MODELLING A BIOMASS BOILER USING AN ARTIFICIAL NEURAL NETWORK

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ABSTRACT
This paper is focused on the application of Artificial Neural Networks to model a recovery biomass boiler from the Joutseno paper mill (Finland). The cross-validation technique has been used to train the neural model. The validation phase has been carried out with new data, which have never been known or seen during the training procedure. As a result of the validation stage, the model has achieve only 1.77% of MAPE error for the main output variable (net steam), and reaching good performance metrics for the estimation of the main gas emissions. This work will be the basis of a future development using Artificial Neural Networks, in order to control and minimise the impact of the air emissions produced by the industrial plant.

Keywords: Artificial Neural Networks, recovery boiler, real plant data.

1. INTRODUCTION
Finland is a country of wood and trees and its main business is the industry of paper and pulp (Suhr et al. 2015). The Kraft process (see Section 2 for details) is a basic process of making paper or pulp from wood. The Kraft pulp process consists of two lines; while in the main has as principal activity the extraction of wood pulp for producing paper the secondary line has the recovering of chemical elements to be reused. This work is focused on the recovery boiler, a key infrastructure as it is the principal responsible of both recover the white liquor and to generate electricity for the plant. Moreover, as any boiler, various chemicals are emitted to the environment so it is fundamental to control and limit those emissions (Vakkilainen 2005).
The principal objective of this work is to develop intelligent control strategies able to improve their performance while keeping under control the emissions. Safety is an important aspect to take into account. While improving the recovery of chemicals, the air emissions shall never go over the safety limits. Therefore, it is very important to have models of the processes that allow us to carry out simulations or to be used within the controller itself. However, the complexity as well as the high computational cost of the mathematical models of these types of processes makes necessary the use of surrogated black-box models.
Artificial Neural Networks (ANN) strategies have been used for years, but there are not commonly implemented in the industry. In process control this black-box modelling technique has been used successfully, but it is still possible to achieve better results. It can be more widely applied to solve some of the most nagging process control problems (Yen-Di Tsen et al. 1996). For example, ANN have been used to model the extraction of lignosulfonates from barley straw (Serna-Diaz et al. 2014). Furthermore, neural modelling has been used to reduce the maintenance cost and to improve the maintenance efficiency of the electricity generation by linking operational data and plant conditions (Fast and Palmé 2009).
The purpose of this work is presented in Section 4 where a model based on ANN of a biomass boiler installed in the secondary line of a Kraft process. The objective is obtained a fast response model to control the air emissions of the boiler
Kraft process and biomass boiler introduction is performed and the main design parameters are presented in Section 2. Next Section describes the datasets that have been used. Then, Section 4 the modelling methodology is presented. Finally, the preliminary results and the obtained conclusions are illustrated in Section 5 and 6 respectively.

2. KRAFT PULPING PROCESS
The Kraft process was introduced in 1879 and currently it is the most distinguished pulp process worldwide. Gaining cellulose is the main purpose of this process (Gustafson et al. 1983). This type of plants use the maximum energy generated by raw materials, and minimises the amount of waste. We can consider these kinds of factories of minimal environmental impact due to the appliance of the energy recovery line.
Figure 1 shows the three main sections in which the manufacturing process is divided. Extraction of cellulose from the wood is considered as a main line. Recovery of chemical elements as a secondary sequence and finally, the last phase is the effluent treatment. The process begins with the logs. Their surface bark is removed and remaining wood is cut it in small pieces called chips. From the stockpile, the chips are extracted, classified and taken to the cooking process-continuous digester with white liquor. White liquor is an alkaline

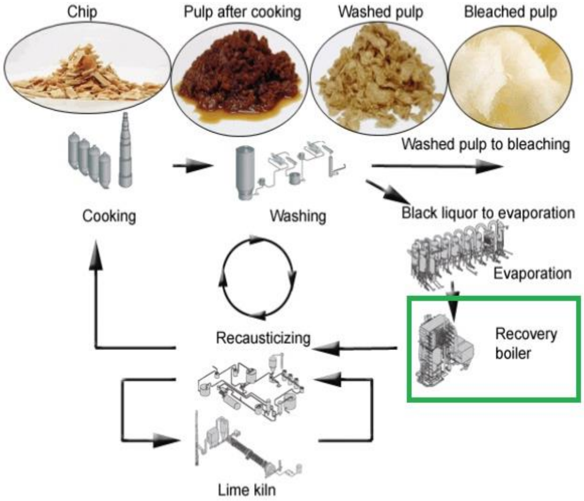

Figure 1: Scheme of the Kraft Process and Situation of the Modelled Recovery Boiler (courtesy of Katriina Mielonen)

