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Prediction of steel coils mechanical properties and microstructure by using deep learning and advanced data preprocessing techniques.

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Abstract

In the production of steel strips, the fulfillment of required product properties is a key factor to improve the company's productivity and competitiveness. Product characteristics can be evaluated online throughout the length of the strip by means of non-destructive tests such as the IMPOC whose output signal is related to mechanical properties and their uniformity. In this work, a novel approach based on the use of deep-neural-networks and advanced analytics is used to develop a model for the prediction of IMPOC signal from process parameters. The model provides plant managers with an insight into the relationships among process conditions, product characteristics and mechanical properties in order to suitably set up process parameters to meet product requirements. In this work, different model architectures and data processing techniques are evaluated leading an overall prediction error lower than 5% that puts the basis for their integration into the plant.

Keywords: neural networks; advanced analytics; steel-making; non-destructive test; variables selection

1. Introduction

In the last years the steel market has become highly competitive due to the continuously increasing number of producers that share the marketplace. This situation is becoming critical for the European steelmakers, which face the competition of companies outside EU that often offer cheaper products. At the same time, worldwide the steel sector is facing the challenge of digitalisation (Branca et al., 2020), which translates in a wide diffusion of sensing and monitoring devices coupled to ever increasing deployment of big data, machine learning and other data-driven techniques, which are required to process the huge volume of collected heterogeneous information. In this scenario methodologies, tools and practices improving product quality while reducing downgraded material can provide a fundamental support to the European sector in preserving its competitiveness (Dai and Zuo, 2020; Windt, 2019; Brandenburger et al., 2016). In effects, such tools allow providing customers with more reliable products that fulfil their demands, by improving productivity as well as energy and resource efficiency through scrap reduction. These considerations are valid in particular for steel strips for automotive applications, a paramount and fiercely contested market that is characterized by tight requirements. In such context, strips quality is continuously monitored throughout the whole production chain by means of non–destructive testing equipments, which provide a real–time *measure* of mechanical properties and microstructural properties deviations. By exploiting such information plant personnel can take suitable counter measures to preserve product quality and ensure uniformity of the main product properties over its length as well as over each production batch. This work is based on the measurements provided by one of these instruments, the *Impulse Magnetic Process Online Controller* (IMPOC) (Scheppe, 2009; Herrmann and Irle, 2009), an online material properties measurement system allowing automatic non–destructive testing of ferromagnetic steel strips, which is formed by two measuring subsystems with induction coils and a magnetic field sensing probe. The measuring heads are placed in front of the two sides of the steel strip that transits in between at the distance of approximately 50 mm each other. The IMPOC signal is derived from electromagnetical measurements of the strip residual field resulting by a magnetization impulse generated by the IMPOC heads (Jolfaei et al., 2018; Matyuk et al., 2006). Since the steel strip continuously moves with a speed value of about 3 m/s between the IMPOC heads, the measurement provided by the instrument is a signal throughout the whole length of the coil. Numerous studies highlight that such signal is strongly correlated to the strip mechanical properties over its length and put the bases for further investigations aiming at modelling such relationship to use it for production process monitoring and control purposes. These works exploit both traditional and advanced data analytics as well as Artificial Intelligence (AI) techniques (Bärwald et al., 2015; Mocci et al., 2018; Van Den Berg et al., 2021). In (Kebe et al., 2011) standard regression techniques are used to estimate strip tensile and yield strength from the IMPOC signal. The research pursued in (Nastasi et al., 2016) focuses on *chill marks* microstructural defects that are put into correlation with IMPOC signal discontinuities by means of advanced statistical analysis. Product uniformity issues are taken into account as well: in the RFCS project PUC (Product Uniformity Control) (Van Den Berg et al., 2017) main EU steel manufacturers and research institutes face the problem under different points of view by analysing through standard and AI techniques the outcome of ultrasonic and electromagnetic tests on actual products. Uniformity is put into relation with process parameters in Mocci et al. (2018) by using a popular type of unsupervised neural network, the Self–Organizing–Map (SOM), that allows continuously monitoring uniformity trend according to the varying plant conditions. In (Van Den Berg et al., 2021) the authors investigate the effect of the Hot Deep Galvanizing (HDG) line process parameters on the IMPOC signal by using two distinct IMPOCs: one at the entry (IMPOC–entry) and one at the exit (IMPOC–exit) of the HDG so as to monitor signal changes. The main outcomes of the work was the analysis of the relation among process conditions and IMPOC signal variations by using polynomial models and simple Artificial Neural Networks (ANNs). In (Colla et al., 2020) a machine learning approach was applied to the data provided by the IMPOC to find process conditions which allow preserving tensile properties uniformity along hot dip galvanized steel strips for automotive applications.

