Application of long short-term memory neural networks for electric arc furnace modelling

Maciej Klimas and Dariusz Grabowski

Silesian University of Technology, Gliwice, Poland
maciej.klimas@polsl.pl, dariusz.grabowski@polsl.pl

Abstract. Worldwide steelmaking industry strongly relies on the use of electric arc furnaces (EAFs). EAFs make use of electric arc phenomenon for melting scrap steel and consequently they can be sources of power quality issues, such as harmonics or voltage flickering. In order to design and implement effective systems for power quality improvement, it is necessary to dispose of an adequate model. Due to the complicated nature of the electric arc phenomenon, it is difficult to develop such an accurate model. Researchers around the world use different approaches, mostly relying on deterministic modelling with the addition of a stochastic ingredient. In this paper, we propose an approach which similarly is based on a deterministic equation enhanced with stochastic ingredients describing its coefficients. The identification of the time series of the equation is carried out by means of genetic algorithms. Next, we developed two models using long short-term memory artificial neural network (LSTM) for recreating the time series of the coefficients while remaining their stochastic properties. The second model also applies another LSTM for the reduction of stochastic-like residuals emerging from comparison of the first model with measurement data.

Keywords: electric arc furnace, EAF, long short-term memory, LSTM, artificial neural network.

1 Introduction

Operation of many branches of the industry rely strongly on the use of steel because this material is commonly used in many different applications. Environmental conditions and limited resources make recycling of the steel especially important. There are different methods for that, but one of the most widely used is via electric arc furnaces (EAFs). Although EAFs support ecology by their contribution to steel recycling, they can also cause some environmental problems. Electric arc which is used for scrap steel melting is a stochastic phenomenon and due to high power consumption it can negatively influence the power system. Discturbances caused by EAFs are harmonics, flickering or voltage sags and swells, among others. This consequently leads to excessive wear of the electrical equipment and additional power losses. In electrical engineering many different

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17

approaches are used to mitigate such problems. Optimal design and implementation of such systems improving power quality require an accurate model of the considered load. The goal of the development of new EAF models is to increase their accuracy in order to ensure that simulations of circuits including EAF models would provide better feedback to the engineers. Consequently, exploitation of the power system would be more optimal.

Nonlinear, dynamic and unpredictable nature of the electric arc makes it difficult to provide such accurate models. Literature shows that there are many different approaches to this problems. Some of them are based only on deterministic solutions connected with piecewise linear approximations of measurement data as in [4], or approaches based on other functions such as exponential or hyperbolic models [2]. Other researchers apply popular Cassie-Mayr models as in [6]. Many try to recreate the stochastic inregients for example with hidden Markov model [16] or Ornstein-Uhlenbeck process [15]. The nature of electric arc phenomenon is so complex that the modelling process can be simplified using machine learning methods. For instance artificial neural networks (ANNs) were used in modelling based on electric arc length [5] or directly on voltage and current measurement data [3]. In this paper we propose an analysis based on the widely used deterministic equation obtained from power balance, but with a stochastic ingredients recreated by long short-term memory (LSTM) networks. Mentioned equation is widely used in modelling of the electric arc phenomenon, and was also used by many researchers [8], [11] or [10]. Such hybrid solutions were also proposed by other authors, as in [7], but our approach is not yet to be met in the literature, due to the application of deep learning methods in hybrid model based on deterministic equation obtained from the power balance. Deep learning modelling in terms of EAFs has been already used only for temperature prediction [12] or material engineering approach [14]. It is worth mentioning that presented models are especially oriented towards deep learning methods because, simpler neural networks have been already investigated in our earlier works, such as [9].

2 Deterministic model of electric arc furnace

2.1 Measurement data

LSTM model is an example of an approach that needs relatively large amount of data for proper training and validation. In order to develop it, we have gathered measurement data of the EAF. It consists of voltage and current waveforms recorded during different stages of industrial size EAF work cycle. The area of interest of our analysis is the part of waveforms connected with the melting stage. The waveforms represent one-phase electric arc phenomenon as our goal is to develop accurate model of single arc column. As presented in Figure 1 the waveforms are characterized by various level of deformation, especially voltage waveform strongly deviates from the sinusoidal shape. Additionally, the data depicts two kinds of stochastic behavior which are the main causes of inaccuracy of the deterministic models. One is connected with the change of the amplitude

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17

(more visible in long-term plot) while the second can be described as a high frequency ripples mostly visible on peaks of the voltage waveform (apparent in short-term plot). Those features of the data are the base for developing LSTM models which should reflect them accordingly.