solution of caustic soda and sodium sulfide, which reacts with the wood lignin. As a result of the cooking process two products are obtained: black liquor, which is the consequence of the reaction between the white liquor and the lignin, and cellulose pulp, which is classified, washed and bleached.

Once the black liquor is obtained, the recovery phase begins. The process is gradually becoming better known and spread throughout the world. The increment of the production, raised up the second production line, which is based on the recovery of chemicals. When production was expanding, they realized that it is cheaper to recycle the black liquid than to buy more chemicals. This operation is carried out in all Kraft factories; here it is why it is called a closed system, due to the recovery of the chemicals used in the beginning of the process.

The purpose of the recovery system is to return the inactivate sodium compounds at the end of the cooking process into activate compounds that can be reused at the beginning. The main operations for recovery the chemicals are based on the evaporation of black liquid, the black liquor combustion in the boiler, the causticizing of the sodium carbonate and the regeneration of lime mud. This recovery is also vital for a profitable process, without this step the waste would be very harmful for the environment and its treatment very expensive.

The acquired black liquor is classified in weak or strong liquor. The weak black liquor is evaporated to remove the water excesses, and the strong black liquor is taken to feed the recovery boiler. The black liquor is burned in the recovery boiler to produce heat and a smelt consisting of the inorganic sodium-containing cooking chemicals. The smelt is dissolved in water to produce green liquor that is recausticized to form the white liquor which constitutes the main fed in the Kraft cooking process (Vakkilainen 2005). Finally, the black liquor is burned in the boiler as combustible to produce heat water and steam. With the steam produced in the boiler, a steam turbine is fed and the generated energy accomplishes to power the entire factory. The main parameters of the burner can be found in Table 1.

Table 1: Main Design Parameters of Joutseno Recovery Boiler (Vakkilainen and Sandegard 1999)

Continuous burning capacity (MCR)	3150tds/24h
Peak Load burning capacity	3500tds/24h
Steam Production	130kg/s
Main steam pressure	9.3e+6 Pascal
Main steam temperature	763.15K

3. MATHERIALS AND METHODS

For this study real data obtained in the boiler shown in Figure 2, from the Joutseno pulp mill located in eastern of Finland has been used (Hamaguchi and Vakkilainen 2011). The main design features of Joutseno plant are shown in Table 1 (Vakkilainen and Sandegard 1999). 32 variables were collected hourly and stored electronically for three non-consecutive months from January 2007 to April 2008 (2016 samples in total). The data has been divided in 1512 samples for training and 168 samples for validation. As in any other dataset, failures always occur due to poor maintenance, human errors or device errors. Less than 4% of the data have been detected with anomalous behaviour, or above the physical possible limits. These values have been replaced by the linear interpolation of the closest valid measures. Table 2 shows the 32 variables, which are divided into sections and grouped by families. Chosen data include winter and summer months due to expert knowledge indicates that during the cold month, the amount of nitrogen embedded in the trees is lower, the quality of the wood is low, and therefore fuel quality decreases. On one hand, the variables related to the black liquor, air, steam, auxiliary flue and on the other hand the variables related to the emissions.

The ANN recognizes the measurable interrelationship between input and output parameters. Hence, the correct determination of training data, from the accessible raw plant data is essential for increase the precision of the developed model (Kaiadi et al. 2007). Once the datasets have been