In this work the main results achieved in (Van Den Berg et al., 2021) are exploited to set up a model for the *coil–wise* simulation of the IMPOC test at the Pickling Line (PL) of a steelworks producing flat steel strips in order to predict the resulting signal. The proposed approach exploits product characteristics as well as process parameters related to the Hot Strip Mill (HSM) and the PL. Due to task complexity, peculiarity of the industrial problem and highly non–linear relationships among input and output variables, advanced preprocessing techniques for data partition and variables selection purposes are exploited together with a Deep Neural Networks (DNN)–based model to capture the relationships among the signal and the product and process parameters. This work is notable with respect to similar ones as it combines data analytics techniques for the selection and preprocessing of the data to a DNN that is able to simulate in real time the IMPOC measurements in order to allow plant manager to exploit this information to improve plant productivity and product quality.

The paper is organized as follows: section 2 is devoted to the description of the approach and of the available dataset used for model tuning and validation. More in detail a short description of the plant and data is provided in section 2.1, while the tested approaches are discussed in 2.2 together with the data pre–processing steps. The results achieved by tested models are presented, compared and discussed in section 3. Finally, some concluding remarks and hints for future developments are provided in section 4.

2. Material and methods

The work presented in this paper exploits the data gathered at the Tata Steel Europe steelworks located in Ijmuiden, The Netherlands. A schematic representation of the whole line is provided in Figure 1, which represents the production chain together with the installed IMPOC system, that is the object of this study.

The hot–strip mill is fed with slabs which have been cast at the steelmaking plant. These slabs, being about 225 mm thick, are reduced in thickness by subsequent steps of hot rolling. Also, by controlled cooling of the strip, the microstructure is determined. During this process, oxides are formed on the surface of the strip, which are removed by sulphuric acid treatments in the pickling line (PL). In the cold–mill, the thickness is further reduced to specified product thickness. Finally, in the hot–dip galvanising line (HDG), the cold–rolled

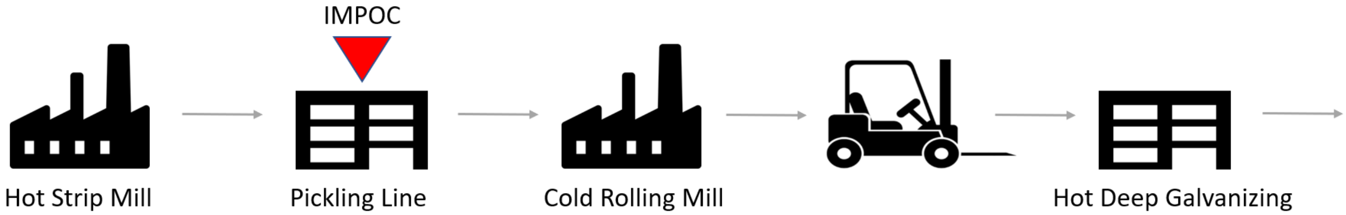

Figure 1. A schematic representation of the whole process pipeline highlighting the position of the IMPOC system employed in this work.

steel strip is annealed to give it the required formability properties, and coated with zinc for anti-corrosion resistance needed for automotive applications. During the process additional operations are pursued to ensure strip flatness. Finally, the strip is coiled and shipped to customers.

2.1. Available data

For the modelling purpose of this work, a set of data coming from the IT system of the plant depicted in figure 1 was suitably selected. The dataset is formed by about 35000 observations sampled every 2 meters along the strip length and are related to 140 coils, all belonging to similar steel grades. The dataset includes 259 variables concerning both product characteristics and plant parameters related to the different stages of the process and can be grouped as belonging to product characteristics (steel type, strip dimensions) or HSM and PL process parameters, including temperatures acquired during the process and tension levelers parameters.