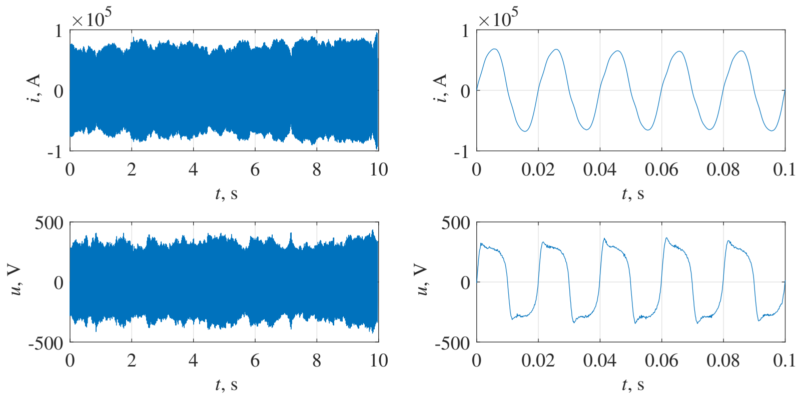

Fig. 1. Long and short-term samples of EAF measured current and voltage waveforms.

2.2 Power balance equation

Proposed concept bases on an equation describing the electric arc phenomenon, introduced in [1]. It originates from power balance approach and results in the following form:

$$k_1 r^n(t) + k_2 r(t)\frac{dr(t)}{dt} = \frac{k_3}{r^{m+2}(t)} i^2(t), \tag{1}$$

where: k_1, k_2, k_3 - model coefficients, m, n - parameters related to EAF work cycle, $r(t)$ - arc radius, $i(t)$ - arc current.

Additional equation allows calculating the arc voltage:

$$u(t) = \frac{k_3}{r^{m+2}(t)} i(t). \tag{2}$$

Equation (1) is widely used in deterministic approaches of EAF modelling and also as a starting point for development of stochastic models. Similarly, we apply this equation to the analysis of the measurement data.

2.3 Estimation of equation coefficients

Parameters of Eq. (1) can take different values depending of current stage of EAF work cycle. It is assumed that in the melting stage (corresponding with

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17

our measurement data) m and n parameters are constant and take values of $m = 0$ and $n = 2$. In that way only k coefficients remain unknown. Our approach assumes that those coefficients are stochastically changed in time in a way that would reflect stochastic changes of the EAF characteristic and that they remain constant for a single period of the measured waveforms, that is 20 ms. In order to estimate their values, the waveforms were divided into period-long frames. Current was then applied as an input to the Eq. (1) with assumed constant values of k coefficients. The output in form of the voltage waveform was then compared with measured voltage. We have used a genetic algorithm in order to minimize the RMSE error between those waveforms for each period-long window. The population size was equal to 50. Mutation was adaptive in terms of direction and step size with respect to the last generation. Crossover was based on a random binary vector, which selected genes from each of the parents. In that way we obtained three separate time series representing values of each k coefficients of Eq. (1) fitted to measurement data. Fig. 2 presents those time series, which later are used for LSTM networks training and validation.

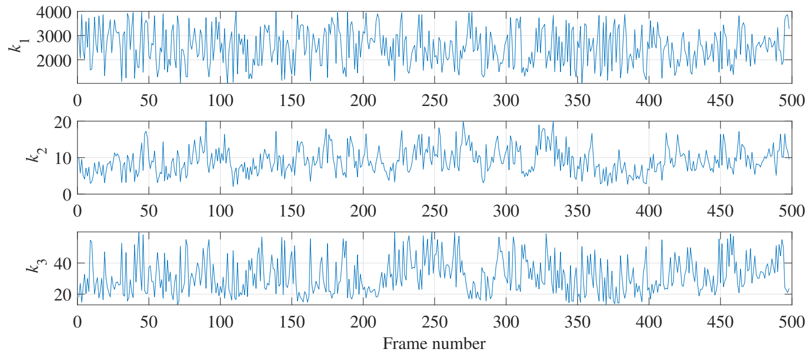

Fig. 2. k coefficients time series estimated from the measurement data.