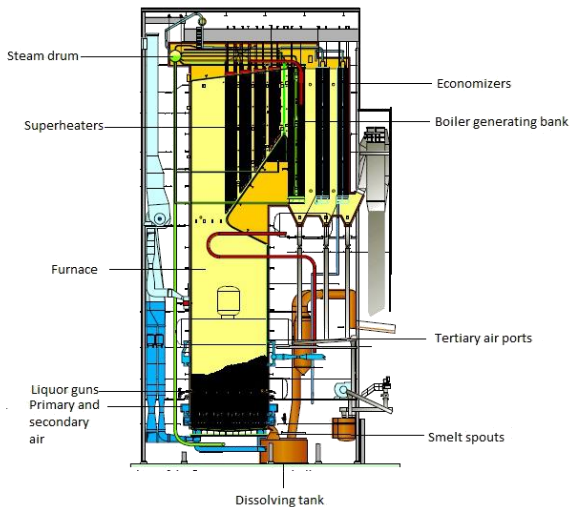

Figure 2: Scheme of the Modelled Recovery Boiler

Table 2: Main Variables of Joutseno Recovery Boiler

Variables to analyse	Units	Input/Output
Black Liquor		
Liquor flow	tds/d	Input
Ds at guns	%	Input
Density at guns	kg/l	Input
Temp in storage tank	ºC	Input
Flow front	l/s	Input
Flow right	l/s	Input
Flow left	l/s	Input
Flow rear	l/s	Input
Water & Steam		
Feed Water	kg/s	Input
CBD	kg/s	Output
SB	kg/s	Output
Net steam	kg/s	Output
Auxiliar fuel in operation		
Load gas	m3n/s	Input
Start up gas	bar	Input
Load gas	bar	Input
Air		
Primary left	m3n/s	Input
Primary right	m3n/s	Input
Secondary left	m3n/s	Input
Secondary right	m3n/s	Input
Load burner air	m3n/s	Input
Tertiary front	m3n/s	Input
Tertiary rear	m3n/s	Input
Strong to combustion	m3n/s	Input
Strong to combustion	kg/s	Input
Flue gas		
CO left	ppm	Output
CO right	ppm	Output
SO_2	mg/m3n	Output
TRS	mg/m3n	Output
NOx	mg/m3n	Output
Dust	%	Output
O_2 after BB left	%	Output
O_2 after BB left	%	Output

pre-processed, a cross validation training procedure is carried out to obtain the neural model which has the best possible goodness fit. Figure 3 illustrates a summary of the steps followed. First a selection of the most relevant output variables have been made, then a reduction of the input variables have been carried out and, finally, the neural structure have been selected (Ruiz 2016).
Different tools have been used in this work: the pre-processing step has been carried out with Microsoft Excel ® (version 2010), the selection of input and output variables have been made with the statistical software R (version 3.3.0) and, finally, the modelling procedure has been implemented using the Neural Network Toolbox package of the programming package MATLAB® (version 8.6, 2015b, Mathworks Company).

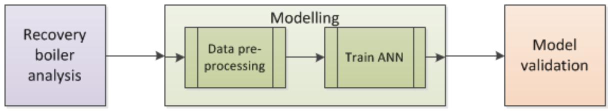

Figure 3: Experimental Methodology

4. NEURAL MODELLING

Correlation analyses between each of the variables have been performed to select the most influential variables in the behaviour of the boiler. These analyses have been used to choose the inputs of the neural model between all the available information and to avoid redundant information. High absolute value of the correlation coefficient (R^2) between two variables indicates the existence of a linear dependence; therefore, one of those variables would be removed because the election of both variables would be redundant. However, near zero R^2 values implies, that there are not linear relations between the studied variables.
First, the most important outputs of the biomass boiler have been chosen as the modelling objectives. The generated Net Steam has been chosen due to be the main product of the boiler in order to feed the steam turbine. The SO_2, NO_x and O_2 (after burning left) output gases are some of the variables that must be kept under control avoiding exceed certain limits. Although SO_2 and NO_x have not shown correlation with any input variable, they have been included to test if the neural model is able to relate them. Instead, the output O_2 (after burning right) has been discarded due to its high correlation with the included variable O_2 (after burning left).
Next, the input variables with higher correlation with the previously chosen outputs of the model have been selected. Those inputs variables not correlated with any output have been excluded. Moreover, some variables correlated with the outputs, such as the front, right, left and rear flows, have been finally discarded due to be highly correlated also with the Liquor Flow and Feed Water which are the main inputs variables of the boiler.
Therefore, after the data pre-processing and variable selection step, only 10 variables were selected, 6 inputs and 4 outputs, due to its impact on the process behaviour. The Figure 4 represents the linear regression curve between the Liquor Flow and the Fed Water. The correlation coefficient is equal to 0.33887 between two analysed inputs, which means that both have varied behaviours and are needed on the final selection.
Another clear example can be seen in Figure 5 between an input and output variables of the boiler. As can be observed the correlation coefficient index is remarkably high, thus it can be deduced that the Feed Water is (obviously) highly related to the Net Steam output.
Table 3 resumes the finally selected variables to model the biomass boiler using the neural modelling approach. The main output variable is the Net Steam which will feed to the steam turbine. The other selected variables are divided in three groups: emissions to the air, air entries and liquid entries. Air emissions (SO_2, NO_x and