Basic data cleansing was performed on the dataset by removing the instances including missing or non numerical values. In addition, outliers removal was achieved by removing the observations selected according to a set of support indicators provided directly by the plant IT system, which assesses the reliability of the collected data.

Despite the uniformity of the so-formed dataset with respect to steel grade, the variety of IMPOC signal trends is remarkable and includes numerous behaviours, by highlighting the effect of the different considered process parameters on such measurement. Figure 2 shows some examples of IMPOC signals, which are included in the dataset.

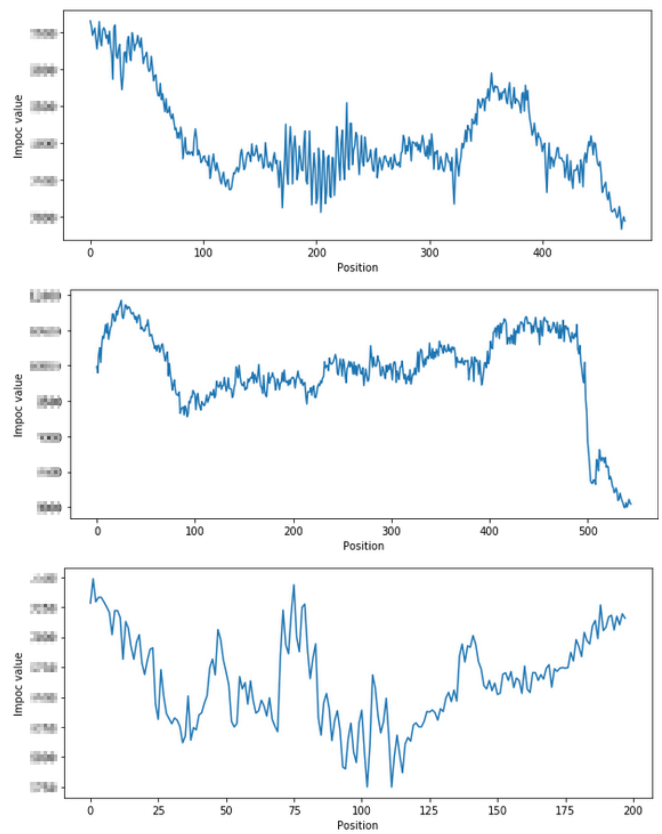

Figure 2. Sample IMPOC profiles that put into evidence the variability in terms of shape and absolute value of the target signal to be predicted. Actual IMPOC values on the Y axis have been pixelated for confidentiality reason

2.2. Models development

In this section the main steps and design choices that led to the implementation of the model for the IMPOC signal prediction are described and discussed. The peculiar characteristics of the problem required the application of special algorithms for data preprocessing to maximize the effectiveness of the model. The design phase of the predictor – schematized in figure 3 – includes three subsequent steps devoted to: (i) de-

