PREDICTIVE MODELLING OF THE HOT ROLLING PROCESS USING AN INTEGRATED BASED NETWORK

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Abstract - The rolling process is considered to be one of the most crucial operational units in the manufacture of finished and semi-finished bulk products. Predicting the final product properties is important because it can aid technologists in determining the adequate process variables required to produce a particular product with predefined characteristics. However, modelling such a process is not a trivial task, in particular when it is significantly affected by many variables and carried-out at high temperatures, the so-called hot-rolling mill process. In this research work, an integrated network based on computational intelligence is presented to model the hot-rolling mill process. In such a network, the output can be predicted via two phases. The first phase consists of a number of models that are trained using the process inputs and the target output (i.e. product characteristics). The second phase relates to utilizing the predicted outputs from the first phase as well as the target output to train another linear or nonlinear model in order to produce the final predicted output. Validated on real industrial data, it has been shown that such a modelling structure has the ability to deal with sparse data and to accurately predict the characteristics of the hot rolled products.

Index Terms - Computational Intelligence, Hot-Rolling Mill, Integrated Networks, Radial Basis Functions, Steel Sections.

I. INTRODUCTION

The manufacturing industry is currently in the middle of a revolution in which predictive analytics is increasingly being deployed to make material manufacturing flexible, predictable and resourceful [1]. This revolution, the so-called "industry 4.0", represents the process by which manufacturing systems become completely autonomous through the deployment of large scale automation systems, data exchange between manufacturing components as well as the utilization of advanced data analytics systems. One process of manufacturing which can benefit significantly from this revolution is the hot-rolling mill process. Such a process involves passing a heated metal product through a set of rolls in order to deform it for various onward practical uses [2]. The structural integrity and the surface quality of the rolled product are of paramount importance to safe design, this is the reason behind the stringent regulations that have been imposed on manufacturing companies. Therefore, it is crucial for these companies to be able to rigorously model and control such a process.

Various modelling paradigms have hitherto been employed to predict the metallurgical, mechanical and geometrical properties of the rolled product [2-4]. In general, these paradigms can be either physical or data based ones. The former models that can normally predict the microstructure and some other mechanical properties have generally been verified by using experimental data, and modified when significant differences between the predictions and the experimental results are noticed. However, physical based models depend on many factors (e.g. chemical compositions and cooling conditions), and, thus, they are quite complicated [2]. In the last 3 decades or so, data-driven models, including artificial neural networks and fuzzy based models, have been developed to simulate the rolling process [3-4]. The core of such models is the process data (i.e. the number of data points and their distribution in the spaces under investigation). Therefore, the performance of these models may not be as expected when the collected data are limited, defective and/or sparse. For instance, sparse data may result in a biased model. In general, all modelling approaches have their own strengths and limitations, and in the process of selecting the most appropriate tool to model the hot-rolling mill process, one should keep in mind that failing to predict the optimal set of operating conditions accurately could lead to a further treatment therapy incurring an unnecessary manufacturing cost.

In this research work, an integrated based network, as a data-driven approach, is employed to model the hot-rolling mill process, and to deal with sparse data, which were provided by Steel industry. The main motivation behind such a structure is to achieve a satisfactory modelling performance, in particular in those areas where the data points are quite limited when compared to other areas in the space under study. The rest of the paper is organised as follows: Section II provides a background on the hot-rolling process and explains in detail how such a process is one of the most important manufacturing processes. Section III details the proposed methodology for tackling the peculiarities of the hot-rolling process modelling from data. Section IV discusses the results of applying the proposed approach on the real-life hot-

rolling process data. Section V provides conclusions on the paper as well as possible future research directions.

II. THE HOT-ROLLING MILL PROCESS

In the reversing hot-rolling mill, a rectangular slab is reheated in a furnace to approximately 1250ºC, and then it is rolled into an H-section beam, as shown in Fig. 1. In order to obtain the desired dimensions and metallurgical properties, the slab usually undergoes various stages in the reheating furnace after which it is delivered to a group of rolls. Typically, there are three reversing stands: two universal stands, namely; universal rougher and universal finisher, and an edger stand. The reheated slab is placed under four rolls in the universal stands to form the H-shaped section and to reduce the thicknesses of the flanges and web. The edger stand reduces the flange lengths by rolling the ends of the flanges. The accurate control of the rolling mill stands is of paramount importance because it determines the dimensions of the finished beam.

In this research work, a data set (approximately 7144 data points after cleaning) on the finished beam dimensions was provided by British Steel (Redcar, UK). In a modern reversing section mill, there exists extensive instrumentation for online process monitoring and control, as well as offline production management and administration. These instruments are connected with multiple online data servers for collecting real-time process data that are usually stored for other purposes including modelling and optimization tasks. The initial data set contains approximately 170 input parameters and 7 outputs, which are flange and web thickness values measured at different locations, as shown in Fig. 1. Such a large number of input parameters can be detrimental for developing a representative data-driven model due to the curse of dimensionality and the confusion in the true input/output relationships. Therefore, and based on expert's knowledge, the number of the parameters was reduced to 22 which includes, for example, hot slab width and depth, universal rougher mill gap setup, edger mill gap setup, universal finisher mill gap setup, etc.

