A Comparative Study on Charge System Modelling in Fine Paper Production

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Abstract: This application-oriented paper provides a comparative study on modelling methods with application to a functional fine paper production machine. The aim is to develop a model for the charge measurement system in wet-end paper making systems for future control purposes. However, a Multi Input Multi Output (MIMO) model has been proposed to further generalise the proposed model. A series of six-month worth machine's input-output data are employed to develop different models. The three models, namely linear, dynamical Neural Network (NN), and a so-called hybrid model are developed to model the paper machine's behaviour. The hybrid model consists of a dynamical linear part and dynamical NN part. The linear part will model the machine around each operating point. The dynamical NN part will help to extract further un-modeled nonlinearities. Simulation results and variety of validation tests confirm that the hybrid model can effectively represent the paper machine dynamics.

1. INTRODUCTION

Paper and paper-related products play an extremely important role in almost all day to day applications. Examples of the paper-based applications are print works, construction materials (plasterboard), medical products, financial documents, i.e., notes, cheques, etc., and even synthetic textiles.

1.1 Paper-making Process in Brief

Paper-making is comprised of multiple stages. Many interacting components influence each other both physically and chemically to produce a uniform sheet of paper with desired attributes. The essential material processing units consist of *Pulping, Refining, Screening, Wet-end , Pressing, Drying and Reeling up* sections, as shown in Fig.1.

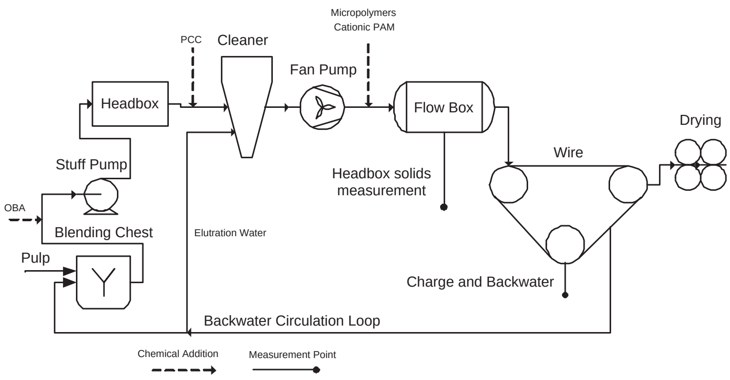

Fig. 1. The Scheme of paper-making process

In Pulping section, fibres are extracted from wood to form a pulp referred to as thick stock, which is later diluted, and mechanically sorted in refining section (based on the desired fibre length distribution). After unwanted materials, e.g., plastics, etc. are removed from the stock by centrifugal clearers in Screening section, the stock is then heavily diluted with water and is fed through the wet end section. This section is comprised of some sub-systems among which the wire section (or forming table) is perhaps the most important with regards to determination of final paper properties. It is here that the structure, referred to as formation, and therefore most of the physical properties of the paper is largely decided. In wet end section the stock is first highly diluted (99% water) and is distributed over the machine wire (i.e., constantly moving piece of mesh) as uniformly as possible. In the first instance the wire acts as a filtration mechanism, retaining solid particles and allowing water to drain through, and secondly as a support surface for the sheet of paper. During this stage a large quantity of water is removed from the sheet by drainage elements and suction boxes raising the solids content of the stock to 20%. The paper then passes to the press and dryer sections where pressure and steam are used to increase the paper to some 92% solids Holmberg (1999); Smook (2002).

1.2 Wet-end Chemistry and Charge Measurement

The work performed is mainly concerned with the wet end of the paper machine, and in particular the chemical and colloidal interactions involved. Wet end chemistry deals with the way that chemical substances and the paper stock interact. The major interactions of concern relate to surface charge, flocculation and coagulation all of which are fundamental to the paper-making process.

The paper-making process is essentially an anionic, negatively charged, process. The stock suspension (fibre and backwater) has a negative charge. This electrical charge, known as *Zeta Potential of suspended paper-making*, plays a considerable role in paper-making process as it controls all substances interactions and the closer that the charge of a material can be brought to zero the more stable the system will be Scott (1996). The charge on pulp can be controlled through the adsorption of positive ions from a donator such as a charge cationic polymer. It is essential that wet end chemistry is controlled to ensure that the system does not become either too anionic or cationic. As such, wet end system modelling and hence charge measurement/prediction provides the opportunity to allow cost effective and production efficient addition of substances to control the final product quality. Currently, there are three major methods to measure the charge, namely, *Microelectrophoresis, Streaming Potential*, and *AC Streaming Current measurement*, each surveyed briefly as follows.

