sub>3</sub> 0.19% – Al<sub>2</sub>O<sub>3</sub> 40.26% – CaO 7.43% – MgO 0.44% – K<sub>2</sub>O 0.3% – Na<sub>2</sub>O 1.92% – SO<sub>3</sub> 0% – LOI)</p>
Electric arc furnace slag (EAF)	Electric arc furnace slag (EAF) as recycled road construction materials	<p>30.66% – CaO 23.9% – Fe<sub>2</sub>O<sub>3</sub> 21.61% – SiO<sub>2</sub> 10.14% – MgO 5.10% – Al<sub>2</sub>O<sub>3</sub> 4.39% – MnO<sub>2</sub> 1.55% – Cr<sub>2</sub>O<sub>3</sub> 1.33% – SO<sub>3</sub> 0.77% – ZnO 0.52% – TiO<sub>2</sub> 0.03% – ZrO<sub>2</sub></p>
Functionalized and unfunctionalized basic oxygen steelmaking slag	Effect of functionalized and unfunctionalized basic oxygen steelmaking slag on the growth of cereal wheat (soil improvement)	Unfunctionalized BOS slag; Isosteric acid; Lauric acid; Lanolin; Cysteic acid
BFG	development prospects of metallurgical by-product gas utilization	<p>25.0~30.0 – CO<sub>2</sub>/%; 1.5~3.0 – H<sub>2</sub>/%; 55.0~60.0 – CO<sub>2</sub>/%; 0.2~0.4 – O<sub>2</sub>/%; 1.29~1.30 – density/(kg/m<sup>3</sup>); 3000~3800 – calorific value/(kJ/m<sup>3</sup>)</p> <p>The advantages are low cost and the possibility of widespread use as a gaseous fuel</p>
LDG	development prospects of metallurgical by-product gas utilization	<p>60.0~70.0 – CO<sub>2</sub>/%; 0.0~3.0 – H<sub>2</sub>/%; 0.0~1.0 – CH<sub>4</sub>/%; 10.0~20.0 – N<sub>2</sub>/%; 15.0~20.0 – CO<sub>2</sub>/%; 0.0~2.0 – O<sub>2</sub>/%; 1.69~1.76 – density/(kg/m<sup>3</sup>); 6800~10000 – calorific value/(kJ/m<sup>3</sup>)</p> <p>It can be directly used for fuel combustion, and as a raw material for the chemical production of high-value products</p>

Continuation of table 1

COG	development prospects of metallurgical by-product gas utilization	55.0~60.0 – H <sub>2</sub> /%; 22.0~28.0 – CH <sub>4</sub> /%; 6.5~10.0 – CO/%; 3.0~5.0 – N <sub>2</sub> /%; 1.0~3.0 – CO <sub>2</sub> /%; 0.3~0.8 – O <sub>2</sub> /%; 2.0~3.0 – C <sub>m</sub> H <sub>n</sub> /%; 0.45~0.48 – density/(kg/m <sup>3</sup> ); 17,580~18420 – caloric value/(kJ/m <sup>3</sup> ) The development of COG for high-value production, such as that of pure hydrogen, methanol, ammonia, NG, and other <u>syngases</u>
High-temperature coal tar (HTCT)	High-temperature coal tar is an important raw material for obtaining value-added aromatics TP, the HP of HTCT, is the main raw material for carbon fibers (CFs), plastics, high-temperature resistant materials, and <u>electrode materials</u>	0.5 ~ 1.0 – benzene, toluene, xylene, and other alkylbenzene; 2 ~ 4 – phenol, cresols, xylenols, naphthalene, and pyridine base; 9 ~ 12 – naphthalene, phenol, cresols, xylenols, and heavy; 6 ~ 9 – naphthalene, anthracene, and fluorene; 20 ~ 24 – anthracene and phenanthrene; 50 ~ 55 – CTP

Thus, the metallurgical sector has a well-founded concept of a closed cycle economy 3 R + co-P (reduce, reuse, recycle, co-products).

According to the statistics of the World Steel Association, in 2021, about 1.4 billion tons of steel were produced in the world's converters, based on about 1.3 billion tons. domain resources and about 240 million tons. scrap The world production of EAF was about 30% of the world steel production (560 million tons), which required 60 million tons. blast furnace production, 120 million tons DRI (direct recovery iron) and 450 million tons of scrap. The average limited results of the accompanying products, which are obtained during the production of 1000 kg of EAF steel: slag (85 kg); dust (10 kg); recovered steam (41.3 kg), converter gas (105 m3), renewable steam (41.3 kg).; 1000 kg of BF/BOF steel: slag (298 kg); dust (925 kg); blast furnace gas (1392 m3), energy (36.44 kW) (Liu and etc., 2020). The average absolute growth in global steel production over the period 2003-2022 is 48.1 thousand tons, with an average annual increase of 3.5%. Thus, we can observe an analytically sound pattern of growth (Table 6), which can be used as input data for Brownian forecasting calculations (He and etc., 2017).