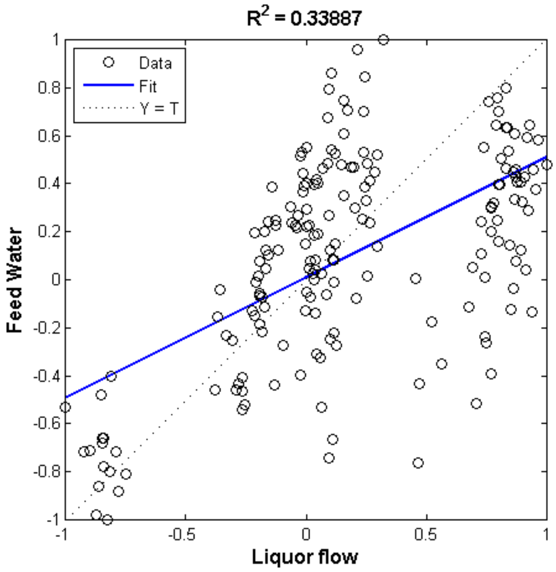

Figure 4: Regression Curve Between the Feed Water and Liquor Flow Inputs Variables

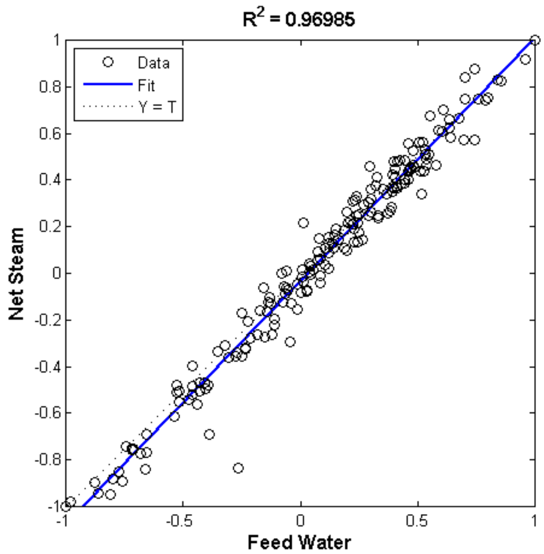

Figure 5: Regression Curve Between the Feed Water Input Variable and the Net Steam Output Variable

O_2) have been selected because one of the final objectives of the model is to maintain these emissions under control. Inputs related to liquids (Liquor Flow and Feed Water) have also a great significance because they are the main combustible of the boiler and, finally the family associated to the air inlets (secondary and tertiary air) are those who control the boiler operation for an optimal combustion.

Once finished the selection of the input and output variables, an iterative methodology modifying the number of layers and neurons in each layer has been carried out. Cross-Validation (CV) technique has been used in order to select the neural model structure that better fits the process. This technique consists of setting aside a set of data from the model training phase and only using them for the validation phase. The process is repeated until every single set of experiments is used in the validation stage. 9 weeks have being used for the training and validation datasets and 1 week for the final testing purpose. Therefore, each training fold is a whole week of data consisting of 168 samples, using the “week” criteria as divider. The chosen weeks have been taken from winter and summer months because expert knowledge indicates that during the cold month, the amount of nitrogen embedded in the trees is lower, the quality of the wood is low, and therefore fuel quality decrease. This implies regimes changes in the behaviour in the variables of the boiler. Consequently, the available data are divided into training, validation and test datasets. The training and validation datasets are used for the selection of the model structure and the most suitable training algorithm. The first one is used to train several models with different structures and using different training algorithms.