III. INTEGRATED BASED NETWORK: MODEL DEVELOPMENT

With the recent advances in computing power, computational intelligence is finding its way into several areas such as health care and manufacturing [5-6], where data based models can be developed to represent various processes whose physical models do not exist or too complex to implement. In general, developing data-driven models relies on the observed data and its distribution on the space area. For a complex process, limited and sparse data may limit the performance of such models, which may not be able to capture the complex input/output relationships. Therefore, in this research work, an integrated based network is presented to represent the hot-rolling mill process. The motivation behind such an integrated structure stems from the fact that (i) having different models that include different number of functions and weights could play a complementary role in considering the various possible patterns of the process, (ii) training the observed data using two phases could improve the modelling performance, in particular, when the collected data are sparse.

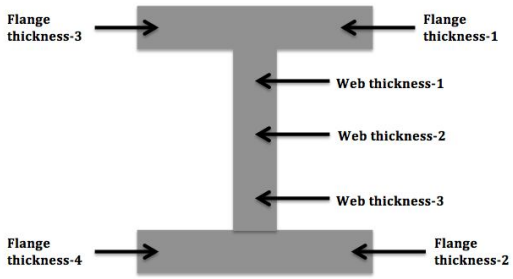


Fig. 1. An H-section beam

The integrated network structure for multi-input single output is depicted in Fig. 2. In such a structure, the output can be predicted via two phases. In the first phase, the process inputs (x_n) and the target output (y_T) are utilized to train a number of models having different structures. The second phase relates to utilizing the predicted outputs from each model in the first phase (y_{P1}, y_{P2}… y_{PM}) and the target output (y_T) to train another model, which should be able to model linear and non-linear relationships, leading to the final predicted output ($\widehat{y}_P$). Since the radial basis function (RBF) model has, as it has been proved in various areas, the ability to capture linear and non-linear relationships, it is employed in the first and second phases.

An RBF model comprises three layers, namely; an input, a hidden including basis functions, which are a function of the radial distance from a predefined centre, and an output layer. These three layers map the inputs to the output, such a mapping is given as follows [7]:

$$y_P(x) = \sum_{i=1}^{I} w_i \phi_i(x) + w_0$$

where w_0 and w_i represent the bias and coefficient connecting the i^{th} basis function (ϕ_i) to the output neuron, respectively. Since Gaussian function has the ability to provide users with a reasonably accurate approximation of any function, it is a common choice for the basis function [7].

By using the RBF model in the two phases, one can analytically represent the integrated network as a combination of superposition and composition of the basis functions. Thus, the final predicted output can be written as follows:

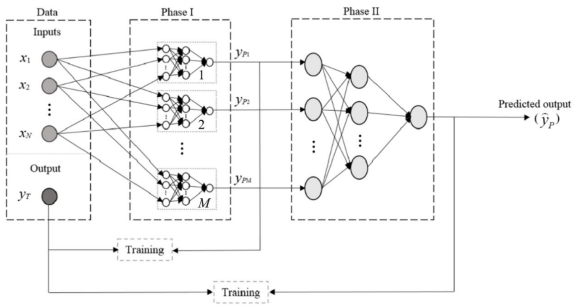


Fig. 2. The structure of integrated based network [6]

$$\hat{y}_P = \sum_{k=1}^{K} w_k^{(2)} \phi_k \left(\sum_{m=1}^{M} w_m \phi_m (y_{Pm}) + w_0 \right) + w_0^{(2)}$$

the parameters are as defined above. The superscript number is utilized to distinguish the second phase parameters from the first phase ones. It has been proved that both the composite and the superposition functions are dense in a convex data space [8-9]. Therefore, the combination of these functions would considerably minimize the difference between the target and the predicted values (i.e. improving the modelling performance).

IV. RESULTS AND DISCUSSIONS

The main aim is to be able to anticipate the difference between the target slab dimensions and the produced ones, where such a difference significantly depends on the process parameters mentioned above. However, predicting such a difference directly using data based model may lead to a biased model because various sets of input parameters may lead to the same difference value but a different percentage one. Therefore in this research work, the target dimensions were predicted, then the difference between predicted dimensions and the target ones can be easily estimated.