Table 2

**Global steel production in 2003-2022**

Year	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Actual production of steel, thousand tons	971	1063	1148	1250	1350	1345	1241	1435	1540	1563
Year	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Actual production of steel, thousand tons	1635	1675	1624	1633	1737	1828	1877	1882	1962	1885

The relevance of the model is justified by the further dynamic development of the markets of decarbonization and related products (El Hafdaoui and etc., 2023; Pavlenko and etc., 2020). The defined functional econometric model will be practically significant if in the future the total volume of sludge, slag, metal scrap and gases (converter and blast

furnace) will increase, and this depends primarily on the dynamics of the main product of metallurgical enterprises – steel. Based on the dynamic trend of retrospective steel production data of the World Steel Association for the period 2003-2022. consider the trends of a certain series. In the practice of statistical forecasting of trends, Brown's model is most often used, which belongs to adaptive forecasting models that are able to quickly adapt their structure and parameters to changing conditions. The forecasting tool in adaptive models, as well as in growth curves, is a mathematical model with a single factor "time" (*World Steel in Figures, 2022*).

In order to use the equations to obtain a forecast, it is necessary to define the initial conditions. First, the initial condition for the smoothed data can be set equal to the first observation, with the initial condition for the trend (bt-1) equal to zero. Second, the initial condition for the smoothed data can be defined as the average of the first k observations. Then the initial condition for the trend can be estimated by the slope of the line formed by these k points.

The parameter  $\alpha$  can be determined by the following formula:

$$\alpha = \frac{2}{n+1} = \frac{2}{20+1} = 0,0952$$

As  $y_0$  we take the arithmetic mean of the first 3 values of the series.

$$y_0 = (971 + 1063 + 1148)/3 = 1060,667$$

The slope angle of the line formed by the 3 points of the first realisation can be found using the least squares method.

The linear trend equation has the following form  $y = bt + a$ . The trend equation is obtained:  $y=88.5 \cdot t+883.667$

The empirical trend coefficients a and b are only estimates of the theoretical coefficients  $\beta_i$ , and the equation itself reflects only the general trend in the behaviour of the variables under consideration.

The trend coefficient  $b = 88.5$  shows the average change in the resultant indicator (in units y) with the change in the time period t per unit of its measurement. In this example, with an increase in t by 1 unit, y will change by 88.5 on average.

The time dependence of y on time t has been studied. A linear trend was chosen at the specification stage. Its parameters were estimated by the method of least squares. The economic interpretation of the model parameters is possible – with each period of time t the value of Y increases on average by 88.5 units.

Initial conditions for trend estimation are equal to  $b_{\text{нач}} = 88.5$

$$a_1 = 0,0952 \cdot 1060,667 + (1-0,0952) \cdot 1060,667 = 1060,667$$

$$a_2 = 0,0952 \cdot 1063 + (1-0,0952)(1060,667+88,5) = 1140,964$$

$$b_2 = 0,0952(1140,964-1060,667) + (1-0,0952) \cdot 88,5 = 87,719$$

$$a_3 = 0,0952 \cdot 1148 + (1-0,0952)(1140,964+87,719) = 1221,002$$

$$b_3 = 0,0952(1221,002-1140,964) + (1-0,0952) \cdot 87,719 = 86,988$$

$$a_4 = 0,0952 \cdot 1250 + (1-0,0952)(1221,002+86,988) = 1302,469$$

$$b_4 = 0,0952(1302,469-1221,002) + (1-0,0952) \cdot 86,988 = 86,462$$

Table 3

**Auxiliary table for calculating the forecast indicator according to the Brown's model**

i	y <sub>t</sub>	Data smoothing, a <sub>t</sub>	Trend smoothing, b <sub>t</sub>	Forecast, y <sub>t</sub> <sup>*</sup>	(y <sub>t</sub> -y <sub>t</sub> <sup>*</sup> ) <sup>2</sup>
1	971	1060,667	88,5	1060,667	8040,111
2	1063	1140,964	87,719	1149,167	7424,694
3	1148	1221,002	86,988	1228,683	6509,693
4	1250	1302,469	86,462	1307,99	3362,784
...		...	...	...	...
19	1962	2145,869	59,296	2165,216	41296,548
20	1885	2174,686	56,394	2205,165	102505,81