3 Stochastic model of the electric arc furnace

3.1 Representation of coefficients time series

Main idea behind LSTM choice for EAF modelling is to provide effective way to represent stochastic behavior of the k coefficients time series. The ability to learn and reproduce such behavior is the main advantage in favor of deep learning methods. Additionally it simplifies overall approach of the EAF modelling because it does not rely of detailed analysis of physical phenomena and reasons behind their stochasticity.

In order to model each time series, we propose using separate LSTM networks, one for each k coefficient. The structure of each network is the same - simple

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17

and suited for the regression problem. Fig. 3 presents their topology. Fig. 4 additionally presents a more detailed view of the single LSTM cell structure, according to software documentation [13]. Various numbers of hidden units were tested and eventually the networks were fitted with 300 hidden units in the LSTM layer. Their training was conducted using Adam optimizer with a variable learning rate starting from 0.005. Number of training epochs was also investigated in order to obtain the best results and generally the training stopped after 500 epochs, with the batch size equal to 128. The training process was also visualized with the exemplary loss curve presented in Fig. 5. The other loss curves were not very different, and because of that we have limited ourselves to presenting an exemplary plot for LSTM network representing k_1 time sequence. The models were designed in Matlab software and the computing infrastructure included a portable computer with Intel Core i7 processor (4 cores, 1.8 GHz), with 16 GB RAM and Windows 10 operating system.

The developed networks allowed simulating each of the k coefficients time series, independently. Applying such simulated time series to the Eq. (1) and providing the current data as an input allows obtaining the final simulated output of the model – the voltage waveform.

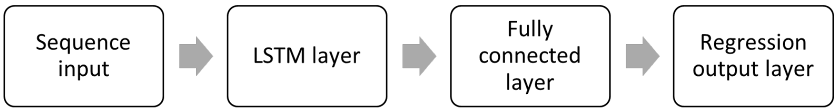

Fig. 3. Structure of used LSTM network.

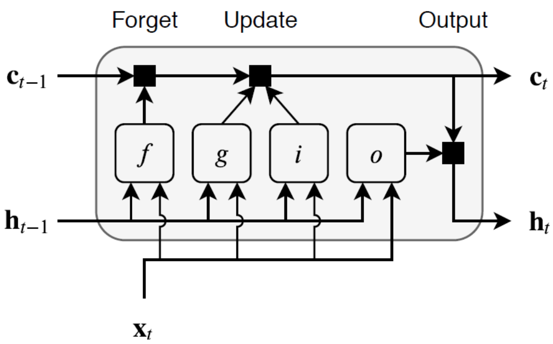

Fig. 4. Structure of single LSTM cell, where c - cell state, h - hidden (output) state and x - input data [13].

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17

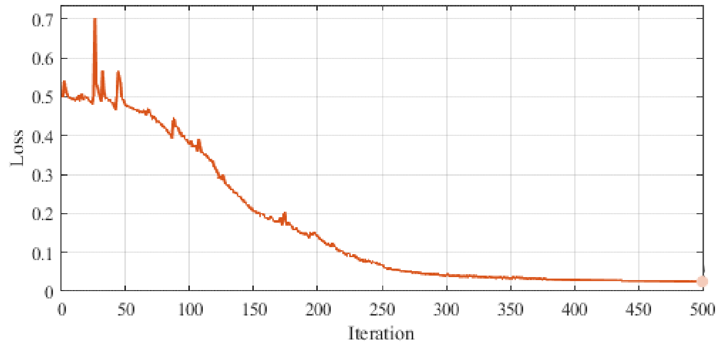

Fig. 5. Exemplary loss curve for training of the LSTM network representing k_1 time sequence.