Microelectrophoresis In this method, the samples is firstly screened to remove fibrous materials to prevent inter-particle interference and is then placed in a cell as shown in Fig.2. Then a voltage is applied across the cell and the migration of velocity of the dispersed, charged particles is measured resulting the electrophoretic mobility. From this the zeta potential is calculated using a form of the Helmholtz-Smoulochowski equation incorporating the fluid's viscosity and dielectric constant Waller (2002).

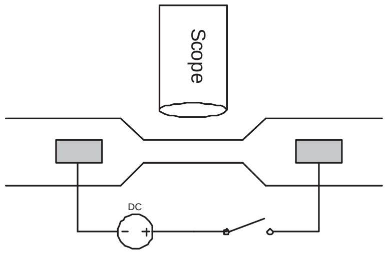

Fig. 2. The scheme of microelectrophoresis cell

Microelectrophoresis has several drawbacks: It requires high sample dilution, it can only measure small particles and the particles must be spherical. Burke and Renaud (2003).

Streaming Potential In streaming potential method, a liquid sample is forced through a plug formed from fibres, fines and other furnish components, as shown in Fig. 3. An electrical streaming current is produced by the charges carried in the direction of flow. The accumulated charges create an electric field which in turn results in an induced current, equal and opposite to the streaming current. Then the steady state voltage between two electrodes, pressure drop across the plug and liquid physical properties are used to calculate the charge.

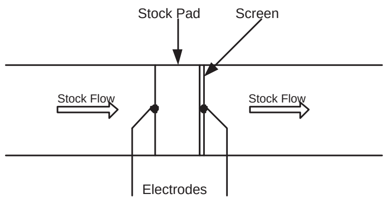

Fig. 3. The scheme of Streaming Potential method

Due to not requiring filtration of the stock the streaming potential method is very advantageous over microelectrophoresis and streaming current. It is however affected by entrained air and stock temperature variations, two very common occurrences in the wet end of a paper machine. Also, the it assumes laminar flow and uniform pad, which are strong assumptions in practice Hubbe and Chen (2005); Stratton and Swanson (1981).

AC Streaming Current measurement As shown in Fig.4, in this method, sample of known volume is placed in a cylinder and a reciprocating piston is used to force the liquid back and forth through a small clearance between the piston and the cylinder. Particles and dissolved ions located loosely in this annulus between the piston and cylinder wall move back and forth and create an AC current that is detected by two electrodes. A polyelectrolyte is then added to the zero point and the charge demand is calculated from this.

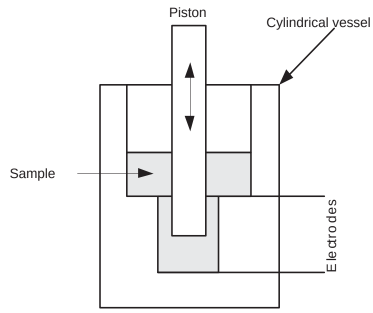

Fig. 4. The scheme of AC Streaming Current measurement

Streaming current requires that the unit is kept clean Scott (1996). To achieve this the piston and cylinder walls are coated in Teflon and the unit goes through a fresh water cleaning sequence after each measurement and a sample "soaking" sequence prior to measuring. The advantage of AC streaming method is that the isoelectric point of suspension correlates with the charge reversal point when polyelectrolyte particles are used to change the charge, resulting to dissolved charge Waller (2002); Scott (1996).

This paper is focusing on stabilizing the wet end chemistry of a paper machine at a UK-based fine paper mill with a large product portfolio to improve overall process stability. The paper is organised as follows. In section 2 the charge measurement system installed at the above mentioned paper mill is briefly introduced and data acquisition, process control and monitoring systems are discussed. Then the details of necessary tools of modelling, including linear, and nonlinear neural networks are proposed in section 3, followed by simulation results and comparisons in section 4. Finally, concluding remarks are provided in section 5.