Forecasting

$$y(20+1) = 2174.686 + 56.394 = 2231.08$$

The forecast error is determined by the formula:

$$s = \sqrt{\frac{\sum (y_t - y_t^*)^2}{n - 2}} = \sqrt{\frac{808506,541}{20 - 2}} = 211,936$$

Let's determine the value of Student's criterion for the number of degrees of freedom k = n-m = 20-2 = 18 and level of significance 0.05: t(18;0.05) = 2.101

Lower forecast boundary:

$$y_1 = 2231.08 - 211.936 = 1785.802$$

Upper forecast boundary:

$$y_2 = 2231.08 + 211.936 = 2676.358$$

The LCA inventory data (OpenLCA software) calculated using the Environmental Footprint (Mid-point indicator) method (Table 4), taking into account the forecasted quantity of steel in the amount of 2231 thousand tonnes, determined the environmental impact. As a result, the greatest impact on environmental indicators was obtained: Aquatic eco-toxicity (-2.26281e+8 Item); Climate change (-1.22161e+8 kg), Land use (-2.19191e+8). The indicators are summarised in the table (the standard is taken as follows Steel cold rolled coil Global 2020 database World Steel Organization)

Table 4

**LCA inventory data Steel cold rolled coil Global 2020 database (WSO)**

Indicator	Steel cold rolled coil Global 2020	Unit
Abiotic resource depletion	-3.49350e+2	kg
Acidification	-5.54452e+4	mol
Aquatic eco-toxicity	-2.26281e+8	Item(s)
Aquatic Eutrophication	-6.83524e+4	kg



Continuation of table 4

Cancer human health effects	-1.73367e-12	Item(s)
Climate change	-1.22161e+8	kg
Ionizing radiation	-1.02574e+6	kBq
Land use	-2.19191e+8	Item(s)
Non-cancer human health effects	-3.05004e-1	Item(s)
other	-2.84398e+8	m3
Ozone depletion	-5.55552e-7	kg
Photochemical ozone creation	-2.31107e+5	kg
Respiratory inorganics	-2.82951e+0	Item(s)
Terrestrial Eutrophication	-2.42566e+5	mol

As a result of the assessment of the product life cycle of metallurgical enterprises (Table 5), the most significant segments of the global steel market will be: sludge (4,06E+04 kg); tails (5,81E+06 kg); exits put in storage (3,19E+08 kg); carbon dioxide (8,48E+02 kg).

Table 5

**Segments of the ancillary services market were calculated using  
the product life cycle model**

Outputs	Amount (1 kg) (Steel cold rolled coil Global 2020)	Segments of the global steel market	Units
<b>Materials production</b>			
carbonyl sulphide	3,78E-20	8,43E-11	kg
Gypsum	9,03E-17	2,01E-07	kg
Iron sulphate dissolution	1,21E-16	2,70E-07	kg
Water (desalinated; deionised)	4,04E-25	9,01E-16	kg
<b>Waste</b>			
Cold rolling emulsion treatment sludge	1,82E-05	4,06E+04	kg
Hazardous waste (deposited)	1,49E-08	3,33E+01	kg
Hazardous waste (underground deposit)	6,42E-17	1,43E-07	kg
High radioactive waste	6,03E-10	1,35E+00	kg
Low radioactive wastes	1,11E-08	2,47E+01	kg
Medium radioactive wastes	5,31E-09	1,18E+01	kg
Overburden (deposited)	0,002602	5,81E+06	kg
Paper (unspecified)	6,03E-21	1,35E-11	kg
Radioactive tailings	5,67E-07	1,26E+03	kg
Slag (deposited)	4,01E-12	8,95E-03	kg
Tailings (deposited)	0,247023	5,51E+08	kg
Waste (deposited)	0,142926	3,19E+08	kg
<b>Emissions to lower stratosphere and upper troposphere</b>			
carbon dioxide (fossil)	3,80E-07	8,48E+02	kg
Methyl borate	3,82E-23	8,52E-14	kg
Noble gases, radioactive, unspecified	3,15E-29	7,03E-20	kBq



Continuation of table 5

Emissions to urban air close to ground			
Benzal chloride	2,44E-27	5,44E-18	kg
Chlorosilane, trimethyl-	1,69E-24	3,77E-15	kg

Therefore, one of the solutions to this issue is to synthesize the proposed concept of a circular economy with the concepts of ELFM (Extraction of valuable materials from landfills) and EWM (Enhanced waste management). EWM consists of two pillars, the first of which is built on the idea that future landfills will become temporary storage sites or future mines for materials that cannot be directly processed using existing technologies or have clear potential for more efficient processing in the near future. The second pillar is essentially the ELFM concept itself. As for this second ELFM component, it aims to increase the value of waste streams in landfills. The trends of these concepts will affect local and regional budgets of cities, as a significant amount of landfill tax revenue will be lost due to the implementation of these concepts. Considering an average tax rate of 42 euros [68], the total amount paid to local budgets globally, only from the metallurgy industry, will exceed 36 million euros.