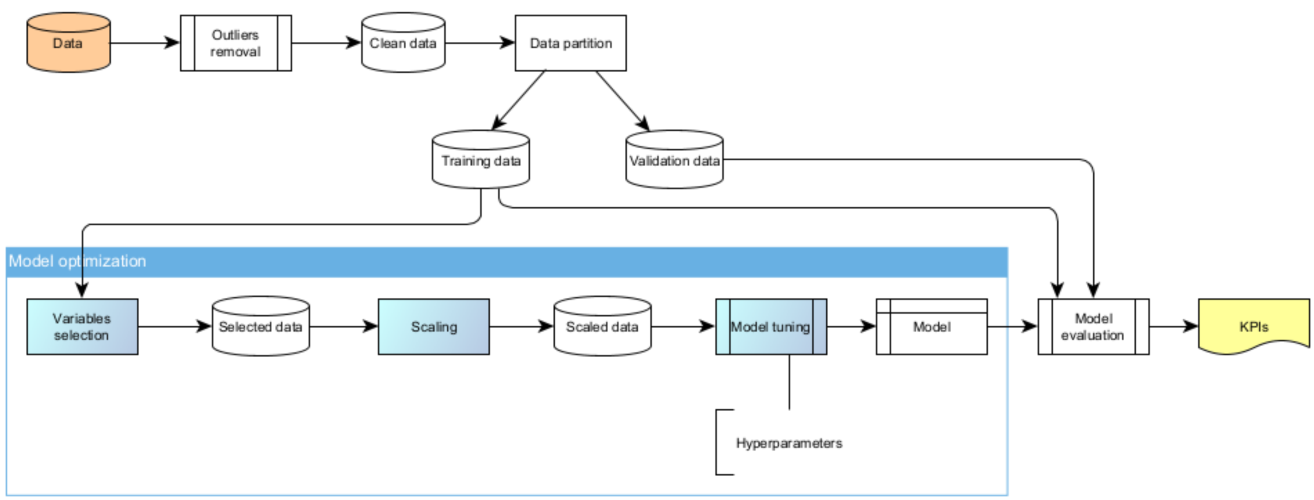

Figure 3. A flowchart representing the main steps of the design and assessment of the model for the IMPOC signal prediction. The components included into model hyperparameters tuning are highlighted in blue.

termination of homogeneous training and validation datasets, which is described in section 2.2.2; (ii) selection of a suitable set of input variables to the model that is discussed in section 2.2.2; (iii) model tuning including optimization of hyper-parameters, which is presented in section 2.2.3.

2.2.1. Data partition

As depicted in Figure 2, there is a variety of different types of profiles for the IMPOC signal despite a relatively low number of coils that can be used for either training or validation of the model. In these cases a purely random partition of the whole dataset into these two subsets could lead to situations, where some arbitrary types of profile are well represented in one of the two sets and neglected in the other one. Such partition would be detrimental for the performance of any data-driven model, since it should have to reconstruct profiles that belong to *unknown* types, i.e. that are not present or not adequately represented in the training dataset. More in general, the predictive capabilities of a data-driven model benefit from the diversity of the training dataset and the homogeneity of the training, validation and test sets. In the light of this consideration, a data partition strategy to form *balanced* training and test datasets was put into practice. The method proposed in this work is based on the use of a Self Organizing Map (SOM), a particular kind of neural network that is suitable to unsupervised learning tasks such as data clustering and dimensionality reduction (Ahmad and Starkey, 2018; Licen et al., 2018; Vannucci and Colla, 2018). The SOM maps the samples from an original domain $\mathbb{R}^N$ into a lower dimension space $\mathbb{R}^M$ where $M < N$ (typically $N = 2$). This mapping has some interesting properties, which make it suitable to this partitioning task. In particular, it is able to preserve the topology and distribution of the input samples in the original domain. In this context, it means that more clusters are devoted to the mapping of the original domain regions, where profiles are more represented (distribution preservation), and that two coils with similar IMPOC profiles are mapped into the same cluster (or, at least, in neighbour ones).

In this work the IMPOC profiles - once resampled into 100 points time series in order to uniform their length - are clustered by a SOM holding 25 neurons, which maps the profiles into 25 clusters. At the end of the clustering, each cluster collects a set of profiles with similar shape - and associate coils -, mapping with more detail (more clusters) the most represented *shape* types. Once clustering is complete, the training and test datasets are formed by picking coils from each cluster: in practice 70% of the coils associated to each arbitrary cluster $C_{i,j}$ form the training dataset, while the remaining 30% are added to the test dataset. This procedure grants the balance of the various types of IMPOC signal profiles within the two datasets. This balancing can be observed from the distribution of the IMPOC exit signal values for the training and test set, which is depicted in Figure 4 through their comparative histograms. The mutual correspondence of the two distributions highlights the similarity of the target IMPOC measures in the two groups.