The validation dataset consists of the excluded experiments from the training at each CV iteration and it is used to calculate the validation error that is used in the early stopping concept to avoid the overfitting. The training is stopped if the validation error increases in a sufficiently high number of consecutive iterations.

Table 3: Selected Variables from the Database to be Included in the Neural Model

Variables to analyse	Units	Input/Output
Black Liquor		
Liquor flow	tds/d	Input
Water & Steam		
Feed Water	kg/s	Input
Net steam	kg/s	Output
Air		
Secondary left	m3n/s	Input
Secondary right	m3n/s	Input
Tertiary front	m3n/s	Input
Tertiary rear	m3n/s	Input
Flue gas		
SO_2	mg/m3n	Output
NOx	mg/m3n	Output
O_2 after BB left	%	Output

Finally, the CV average error, calculated over the data that were excluded from the training at each iteration, is used to compare the model structures. This type of technique tests the generalization capability of a model structure (Kashani and Shahhosseini 2010). The error performance metric used in this procedure for the comparison of the model structures has been the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) (Equations 1, 2 and 3).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Act-Pred)^2}{n}} \quad (1)$$

$$MAE = \frac{\sum_{i=1}^{n}|Act-Pred|}{n} \quad (2)$$

Table 4: Average Errors for Each Normalized Output Variable, Neural Structure and Training Function

	Training function	Best Structure	Output	RMSE	MAE	MAPE (%)
NARX	BR	6-100-4	Net steam	0.01096	0.00744	1.56
			SO_2	0.02408	0.01469	2.00
			NOx	0.09197	0.06130	83.17
			O_2	0.02733	0.02120	2.81
	LM	6-4-4	Net steam	0.05637	0.04620	11.68
			SO_2	0.12369	0.08945	41.28
			NOx	0.28522	0.23312	166.52
			O_2	0.08927	0.06856	9.77
	LM	6-11-4-4	Net steam	0.06593	0.05386	14.67
			SO_2	0.12804	0.08995	40.58
			NOx	0.26994	0.22028	155.11
			O_2	0.09336	0.06855	9.57
Feed-Forward	BR	**6-130-4**	Net steam	**0.00959**	**0.00636**	**1.23**
			SO_2	**0.02272**	**0.01353**	**1.78**
			NOx	**0.09016**	**0.05924**	**82.64**
			O_2	**0.02550**	**0.01952**	**2.55**
	LM	6-8-4	Net steam	0.06229	0.04947	12.05
			SO_2	0.13700	0.10143	40.64
			NOx	0.28147	0.22480	170.82
			O_2	0.08958	0.06483	9.70
	LM	6-3-4-4	Net steam	0.08174	0.06570	16.59
			SO_2	0.12523	0.08844	38.64
			NOx	0.26801	0.22182	170.69
			O_2	0.09411	0.07085	10.71

$$MAPE\ (\%) = 100\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Act-Pred}{Act}\right| \quad (3)$$

Once the neural model structure is selected and properly validated, the final model is trained with all the available data except for the test dataset which is used to estimate the generalization error of the fitted model. Nonlinear AutoRegressive with eXogeneous inputs (NARX) and Feed-Forward neural structures have been compared in this work in order to prove which is able to fit better the process. Furthermore, two different training functions have been test in both of the structures; Bayesian regularization backpropagation (BR) and Levenberg-Marquardt backpropagation (LM).
In order to carry out properly the training procedure, giving equal weight to all the variables, all them have been normalized in the range [-1, 1]. Due to be a stochastic training procedure, all the training procedure has been repeated 10 times, in order to smooth the results Several neural structures have been test with neurons from 1 to 200 in the hidden layer and with 1 or 2 hidden layers. Note that due to its high computational cost, for the NARX structure trained with BR function, it has been tested only up to 100 neurons.
Based on the minimum average CV errors, the number of hidden neurons has been selected for each output. The RMSE has been selected as main indicator according to the literature (Chai and Draxler 2014).
Figure 6, represents the CV RMSE error of output variables versus the number of hidden neurons. As can