2. CHARGE MEASUREMENT: FINE PAPER MILL

The practical charge measurement system selection often incorporates consideration of a variety of factors. In the above mentioned mill, it was necessary to select a unit that would give a worthwhile measurement, be robust enough to deal with the wide charge variation that the system has, be suitable for the environment that it would be exposed to and most importantly provide a return on investment that would allow for it to be purchased. The selected unit measures the charge demand of a sample through a modified Streaming Current measurement method described as follows.

2.1 Unit Operation

Due to the complexities of charge measurement, and therefore the method of measurement employed by the unit, continuous measurement is impossible and therefore batch samples are taken with a typical sampling and measurement cycle of once every 6 to 8 minutes. A sample of backwater is passed through two coarse and then one fine filter to remove fibres and heavy solids from the sample. A one litre sample then passes into a reactor chamber and is recirculated through the measurement sensor, as described above, by a pump. The Titrant is then dosed by a Liquid Metering Instruments (LMI) pump to the sample at a rate proportional to the level of charge demand(i.e. the closer the charge demand is to zero the lower the dose rate). Once the zero-point has been reached the unit discharges the sample to drain and then performs a wash cycle with fresh water. At this point the unit transfers the number of pulses to the data acquisition system.

2.2 Charge System and Data Acquisition System

In order to build up a comprehensive model of the system it is necessary to log not only the charge and retention signals (headbox and backwater solids) but also five other system inputs. Due to company's financial limitations, the inputs that can be logged are limited and as such they do not represent an "ideal" list of inputs to the system. However the ability to display trend data together with other wet end variables allows the wet end interaction to be better understood so that the correct changes can be made to the process. Table 1

Table 1. wet end I/O list

Variable	Range	Unit	Tag
Charge cationic polymer	0-2000	l/h	u_1
OBA	0-100	l/h	u_2
Charge Anionic polymer	0-2000	l/h	u_3
PCC	0-2000	l/h	u_4
Sizing Agent	0-250	l/h	u_5
Backwater Consistency	0-2500	mg/l	y_1
Headbbox Consistency	0-9000	mg/l	y_2
Charge	0-570	$\mu eq/l$	y_3

The paper mill mentioned above is not equipped with a Distributed Control System (DCS), rather it has a large number of independent controllers, however is in the process of upgrading to a new Distributed Control/Quality Control System (DCS/QCS) which is a paper-making control and monitoring solution. The system will cover the essential needs for the measurement, data logging, and monitoring purposes of PM. Fig. 5 illustrates a typical trend page of the data acquisition system ABB (2005).

The data recorded over six months have been used to model the wet-end part of the paper machine. Before the data is used for modelling purposes, some data pre-processing tasks are performed. For instance, the data recorded during machine's down time, maintenance, or malfunctions/faults are extracted and omitted from those in normal operation mode. Also, some noise filtering, and normalisations are performed to obtain reliable input-output data changing between 0 and 1. After the model is trained and validated, the post-processing is applied to return the values to actual variation ranges. The details of the different modelling schemes are proposed in the next section.

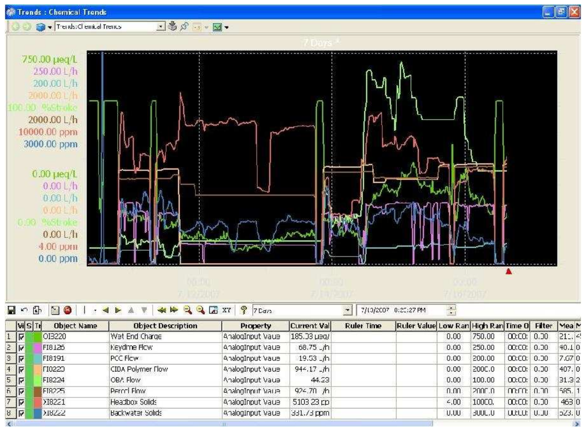

Fig. 5. PM's wet end chemistry trend page

3. MODELLING THE WET-END OF THE PM

The wet end of PM is assumed as a 5-input, 3-output system with inputs and outputs as expressed in table 1. The modelling is performed in an off-line mode based on the recorded input-output data. Three different classes of modelling have been employed to model PM's wet end. The methods include *Dynamical Linear*, *Non-linear NN*, and a so-called *Hybrid* models (a combined model of dynamical linear and NN model), each studied in upcoming sections. It should be noted that Y and U are $(3 \times N_s)$ and $(5 \times N_s)$ matrices, respectively, where N_s refer to the number of total data samples.