2.2.2. Variables selection strategies

As reported in section 2.1 the available dataset include a high number of potential input variables for the predictive model. Not all of these features influence the IMPOC signal thus their use for modelling purposes is not beneficial. Variables selection is required to filter out these negligible features, to limit the number of input variables fed to the subsequent models. This op-

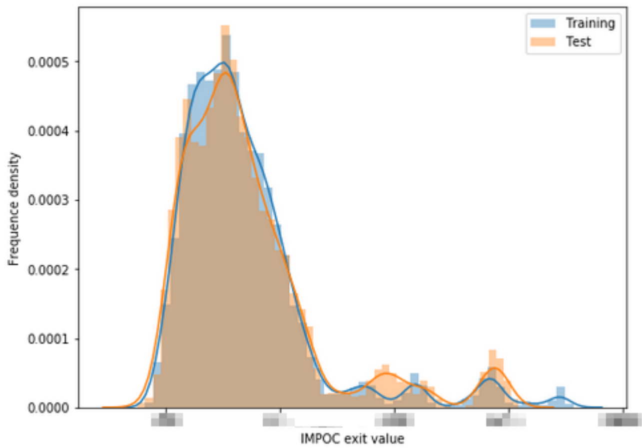

Figure 4. Histogram representing the distribution of the IMPOC exit signal value for the training and test sets. Actual IMPOC values on the X axis have been pixelated for confidentiality reasons.

eration was demonstrated to improve the performance of data-driven models, as it limits the sources of potential noise and the number of free parameters, by making the training process faster and more stable (Cateni and Colla, 2016b,a). In this work two different variables selection approaches are tested:

- *correlation* based selection uses the Pearson's correlation index (Pearson, 1895) to detect the input variables that are most related to the target (IMPOC value). This method, belonging to the filter variables selection approaches, is very fast but has the limitation of not considering the interactions among variables (Mehmood et al., 2012; Cateni et al., 2017). In this work the variables with an absolute value of the correlation coefficient higher than 0.7 are selected. The resulting set is formed by 13 features including process parameters and product characteristics;
- *genetic algorithms variables selection (GaVarSel)* belongs to the wrappers family of variables selection methods. By exploiting the optimization capabilities of Genetic algorithms (GA) it evolves the set of selected variables by mixing existing and efficient solutions according to their so-called *fitness*, an index that measures the performance of candidate input variables sets. This method benefits from the efficient search strategy of GA in order to find optimal solution requiring a limited computation burden. *GaVarSel* takes into account the contribution of individual variables and their interactions and is proven to be very efficient, specially when coping with industrial tasks, which are characterized by the presence of a high number of input variables that are often redundant and poorly correlated to the target (Cateni et al., 2010; Matino et al., 2019). More detail on this method can be found in (Cateni et al., 2009). The use of *GaVarSel* led to the selection of 48 input variables associated to both product and process characteristics.

2.2.3. Models tuning

The available data, splitted into a training and test set according to the method described in Section 2.2.1, are used to develop and validate a Artificial Neural Network (ANN)-based model for the prediction of the single coils IMPOC signal from the variables, which have been selected according to the *correlation* and *GaVarSel* criteria described in Section 2.2.2. ANNs were selected for this modelling task to exploit their well known capabilities of being a universal approximator, their generalization ability and robustness, which make them particularly suitable to industrial applications where a target value need to be inferred from a large number of features. In particular, a DNN model is developed and evaluated by using the popular Keras package within the Python programming language. Keras is actually one of the most popular and powerful frameworks for the development and deployment of deep-learning models (Bloice and Holzinger, 2016; Lee and Song, 2019). More in detail, the models are multi-layer perceptron feed-forward neural networks (MLP-FFNN). In order to find the optimal configuration of the model a grid-search through the combinations of its main hyper-parameters and the previously mentioned methods for variables selection was performed. The following hyper-parameters were taken into consideration together with their tested values:

network architecture expressed as the number of neurons in each hidden layer of the network. An arbitrary configuration is expressed as a list of integer values $[H_1, H_2, .., Hn]$ where H_i represents the number of neurons in the $i-th$ layer of the net. The following architectures are evaluated: [20,10],[40,20],[50,25],[20,10,5]. In this context the number of input variables is determined by the variables selection process while one single output neuron is envisaged for the prediction of the target;

optimizer defines the algorithm used to change the internal parameters of the ANN during its training, solving the optimization problems framed by the loss function minimization. In this work two different methods are investigated: *adam*, an approach based on stochastic gradient descent (Kingma and Ba, 2015; Reddi et al., 2018), and *sgd* that implements the gradient descent with momentum;

variable selection identifies the employed variable selection strategy among *correlation* and *GaVarSel*

scaling refers to the method employed to scale input variables values to mitigate the effect of different orders of magnitude that could affect the network training. Three methods are evaluated: *MinMax* scaler transforms features by scaling each one to