The collected data was utilized to develop the integrated based network. The data set was divided into two sets; a training set (70%), which captures the input/output relationships, and a testing set (30%), which assesses the model generalization capabilities. Ten RBF models and a single one in the first and second phases, respectively, were initialized using different numbers of basis functions and different values of model parameters (i.e. connecting coefficients). The number of RBFs for each network that was selected corresponds to the minimum error evaluated via the root mean square error (RMSE). The connecting coefficients of all the models were optimized using scaled conjugate gradient algorithm. The performance of the integrated network for the flange thickness-1 is RMSE (training, testing) = [1.07, 1.11], as shown in Fig. 3. It is noticeable that most of the predictions fit properly within a 90% confidence interval. However, some of the data points are outside the 90% confidence interval, these measurements are produced by the process itself. It is confirmed by a process expert that these data points are carrying meaningful information about the process, and thus they can not be considered as outlier and removed. In a similar manner, the performance measures obtained for the other dimensions are summarized in Table I.

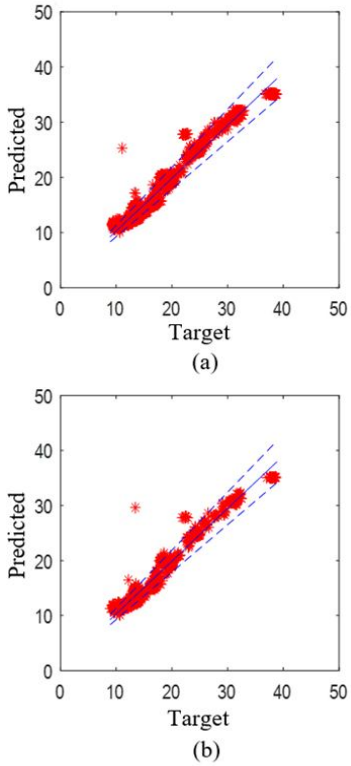


Fig. 3. The integrated network based on 10 RBF models for the flange thickness-1 (mm): (a) Training, (b) Testing (with 10% bands).

For comparison purposes, a single RBF network was developed to represent hot-rolling mill process. The data set was divided as mentioned above. The scaled conjugate gradient algorithm was employed to optimize the model parameters. For the flange thickness-1, the RBF network performance is presented in Fig. 4, with a RMSE (training, testing) = [2.26, 2.40]. It is noticeable that the integrated network modelling performance is superior to that of the single RBF network, where the RMSE value for the RBF model is approximately twice the value for the integrated network. In a similar manner, the RBF model was utilized to predict the other dimensions of the rolled product, the performance measures for these dimensions are summarized in Table I. It is noticeable that the overall modelling performances of the integrated network for all dimensions are better than the ones of the RBF model.

CONCLUSIONS

In this research, the integrated based networks, as a data-driven model, is presented to model the hot-rolling mill process, and to predict the dimensions of the rolled product. Such a network predicts the outputs

by training the observed data via two consecutive phases. Although the data are sparse, the integrated structure has the ability to accurately map the process inputs to its outputs, this being due to the number of basis functions and weights included in such a structure. Furthermore, such an integrated structure allows one to circumvent the problem of defining the best structure by using different structures in the first phase.

The effectiveness and efficiency of the integrated framework was demonstrated and validated on real industrial data. However, it would be worth improving the interpretability of a process. Therefore, incorporating the integrated structure with other models such as fuzzy logic systems, which can describe the process under investigation linguistically in a way one can understand it, would be advantageous. In addition, such models, as it is well-known, can handle uncertainties more effectively.

Model	RBF		Integrated Network	
Output	R^2	RMSE	R^2	RMSE
Flange thickness-1	0.91	2.30	0.96	1.08
Flange thickness-2	0.94	1.41	0.98	0.92
Flange thickness-3	0.84	2.81	0.96	1.03
Flange thickness-4	0.86	2.34	0.97	0.98
Web thickness-1	0.92	0.93	0.94	0.82
Web thickness-2	0.89	1.14	0.95	0.73
Web thickness-3	0.91	0.98	0.96	0.69

TABLE I. The overall performances of the models represented by R^2 and RMSE

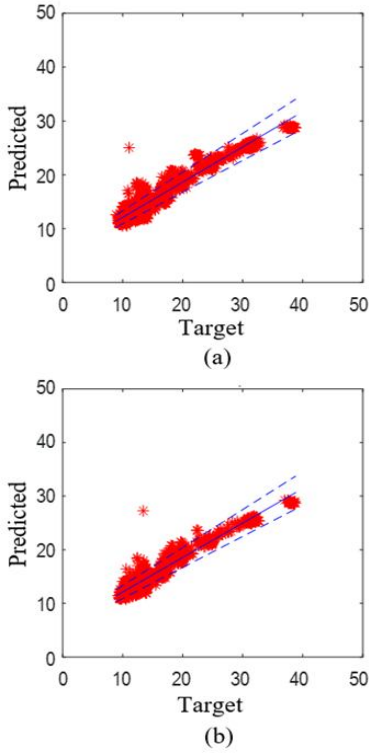


Fig. 4. The RBF model for the flange thickness-1 (mm): (a) Training, (b) Testing (with 10% bands).

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