3.2 Representation of high frequency ripples

Approach described in previous section can be considered as a complete model of the electric arc phenomenon. However, it only simulates the stochasticity of k coefficients, and assumes their constancy throughout each period of the signal. Changes in their values only cause variations in the shape of period-long frames of the EAF characteristic – the high frequency ripples around peak values are not modelled.

In order to enhance the previous model, we propose application of the second parallel path of signal analysis. The idea is to apply a high-pass filter to the voltage waveform and then develop separate deep learning model which will be trained and validated with such data. The waveform obtained after application of the high pass filter with 600 Hz cut off frequency is presented in Fig. 6 In this way overall output voltage would be a sum of the output of the first LSTM model and the second LSTM model.

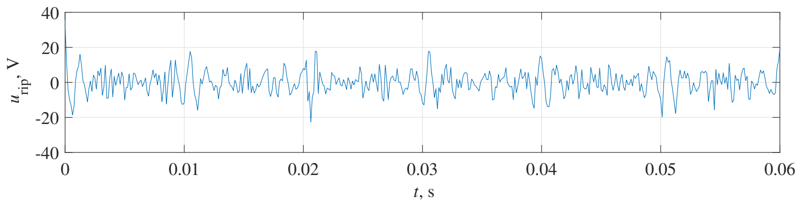

Fig. 6. Waveform of the high frequency ripples filtered from the measurement data.

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17

4 Simulation results

This section presents simulation results for each of the proposed models. Fig. 7 shows exemplary realizations of k coefficients time series, as the first step of the modelling procedure. This data was then used to obtain output voltage waveform of the first LSTM model, which is presented in the same figure. The plot also presents whole u-i characteristic of the EAF compared with the measurement data. In terms of qualitative assessment of the results, as presented, first model correctly reflects changes in the shape of the characteristic.

Previous section also justifies application of the next model which is specifically designed to recreate high frequency ripples of the voltage waveform. This waveform was added to the output of the first LSTM model resulting in overall output which reflects both kinds of stochastic behavior of the EAF characteristic – changes in the amplitude and high frequency ripples. Fig. 8 shows output of the second LSTM network and the u-i characteristic of EAF obtained as overall output of the second LSTM model compared with measurement data.

Problems related to stochasticity of the EAF modelling also extend to the evaluation aspects. Direct comparison of exemplary realizations with measurement data cannot provide any objective error measure. Although the realizations of the voltage waveform seem similar, as presented in Fig. 9, it is not correct to compare them directly with classic error measures used in signal processing. In this paper we limit our research to qualitative comparision of the exemplary realizations of the stochastic time series of k coefficients, the voltage ripples and the output of the models.

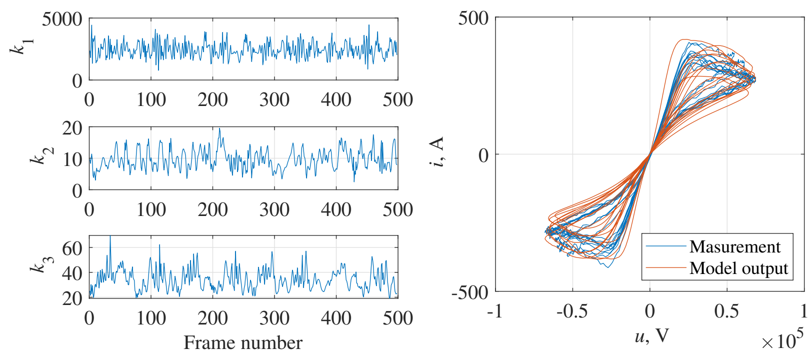

Fig. 7. Exemplary realization of k coefficients time series and comparison of the u-i characteristic obtained from the LSTM model and measurements.

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17

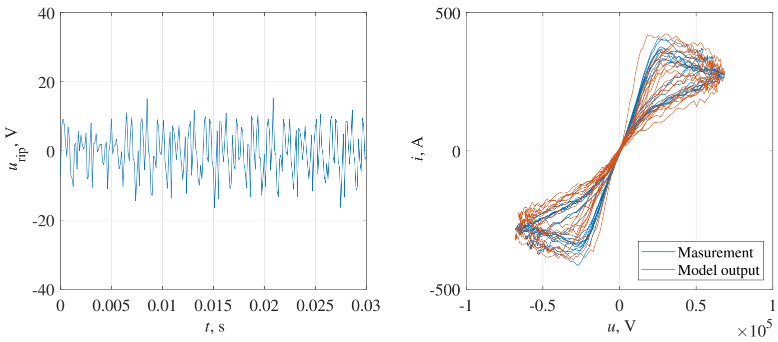

Fig. 8. Exemplary realization of voltage ripples and comparison of the u-i characteristic obtained from the second LSTM model and measurements.