Table 1. Results achieved by top–20 model configurations

Net. architecture	Optimizer	Var. Sel.	Scaler	Batch size	MAPE Tr	Std. Tr	MAPE Ts	Std. Ts
40–20	adam	GaVarSel	minmax	64	4.026	0.153	4.191	0.219
50–25	adam	GaVarSel	minmax	64	3.474	0.120	4.238	0.550
50–25	adam	correlation	standard	64	4.033	0.077	4.255	0.237
40–20	adam	correlation	standard	64	3.501	0.250	4.283	0.200
20–10	adam	GaVarSel	minmax	64	3.643	0.180	4.477	0.115
20–10	adam	correlation	robust	64	4.405	0.074	4.502	0.105
50–25	adam	correlation	robust	256	4.267	0.161	4.507	0.101
20–10	adam	correlation	standard	64	4.366	0.068	4.530	0.226
20–10–5	sgd	correlation	minmax	64	3.921	0.300	4.535	0.267
20–10	sgd	correlation	minmax	64	4.165	0.221	4.537	0.480
50–25	sgd	correlation	minmax	64	4.000	0.091	4.537	0.152
50–25	adam	GaVarSel	minmax	256	3.798	0.420	4.546	0.404
40–20	sgd	correlation	minmax	64	4.000	0.350	4.568	0.369
40–20	adam	correlation	robust	256	4.268	0.173	4.575	0.084
20–10–5	adam	correlation	standard	64	4.390	0.102	4.582	0.170
20–10–5	adam	GaVarSel	minmax	64	3.685	0.055	4.600	0.021
50–25	adam	correlation	robust	64	4.305	0.150	4.617	0.085
40–20	adam	correlation	robust	64	4.275	0.134	4.623	0.047
20–10–5	adam	correlation	robust	64	4.465	0.052	4.669	0.133
20–10–5	sgd	correlation	robust	64	4.863	2.135	4.745	2.367

the [0;1] range; *Standard* scaler standardizes the features by removing their mean (that is set to 0) and scaling to unit their variance; *Robust* scaler takes into account noise and outliers in the data;

batch size sets the number of data samples that is used during training to estimate the network error gradient and subsequently update the weights. This parameter controls the dynamics of the network training. The tested values are 64 and 256.

In this context, for each of the resulting 96 combinations of hyper–parameters 10 tests are performed: in each test, a model is trained according to the selected set of hyper–parameters using the training dataset and its performance are evaluated on the tests dataset.

3. Results and discussion

The results have been assessed in terms of average Mean Absolute Percentage Error (MAPE) through the coils belonging to the test set. MAPE for an arbitrary coil is calculated according to the following equation:

$$MAPE = \frac{100}{p}\sum_{i=1}^{p}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{1}$$

where p is the number of points forming the IMPOC exit profile of the coil, y_i is the actual value of the target at point i^{th} and $\hat{y}_i$ its predicted value. The results obtained during the test campaign are reported in Table 1 for the training and validation set. The standard deviation of the adopted error measure through the 10 performed tests is depicted as well, to evaluate the stability of the model configuration. For the sake of brevity only the top–20 best performing results are reported in the table.

According to the results depicted in Table 1, the performance achieved by the tested models is satisfactory. The best performing configurations achieve an average percent error of about 4.2% with respect to actual IMPOC measurements. More in general, percent error is lower than 5% for all of the 96 tested configurations. The goodness of the prediction can also be assessed from Figure 5, which shows the predicted versus measured IMPOC values for all the coils within the test dataset as obtained by using the best performing configuration of the model. The scatter plot puts into evidence a substantial agreement between the two quantities throughout the whole IMPOC values.