3.1 Dynamical Linear Wet-end Model of PM

Perhaps the most basic relationship between the input and output is the linear difference equation that can be further expressed as an ARX model as in Ljung (1999). As such, the ARX estimation model of the PM can be expressed as follows.

$$\hat{Y}(i) = \Theta_L^T \Phi_L(i) + e_{app} \qquad (1)$$

Where Φ_L and Θ_L are regression vector and unknown parameter matrix to be determined. Also e_{app} stands for the approximation error. The regression vector contains the past input and output values based on the dynamical order of the model. The dynamical orders will be chosen in a trial and error way.

After the model structure and its dynamical order is considered, the model must be trained with an appropriate training algorithm. It is desirable to minimise the squared estimation error as expressed as follows.

$$J(i) = \frac{1}{2} E^T(i) \times E(i), \quad E(i) = Y(i) - \hat{Y}(i) \qquad (2)$$

The Recursive Least Squared (RLS) method with exponential forgetting has been chosen for this purpose. The RLS algorithm for a p^{th} order RLS filter can be summarised follows.

$$\Theta_L(i+1) = \Theta_L(i) + g(i)\alpha(i) \qquad (3)$$

$$\alpha(i) = Y(i) - \Theta^T \Phi_L(i) \quad (4)$$

$$g(i) = \frac{P(i-1)\Phi_L(i)}{\lambda + \Phi_L^T(i)P(i-1)\Phi_L(i)} \quad (5)$$

$$P(i) = \frac{1}{\lambda}(I - \frac{(P(i-1)\Phi_L(i)\Phi_L^T(i))}{\lambda + \Phi_L^T(i)P(i-1)\Phi_L(i)})P(i-1) \quad (6)$$

where P is the covariance matrix which is initially chosen as a big constant of order, say 1000. All the incorporating matrices are assumed to be of appropriate sizes. After the parameter matrix Θ_L is trained, a transfer function matrix $G(s)$ can be extracted from the parameter vector. However, for the sake of simplicity, the transfer function matrix calculations are not provided in this paper.

3.2 Dynamical Neural Network Model

It id well known that the application of linear models to practical systems is restricted to a limited number of operating points. Apart from the generality of such a dynamical model, this means that the model would not be valid if the operating point is changed. Furthermore, its performance will deteriorate in presence of any un-modeled dynamics, environmental noises. Therefore, development of a generalised nonlinear dynamical model should be considered. For this purpose, a neural network which is shown in Fig.6 is employed to model the plant.

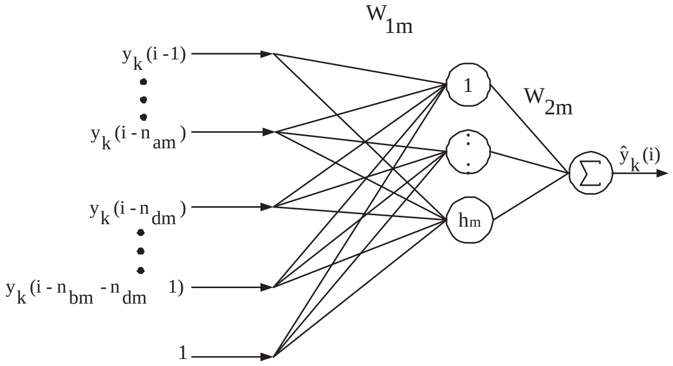

Fig. 6. The dynamic neural network model structure

As seen in the Fig.6, n_a is the number of past plant outputs, n_b is the number of past inputs, and the n_d is the number of pure delays associated with the nonlinear ARX model. Subsequently, the nonlinear output equation can be expressed as

$$\hat{Y}(i) = f_m(\Phi_N) \quad (7)$$

where the regression vector Φ_N is expressed as

$$\Phi_N = \big[Y(i-1), \cdots, Y(i-n_a); U(i-n_d), \cdots, U(i-n_b - n_d + 1)\big]^T$$

Although network activation functions can be either hyperbolic tangent or linear, only hyperbolic tangent hidden layer activation functions and linear output layers have been employed to model PM as following vector form.