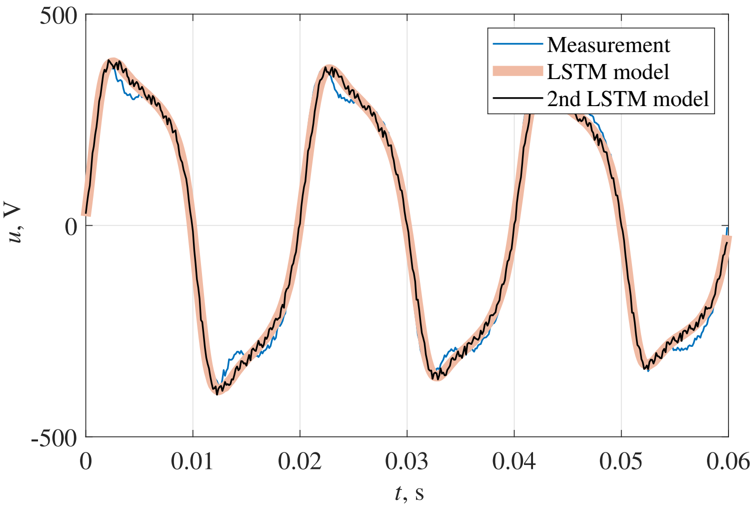

Fig. 9. Exemplary realizations of voltage obtained from both LSTM models compared with measurement data.

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17

5 Conclusions

This paper proposes two models of the EAF, both based on LSTM networks. The first is based on the estimation of coefficients of the equation describing electric arc phenomenon. Variations of each coefficient are described with a time series representing their value in following periods of 20 ms. Those time series are recreated with three separate LSTM networks with the same topology. The second model is based on the first one. It uses additional LSTM network trained to recreate high frequency ripples which can be observed after applying high pass filter to measured voltage weaveform. Overall output of the second model is the sum of first model output and the ripples waveform simulated with the second model.

As presented in Sect. 4 the exemplary realizations of the stochastic signals are similar to the measurement data. Both estimated k coefficients time series, voltage ripples and output u-i characteristic are characterized by the same features as the estimations from measured waveforms. Qualitatively, proposed approach gives promising results which meet the expectations of possible implementations based on deep learning models in the EAF modelling. Presented approach however, does not yet propose detailed optimization of LSTM models parameters. This idea requires an introduction of the objective measure of the discrepancy between two realizations of stochsatic processes. The stochasticity prevents from using classic measures such as root mean square error (RMSE). In order to correctly measure the accuracy of the new models and to provide a goal function for optimization of LSTM parameters, introduced formula should be based on the probability distributions of the signals and their autocorrelations. The performance of the presented models is good and comparable with the results obtained through other approaches. Due to the aforementioned issues, a direct comparison with other solutions is not trivial. However, the presented work reflects the first trials related to the application of deep learning in this context. In future, further improvements in terms of network topology or applied algorithms will be considered. Planned work includes the application of stochastic differential equations, fractional calculus, and chaos theory. Final conclusions based also on the performance comparision will consider not only new models, including the ones presented in this paper, but also existing approaches that can be found in the literature.

Acknowledgments Research co-financed from government funds for science for years 2019-2023 as part of "Diamond Grant" programme and co-financed by the European Union through the European Social Fund (grant POWR.03.05.00-00-Z305).