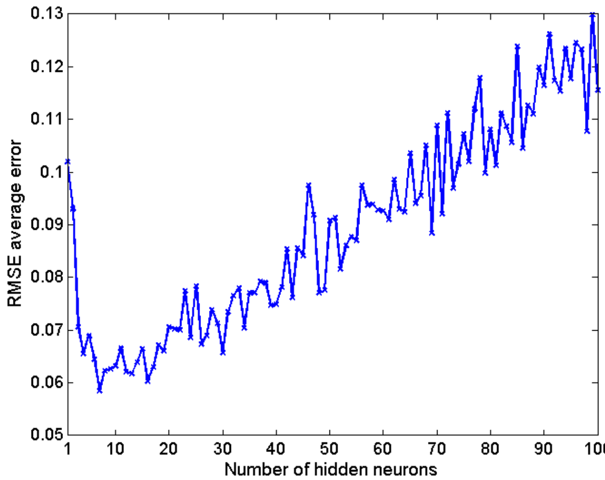

Figure 6: Evolution of the Cross Validation Average Error for the Net Steam Output with the Number of Neurons in the Hidden Layer

be seen, the CV error reaches a minimum value with the selected hidden neurons. However, each output reaches a minimum CV error with a different number of neurons. Thus, between the "best structure" for each output is selected one that has the lower average error of the CV errors for all the variables.
Table 4 illustrate the average CV results for each neural structure and for each output variable and training function. Hence, Figure 7 shows the selected ANN configuration which is a Feed-Forward neural network

with 1 hidden layer with 130 neurons, and trained with the BR function.
Finally, the above selected neural structure is trained with all the available data except from the test data and validated using that unseeing dataset in order to test its generalization ability and to measure the goodness of fit of the final model. Table 5 shows the validation errors of the final model for the denormalized test dataset. The obtained results presents reasonable error values that allow to stand that the neural network based model has been able to successfully assimilate the behaviour of the process with an acceptable accuracy. The behaviour of the Net steam output has been simulated with a MAPE error of 1.77%. Moreover, the NOx and O_2 presents MAPE of 5.75 and 3.73% respectively. Only the SO_2 gas emissions present a MAPE error near the 15%. Figure 8 shows the real and the estimated data of all output variables for 1 week of simulation time (1 sample per hour). Note that the values are normalized in the range [-1, 1]. As expected, the selected model is able to follow the behaviour of each output variable, with more difficulties for the SO_2 and NO_x. Note that during the winter the nitrogen is stored in the root of the tree which radically changes the behaviour of the output variables depending the season of the year. Therefore, the operation regimes change with higher or lower values for the whole week, scrolling along the operation range.

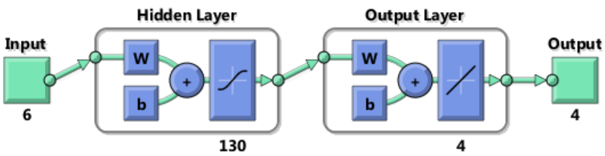

Figure 7: Neural Network Used to Model the Biomass Boiler

Table 5: Validation Errors of 1 Week Unseeing Data for the Output Variables Using the Selected Neural Network

Output	RMSE	MAE	MAPE (%)
Net steam (kg/l)	3.0543	2.6979	1.77
SO_2 (mg/m3n)	0.4908	0.3607	14.72
NOx (mg/m3n)	13.748	10.173	5.75
O_2 (%)	0.1260	0.1006	3.73

Additionally, Table 6 shows the validation errors obtained with an alternative neural model for the denormalized test dataset. Note that this alternative model is a NARX neural network with 2 hidden layers, the first one with 11 neurons and the second one with 4 neurons, and trained with the LM function. The results obtained with this model are slightly worse but model size is noticeably smaller.

5. DISCUSSION AND FUTURE WORKS

In this work an Artificial Neural Networks based model of the recovery boiler of a Kraft process has been presented. The results suggest that a Feed-Forward neural model is able to assimilate the dynamics of the process just with the information of the selected inputs: liquor flow, feed water and secondary and tertiary input air. The best results have been obtained with a neural model with 130 hidden neurons.