$$\hat{Y}(i) = W_{2m} \tanh(W_{1m}\Phi_N(i-1)) + e_m(i) \quad (8)$$

where $W_{1m} \in \mathbb{R}^{n_h \times n_\phi}$ and $W_{2m} \in \mathbb{R}^{n_Y \times n_h}$ represent the weight matrices from the input-to-hidden, and from the hidden-to-output layers, respectively. All the mentioned matrix elements are gathered into a network parameter vector Θ_N to be determined by a training algorithm. Also in (8), $e_m(i)$ stands for the network modeling error at the i^{th} instant. After the network structure for the plant modeling is obtained, a neural network training algorithm must be used to train the network.

Levenberg-Marquardt Method for Training Plant Model
This training method is a popular alternative to the Gauss-Newton optimisation method since it was designed to approach second-order training speed without having to compute the Hessian matrix. The objective of the system identification problem is to solve the following optimisation problem.

$$J_m = (Y(i) - \hat{Y}(i))^2 = \|e_m(i)\|^2 \quad (9)$$

The search direction p_i is defined as the solution of (9).

$$(J_m^T(i)J_m(i) + \lambda_i I)p(i) = -J_m^T(i)e_m(i) \quad (10)$$

where $J_m(i)$ is the associated plant Jacobian and λ_i is a non-negative scalar. The detailed Levenberg Marquardt algorithm for the plant model training can be expressed as follows.

$$\Theta_N(i+1) = \Theta_N(i) - (H(i) + \lambda_i I)^{-1}G(i) \quad (11)$$

$$G(i) = J^T(i)e_m(i) \quad (12)$$

$$H(i) = J_m^T(i)J_m(i) \quad (13)$$

where J is the Jacobian matrix and it can be computed through a standard back-propagation technique. The learning rate λ_i is decreased after each successful step, and is increased only when a tentative step would increase the performance function. In this way, the performance function is always guaranteed to reduce at each iteration of the algorithm Haykin (1999).

3.3 Hybrid Model

Although dynamical neural network model can be considered as a general solution for modelling the wet end process, it can be used as a co-operative agent besides the dynamical linear model to extract the nonlinearities that might occur in each operating point's neighbourhood. In addition, it can make compensate the linear model's performance degradation if the operating point is changed. The method is in fact a combination of both models introduced above. The difference is that the NN receives the linear model's estimation error as input to model the plant's output to give

$$\hat{Y}(i) = \Theta_L^T \Phi + f_m(\Phi_N) + e_{app} \quad (14)$$

After the identification process is done, the trained model is validated by a fresh set of input data. Several validation tests such as correlation and prediction error distribution tests are performed to evaluate the model validity.

4. SIMULATION RESULTS

In this section, the simulation results for wet end modelling are proposed.

4.1 Linear Model Results

The first model studied is a dynamical linear model with the following dynamical order.

$$n_a = [6, 8, 5],\ n_b = [6, 5, 8, 8, 6],\ n_d = [1, 7, 1, 4, 6]$$

As such, the model would be a 52-parameter, MIMO one with time delays considered as there are delays involved from the instant of chemical addition to the point they take effect. The values of time delays have been determined based on expert knowledge from PM operators. Also, the initial parameter values chosen are

$$P(0) = 10^5 I,\ \Theta = \mathbf{0},\ \lambda = 0.95$$

As shown in Fig.7, the model does not show satisfactory tracking performance, implying that the linear model applied is not enough to describe the dynamics of PM. In order to validate the resulting model, the prediction

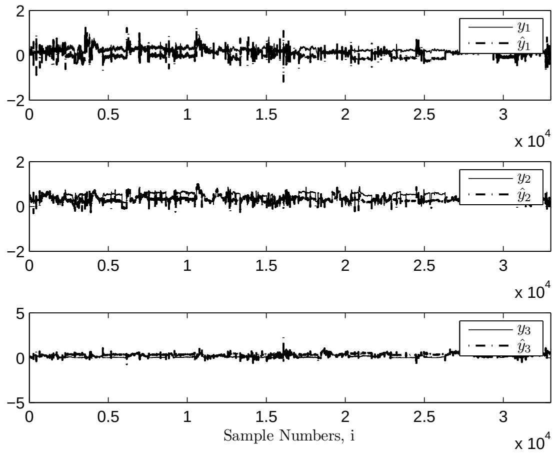

Fig. 7. The measured and Predicted outputs-linear model

error PDF can be examined. Ideally, it should be shaped as narrowly symmetrically as possible. However, Fig. 8 confirms that the obtained model does not adequately fit the PM data