#### 4. Conclusions

Using the forecast trend of global steel production based on the Brown's adaptive model and taking into account the output of products using the LCA method, the article determines the forecast capacity of potential markets for decarbonisation and related products. The most significant segments of the global steel market for by-products will be: sludge (4,06E+04 kg); tails (5,81E+06 kg); exits put in storage (3,19E+08 kg); carbon dioxide (8,48E+02 kg). As the further positive trend of global steel production will lead to the expansion of co-product segments and increased pressure on the environment (climate change, ecotoxicity of water resources, soil damage), which is proven in the study, this problem identification provides valuable information for local governments, helping to shape the vector of development of the industrial sector and possible prospects for transformation of some old industrial regions with a significant percentage of primary and secondary eco-industrial sector.

Product Life Cycle Assessment of the metal mining sector provides senior and middle-level decision makers with an understanding of how to balance the operating cycle, future financial performance and possible changes in environmental conditions. Understanding the quantitative composition of industrial end products enables the implementation of circular economy levels to avoid a significant tax burden on solid waste.

#### References

1. Fliedner, G. (1999). *An investigation of aggregate variable time series forecast strategies with specific subaggregate time series statistical correlation*. *Computers & Operations Research*, 26(10-11), 1133–1149. [https://doi.org/10.1016/s0305-0548\(99\)00017-9](https://doi.org/10.1016/s0305-0548(99)00017-9)
2. Dekker, M., van Donselaar, K., & Ouwehand, P. (2004). *How to use aggregation and combined forecasting to improve seasonal demand forecasts*. *International Journal of Production Economics*, 90(2), 151–167. <https://doi.org/10.1016/j.ijpe.2004.02.004>
3. Gardner, E. S. (1985). *Exponential smoothing: The state of the art*. *Journal of Forecasting*, 4(1), 1–28. <https://doi.org/10.1002/for.3980040103>