References

1. Acha, E., Semlyen, A., Rajakovic, N.: A harmonic domain computational package for nonlinear problems and its application to electric arcs. IEEE Transactions on Power Delivery 5(3), 1390–1397 (1990)

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17

2. Bhonsle, D.C., Kelkar, R.B.: New time domain electric arc furnace model for power quality study. In: 2014 IEEE 6th India International Conference on Power Electronics (IICPE). pp. 1–6 (2014)
3. Chang, G.W., Shih, M.F., Chen, Y.Y., Liang, Y.J.: A hybrid wavelet transform and neural-network-based approach for modelling dynamic voltage-current characteristics of electric arc furnace. IEEE Transactions on Power Delivery 29(2), 815–824 (2014)
4. Chittora, P., Singh, A., Singh, M.: Modeling and analysis of power quality problems in electric arc furnace. In: 2015 Annual IEEE India Conference (INDICON). pp. 1–6 (2015)
5. Garcia-Segura, R., Vázquez Castillo, J., Martell-Chavez, F., Longoria-Gandara, O., Ortegón Aguilar, J.: Electric arc furnace modeling with artificial neural networks and arc length with variable voltage gradient. Energies 10(9) (2017), `https://www.mdpi.com/1996-1073/10/9/1424`
6. Golestani, S., Samet, H.: Generalised cassie–mayr electric arc furnace models. IET Generation, Transmission & Distribution 10(13), 3364–3373 (2016), `https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-gtd.2016.0405`
7. Golestani, S., Samet, H.: Polynomial-dynamic electric arc furnace model combined with ann. International Transactions on Electrical Energy Systems 28(7), e2561 (2018), `https://onlinelibrary.wiley.com/doi/abs/10.1002/etep.2561`, e2561 ITEES-17-0706.R1
8. Gomez, A.l., Durango, J.J.M., Mejia, A.E.: Electric arc furnace modeling for power quality analysis. In: 2010 IEEE ANDESCON. pp. 1–6 (2010)
9. Grabowski, D., Klimas, M.: Application of shallow neural networks in electric arc furnace modelling. In: 2021 21th International Conference on Environment and Electrical Engineering (to appear)
10. Grabowski, D., Walczak, J.: Analysis of deterministic model of electric arc furnace. In: 2011 10th International Conference on Environment and Electrical Engineering. pp. 1–4 (2011)
11. Grabowski, D., Walczak, J.: Deterministic model of electric arc furnace – a closed form solution. COMPEL - The international journal for computation and mathematics in electrical and electronic engineering 32(4), 1428–1436 (Jan 2013), `https://doi.org/10.1108/03321641311317220`
12. Leon-Medina, J.X., Vargas, R.C.G., Gutierrez-Osorio, C., Jimenez, D.A.G., Cardenas, D.A.V., Torres, J.E.S., Camacho-Olarte, J., Rueda, B., Vargas, W., Esmeral, J.S., Restrepo-Calle, F., Burgos, D.A.T., Bonilla, C.P.: Deep learning for the prediction of temperature time series in the lining of an electric arc furnace for structural health monitoring at cerro matoso (cmsa). Engineering Proceedings 2(1) (2020), `https://www.mdpi.com/2673-4591/2/1/23`
13. MATLAB: version 9.7.0.1261785 (R2019b). The MathWorks Inc., Natick, Massachusetts (2019)
14. Son, K., Lee, J., Hwang, H., Jeon, W., Yang, H., Sohn, I., Kim, Y., Um, H.: Slag foaming estimation in the electric arc furnace using machine learning based long short-term memory networks. Journal of Materials Research and Technology 12, 555–568 (2021), `https://www.sciencedirect.com/science/article/pii/S2238785421002118`
15. Starkloff, H.J., Dietz, M., Chekhanova, G.: On a stochastic arc furnace model. Studia Universitatis Babes-Bolyai, Mathematica 64(2) (2019)
16. Torabian Esfahani, M., Vahidi, B.: A new stochastic model of electric arc furnace based on hidden markov model: A study of its effects on the power system. IEEE Transactions on Power Delivery 27(4), 1893–1901 (2012)

Klimas, M., Grabowski, D. (2021). Application of Long Short-Term Memory Neural Networks for Electric Arc Furnace Modelling. In: , et al. Intelligent Data Engineering and Automated Learning – IDEAL 2021. IDEAL 2021. Lecture Notes in Computer Science(), vol 13113. Springer, Cham. https://doi.org/10.1007/978-3-030-91608-4_17