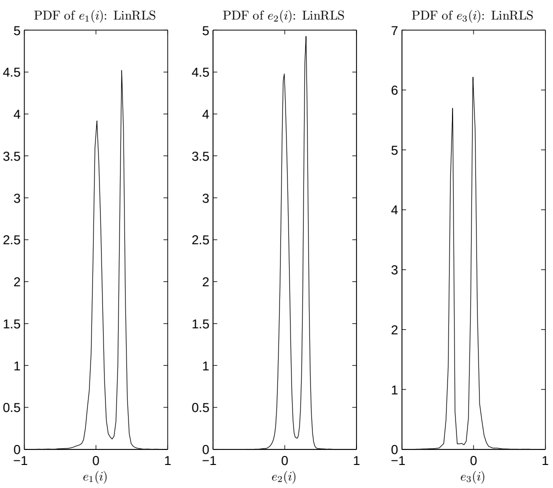

Fig. 8. The Prediction error PDF-linear model

4.2 Dynamical NN Results

Provided that the dynamical linear model is not adequate, a dynamical 2-layer MLP-type NN with 10 hidden hyperbolic tangent and 3 linear output neurons and the following dynamical order has been used to model PM's wet end.

$$n_a = [5, 8, 7],\ n_b = [2, 3, 4, 5, 3],\ n_d = [1, 7, 1, 4, 6]$$

After 100 iterations of training, the model's response to a fresh set of PM's data would be as shown in Fig.9.

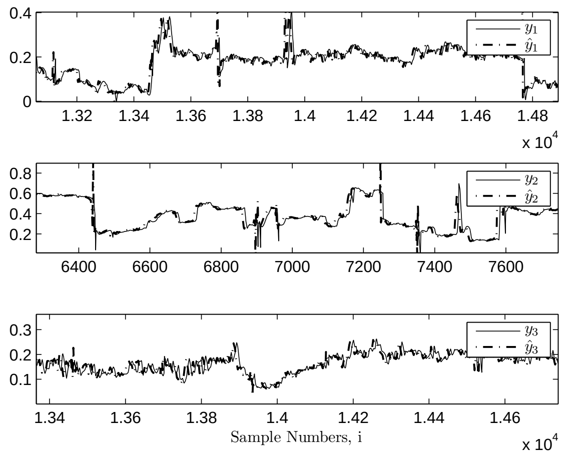

Fig. 9. The predicted and measured output-NN model

Also as shown in Fig.10, NN's prediction error is shaped as a narrow and symmetrical distribution, confirming the efficiently of dynamical NN model used.

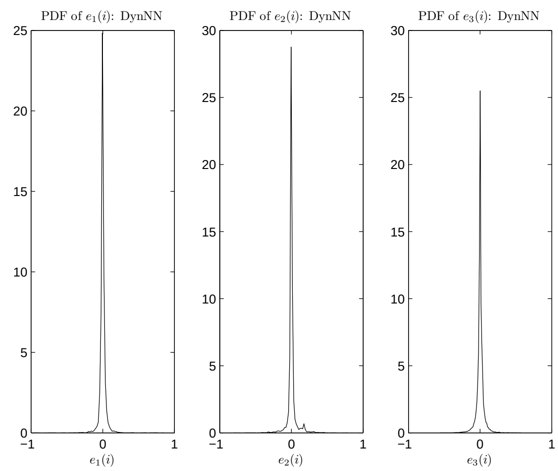

Fig. 10. The prediction error PDF-NN model

4.3 Hybrid Model results

As mentioned before, a combination of both linear and NN models as introduced in 14 can be a practical method to describe the dynamical behaviour of wet-end process. In the so-called hybrid modelling method, the model structure and dynamical order is not changed to obtain comparable results to the first two methods. It means that the same model parameters with initially zero parameter vector matrices are applied to model the wet end process. Fig.11 show the tracking performance of the obtained hybrid model.