The model stability – in terms of performance – is satisfactory as well, since the standard deviation of the MAPE through the 10 performed tests for each configuration is always acceptable (in the range 0.1%–0.6% with respect to IMPOC value in the test set). High stability in the performance assesses the reliability of the produced models. The performance of the best model can also be evaluated from a qualitative point of view from Figure 6, which shows the actual and predicted IMPOC profile of some sample coils in the test dataset. The plots show that the predicted profile follows the trend of the measured signal with sufficient precision and does not seem sensitive to small fluctuations observed in the original signal. Table 1 give some important direction on the choice of the most suitable model hyper–parameters and pre–processing techniques to be adopted that can be summarized as follows:

- medium–size network are preferable, as they are able to achieve a lower prediction error with respect to the other ones. Smaller networks are affected by higher MAPE, probably due to the limited number

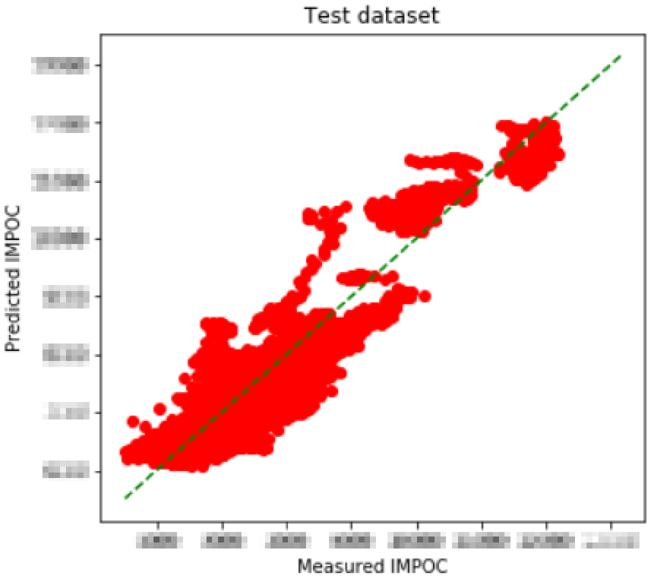

Figure 5. Measured vs. predicted IMPOC value for coils within the test dataset achieved by the best performing model according to Table 1. Actual IMPOC values on the axis have been pixelated for confidentiality reasons.

of parameters that do not fully relate input variables and target. On the other hand, bigger networks generally achieve better results on the training set but worse on the test coils, by putting into evidence some overfitting issues;

- *GaVarSel* variable selection approach is the one adopted by the best performing models, although the correlation based method obtain similar results. The slight improvement of the former approach is likely due to the higher number of employed variables and related interactions that are taken into account;
- the *adam* training algorithm – being the one employed by the majority of the top 10 models – provides better performance than *sgd* in this application;
- among the scaling methods, *minmax* is the one that obtains better results: the other approaches, which should be more reliable when coping with noise and outliers, perform worse than this basic scaling method.

4. Conclusions and future work

In this paper the design and development of a model for the prediction of the IMPOC profile on steel strip during manufacturing was presented. The IMPOC is a non–destructive test that can be used for the monitoring of steel strips mechanical properties – to whom it is strictly related – and its analysis is of utmost importance in order to grant the fulfilment of product properties among which uniformity. The simulation of IMPOC measurement as achieved by the proposed model aims at linking the semi–manufactured product properties and the process conditions to the IMPOC signal for a twofold scope: the first goal is the achievement of a preliminary estimation of the profile in the initial phases of the process, to allow plant managers operating suitable counter–measures in case some problem arises; secondarily, the model can improve the understanding of the product and process characteristics that mostly affect the IMPOC outcome. The described work includes the investigation of the preprocessing methodologies for data partitioning, scaling and variables selection that lead to the best predictive performance of the associate models.

The achieved results are satisfactory, as the average MAPE through the test coil is durably lower than the threshold value of 5% and around 4% for the best performing models. Furthermore, from a qualitative point of view, the predicted profiles trace the actual profiles and are able to reproduce the trend of the IMPOC signal throughout the whole strip length. The results are indeed encouraging, but the research activity is just beginning. Actually the model is fed with coils belonging to a limited number of steel grades and product types; for this reason, in future work, in order to improve its generalization capabilities and consolidate the results, further steel grades and product types (i.e. different strip widths) will be included in the training and test dataset of the model. Moreover, the possibility of using the model for a preliminary and automatic tuning of process parameters will be investigated: in this case the IMPOC profile predictor will be exploited by an optimization engine whose aim is the determination of the process conditions that lead to an arbitrary desired profile, or features of the profile.