Table 6: Validation Errors of 1 week Unseeing Data for the Output Variables Using the Alternative Neural Network

Output	RMSE	MAE	MAPE (%)
Net steam (kg/l)	3.4975	3.3480	2.22
SO_2 (mg/m3n)	0.9177	0.7807	31.00
NOx (mg/m3n)	13.7195	9.9763	5.85
O_2 (%)	0.1958	0.1688	6.10

The implemented model has been able to estimate the main output variable (Net steam) over the denormalized test dataset with a MAPE error of only 1.77 percentage points. The model also presents good performance for the O_2 and NOx. By contrast, it has not been able to properly model the behaviour of the SO_2 gas emissions.
However, to obtain the best results a high number of neurons are needed. While more simple structures such as a NARX neural network with 2 hidden layers, are able to obtain similar errors for three of the output variables.
The final neural model will support future works in order to study the influence of the input variables and control set points into the electricity generation and contaminant emissions.

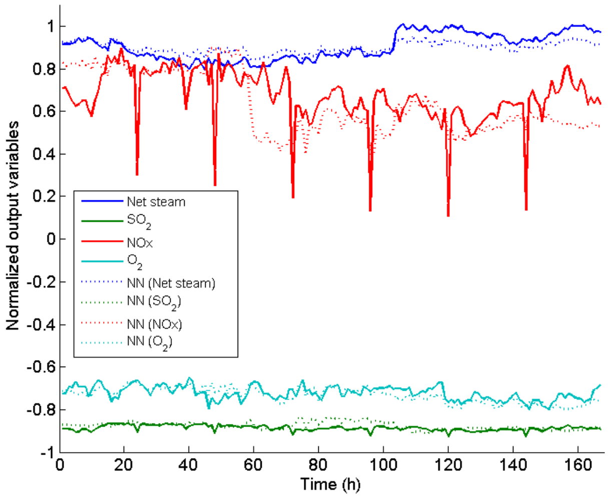

Figure 8: One Week Simulation of the Biomass Boiler for all the Normalized Output Variables with the Selected Neural Model

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REFERENCES

Chai, T. and Draxler, R.R. 2014, Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature, Geoscientific Model Development, vol. 7, no. 3, pp. 1247 -1250.

De, S., Kaiadi, M., Fast, M. and Assadi, M., 2007. Development of an artificial neural network model for the steam process of a coal biomass cofired combined heat and power (CHP) plant in Sweden. Energy, 32(11), pp. 2099-2109.

Fast, M. and Palme, T., 2010. Application of artificial neural networks to the condition monitoring and diagnosis of a combined heat and power plant. Energy, 35(2), pp. 1114-1120.

Gustafson, R.R., Sleicher, C.A., McKean, W.T. and Finlayson, B.A., 1983.Theoretical model of the kraft pulping process. Industrial & Engineering Chemistry Process Design and Development, 22(1), pp. 87-96.

Hamaguchi, M. and Vakkilainen, E., 2011.Effect of timescale on emission levels from pulp mills. 1(1).

Kashani, M.N. and Shahhosseini, S., 2010. A methodology for modeling batch reactors using generalized dynamic neural networks. Chemical Engineering Journal, 159(1), pp. 195-202.

Ruiz, P., 2016. Modelling a recovery boiler using artificial neural networks. Final Degree Project. University of Deusto.

Serna-Diaz, M.G, Medina-Marin , J, Arana-Cuena, A, Seck-Tuoh-Mora, J.C, Tellez-Jurado, A, Mercado-Flores, Y, Jimenez-Gonzalez, A, Hernández-Romero, N, 2014, Modeling and optimization of the extraction of lignosulfonate from barley straw by using artificial neural networks. Proceedings of the European Modeling and Simulation Symposium, 978-88-97999-38-6; pp 469-473.

Suhr, M., Klein, G., Kourti, L. and Gonzalo, M.R., 2015.Best Available Techniques (BAT) Reference Document for the Production of Pulp, Paper and Board.

Tsen, A.Y., Jang, S.S., Wong, D.S.H. and Joseph, B., 1996. Predictive control of quality in batch polymerization using hybrid ANN models. AIChE Journal, 42(2), pp. 455-465.

Vakkilainen, E., 2005. Kraft recovery boilers–Principles and practice.

Vakkilainen, E., Sandegard, P., Ahlstrom Machinery Corporation, Veitola, J. and Oy Metsä Botnia A.B, JOUTSENO PULP, 2006. New Ahlstrom recovery boiler at Metsä-BotniaJoutsenomill.

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