4. Makridakis, S., & Hibon, M. (2000). *The M3-Competition: results, conclusions and implications*. *International Journal of Forecasting*, 16(4), 451–476. [https://doi.org/10.1016/s0169-2070\(00\)00057-1](https://doi.org/10.1016/s0169-2070(00)00057-1)
5. Smyl, S. (2020). *A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting*. *International Journal of Forecasting*, 36(1), 75–85. <https://doi.org/10.1016/j.ijforecast.2019.03.017>
6. Liu, M., Taylor, J. W., & Choo, W.-C. (2020). *Further empirical evidence on the forecasting of volatility with smooth transition exponential smoothing*. *Economic Modelling*, 93, 651–659. <https://doi.org/10.1016/j.econmod.2020.02.021>
7. Rendon-Sanchez, J. F., & de Menezes, L. M. (2019). *Structural combination of seasonal exponential smoothing forecasts applied to load forecasting*. *European Journal of Operational Research*, 275(3), 916–924. <https://doi.org/10.1016/j.ejor.2018.12.013>
8. ISO. ISO 14044:2006. *Environmental Management—Life Cycle Assessment—Requirements And Guidelines ISO 14044*. Int. Organ. Stand. 2006, Available online: <https://www.iso.org/obp/ui/es/#iso:std:iso:14044:ed-1:v1:en>
9. Makepa, D. C., Chihobo, C. H., Manhongo, T. T., & Musadamba, D. (2023). *Life-cycle assessment of microwave-assisted pyrolysis of pine sawdust as an emerging technology for biodiesel production*. *Results in Engineering*, 101480. <https://doi.org/10.1016/j.rineng.2023.101480>
10. Sangma, C. B. K., & Chalieu, R. (2023). *Life cycle assessment of wastewater treatment by microalgae. V Valorization of Microalgal Biomass and Wastewater Treatment (c. 137–178)*. Elsevier. <https://doi.org/10.1016/b978-0-323-91869-5.00008-9>
11. S. Belodedenko, O. Hrechanyi, T. Vasilchenko, K. Baiul, A. Hrechana, *Development of a methodology for mechanical testing of steel samples for predicting the durability of vehicle wheel rims*, *Results in Engineering*, Volume 18, 2023, 101117, <https://doi.org/10.1016/j.rineng.2023.101117>
12. World Steel. *Steel – the permanent material in the circular economy*. Available at: <https://worldsteel.org/wp-content/uploads/worldsteel-circular-economy.pdf> (accessed Nov. 01, 2023).
13. Sui, P., Ren, B., Wang, J., Wang, G., Zuo, H., & Xue, Q. (2023). *Current situation and development prospects of metallurgical by-product gas utilization in China's steel industry*. *International Journal of Hydrogen Energy*. DOI: <https://doi.org/10.1016/j.ijhydene.2023.04.050>
14. Arastoa A., Tsuparia E., Kärkia J., Sihvononb M., Liljab J. (2013) *Costs and Potential of Carbon Capture and Storage at an Integrated Steel Mill*, *Energy Procedia*, vol. 377. pp. 117-7124. DOI: <https://doi.org/10.1016/j.egypro.2013.06.648>.
15. World Steel. *Blog: The future of global scrap availability*. Available at: <https://worldsteel.org/media-centre/blog/2018/future-of-global-scrap-availability/>
16. Jiang, W., Li, X., Lv, Y., Jiang, D., Liu, Z., & He, C. (2020). *Mechanical and hydration properties of low clinker cement containing high volume superfine blast furnace slag and nano silica*. *Construction and Building Materials*, 238, 117683. <https://doi.org/10.1016/j.conbuildmat.2019.117683>
17. Sukmak, P., Sukmak, G., De Silva, P., Horpibulsuk, S., Kassawat, S., & Suddeepong, A. (2023). *The potential of industrial waste: Electric arc furnace slag (EAF) as recycled road construction materials*. *Construction and Building Materials*, 368, 130393. <https://doi.org/10.1016/j.conbuildmat.2023.130393>
18. Fisher L.V., Barron A. R. (2022) *Effect of functionalized and unfunctionalized basic oxygen steelmaking slag on the growth of cereal wheat (Triticum aestivum)*. *Resources, Conservation & Recycling Advances*. Vol.15. <https://doi.org/10.1016/j.rcradv.2022.200092>.

19. Sui, P., Ren, B., Wang, J., Wang, G., Zuo, H., & Xue, Q. (2023). Current situation and development prospects of metallurgical by-product gas utilization in China's steel industry. *International Journal of Hydrogen Energy*. <https://doi.org/10.1016/j.ijhydene.2023.04.050>
20. Ma, Z.-H., Wei, X.-Y., Liu, G.-H., Liu, F.-J., & Zong, Z.-M. (2021). Value-added utilization of high-temperature coal tar: A review. *Fuel*, 292, 119954. <https://doi.org/10.1016/j.fuel.2020.119954>
21. Ma, S.-h., Wen, Z.-g., Chen, J.-n., & Wen, Z.-c. (2014). Mode of circular economy in China's iron and steel industry: a case study in Wu'an city. *Journal of Cleaner Production*, 64, 505–512. <https://doi.org/10.1016/j.jclepro.2013.10.008>
22. Liu, M., Taylor, J. W., & Choo, W.-C. (2020). Further empirical evidence on the forecasting of volatility with smooth transition exponential smoothing. *Economic Modelling*, 93, 651–659. <https://doi.org/10.1016/j.econmod.2020.02.021>
23. He, H., Guan, H., Zhu, X., & Lee, H. (2017). Assessment on the energy flow and carbon emissions of integrated steelmaking plants. *Energy Reports*, 3, 29–36. <https://doi.org/10.1016/j.egy.2017.01.001>.
24. El Hafdaoui, H., Khallaayoun, A., & Ouazzani, K. (2023). Long-term low carbon strategy of Morocco: A review of future scenarios and energy measures. *Results in Engineering*, 101724. <https://doi.org/10.1016/j.rineng.2023.101724>
25. Pavlenko, D. V., Belokon', Y. O., & Tkach, D. V. (2020). Resource-Saving Technology of Manufacturing of Semifinished Products from Intermetallic  $\gamma$ -TiAl Alloys Intended for Aviation Engineering. *Materials Science*, 55(6), 908–914. <https://doi.org/10.1007/s11003-020-00386-1>
26. World Steel in Figures 2022. World Steel Association Available at: <https://worldsteel.org/wp-content/uploads/World-Steel-in-Figures-2023-4.pdf> (accessed Nov. 01, 2023)