5. Acknowledgements

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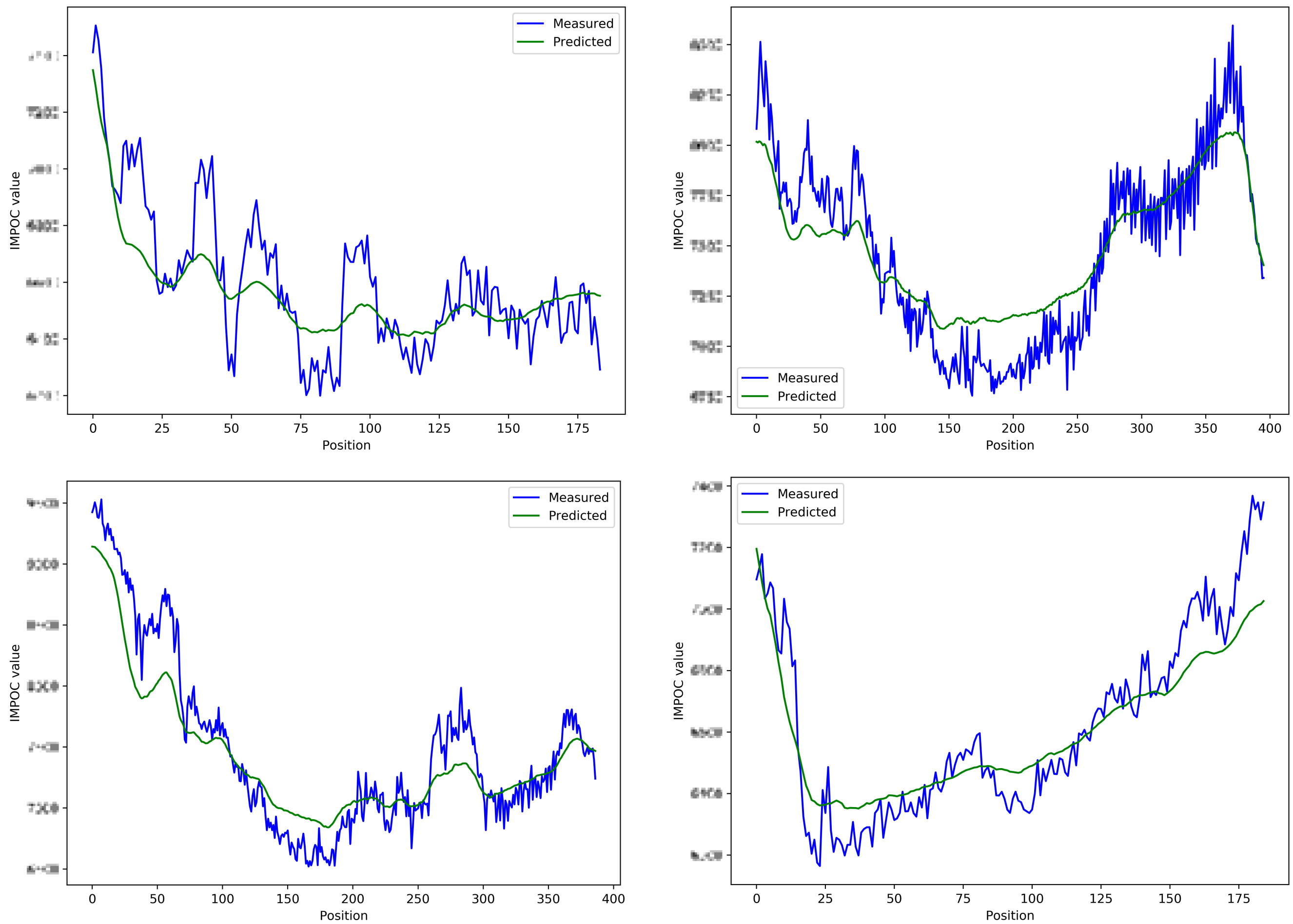

Figure 6. Exemplar IMPOC profile prediction for different coils within the test dataset. Actual IMPOC values on the Y axis have been pixelated for confidentiality reasons.

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