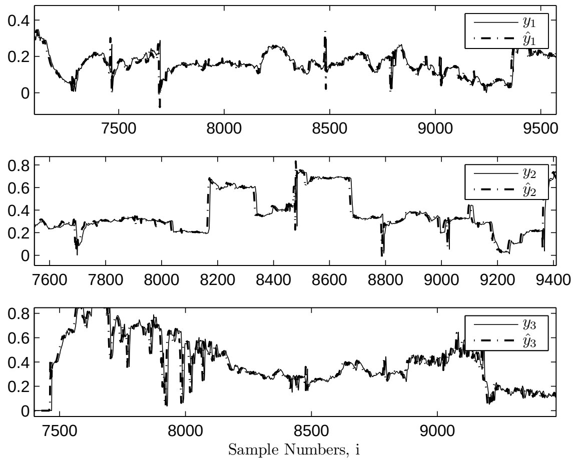

Fig. 11. The predicted and measured output-Hybrid model

Compared to identical figures produced by other two methods, the hybrid model represents closer tracking performance, as the NN part has modeled the nonlinear dynamics in linear model's residual signal. As illustrated in Fig.12, the PDF of the prediction error is narrowly and symmetrically shaped. The demonstrated performance is considerable as the resulting PDF is more symmetrical than the one obtained with dynamical NN.

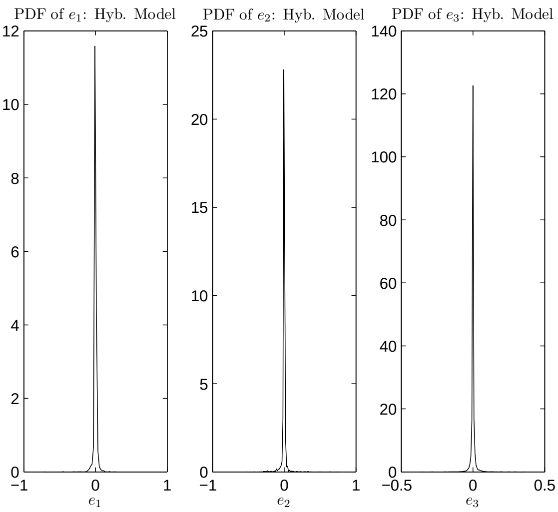

Fig. 12. The prediction error PDF-Hybrid model

To further investigate the effectiveness of the hybrid model over the other two, the correlation test is also carried out as a validation test. For the sake of briefness, only the results of Charge signal's correlation with a selected number of inputs is proposed in Fig.13.

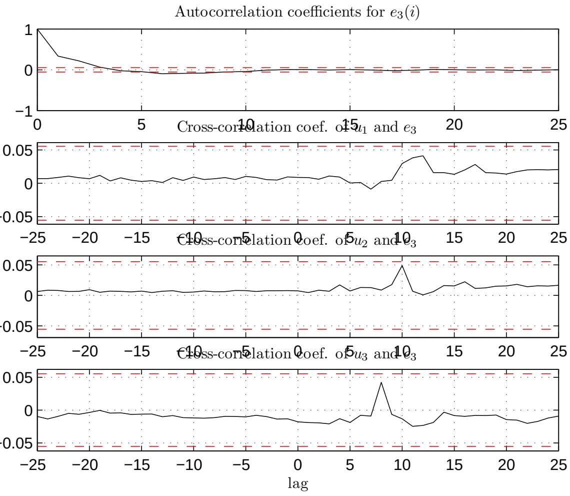

Fig. 13. Correlations of prediction error e_3-Hybrid model

5. CONCLUSIONS

A comparative study on dynamic system modelling has been performed for a UK-based paper machine's wet end process. The aim has been to effectively model the dynamics of the charge system. Due to several interconnections among process variables, the whole wet-end process has been modeled. Different approaches have been studied and compared. The hybrid model (combination of dynamical linear and NN) is confirmed to be a reliable model. While incorporated linear dynamics in hybrid model is used as primary (at equilibrium points), NN makes the model capable of coping with other sources of nonlinearity. In addition, as the NN part models the linear system's prediction error, it will be less computationally complex. This means while the nonlinearities are negligible, the linear model can be appropriately used together with linear controllers, which are easier to implement and operate. Simulation results confirm that the hybrid model shows better relative performance than the pure nonlinear model in terms of the prediction error's distribution and correlation.

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