MODELLING OF A NONLINEAR MULTIVARIABLE BOILER PLANT USING HAMMERSTEIN MODEL, A NONPARAMETRIC APPROACH

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ABSTRACT
Of the many model structures that can represent a nonlinear process effectively, the Hammerstein model is one such model which has attracted a lot of attention. This paper considers a real industrial problem of modelling a nonlinear multivariable steam generating plant using the methods of system identification. The work uses Hammerstein model to model the plant from sampled data collected at Abbott Power Plant in Campaign, IL. Neural networks and state-space model are used to model the nonlinearities and the dynamics of the system respectively. A recursive algorithm is developed which makes use of Particle Swarm Optimisation (PSO) and Subspace Identification Method (SIM) to estimate the parameters of the nonlinear and linear parts respectively. Validation results using computer simulation are included at the end to demonstrate the good fit and concordance of predicted outputs with actual data.

KEY WORDS
Hammerstein models, Nonlinearity, Dynamics, Neural network, Particle Swarm Optimisation, State-space models.

1 Introduction

Effective and successful control of real life processes in the industry is a meticulous and non-trivial task and requires a model that is able to accurately predict the behaviour of the process over complete operating range of the plant. One method for obtaining mathematical models is by using first principles, i.e. by considering the laws of physics in the interaction of different components and materials during the process. The other method which has proved instrumental in modelling real life processes is by using the methods of system identification. Models obtained by this method have provided meaningful engineering alternatives to physical modelling, and have been significantly helpful in making model-based control system mathematically and practically tractable.

Boilers are industrial units, which are used for generating steam and hot water for industrial process and electrical energy generation. They transmit heat by combustion of fuel. Boiler operation is a complex operation in which hot water must be delivered to a turbine at constant rate, pressure and temperature in order to ascertain reliable operation. Therefore, design of a proper control strategy for a boiler is of significant importance in industrial environment. However, a necessary element for controller design is a valid and accurate mathematical model.

The idea of creating mathematical representations of physical processes from physical laws can sometimes be very difficult, especially with nonlinear systems. Often, this type of modelling approach ends up producing a large number of complex equations that may or may not characterise the system's behaviour completely. Another way to look at generating models of systems, is from the system identification point of view which uses a system's measured inputs and outputs to construct mathematical models, in the absence of a priori knowledge of the system's underlying structure. The application of such models is popular in situations where the key goal is output prediction for control purposes.

This work focuses on identification of a steam generating plant in operation at Abbott Power Plant in Campaign, IL using measured data. It is a dual fuel (oil/gas) fired unit used for heating and generating electric power. The plant has 4 inputs and 4 outputs which are described in table 1. The plant is rated at 22.096 kg/s of steam at 22.4 MPa (325psi) of pressure. The plant has dynamics of high order, as well as nonlinearities, instabilities, and time delays [1, 2]. Figure 1 shows the structure of the plant.

Table 1
Inputs and outputs of steam generating plant

Inputs	Units
Fuel flow rate	scaled 0-1
Air flow rate	scaled 0-1
Reference level	inches
Changes in steam demand	scaled 0-1
Outputs	**Units**
Drum pressure	psi
Excess oxygen in exhaust gases	%
Water level in the drum	inches
Steam flow	Kg/sec

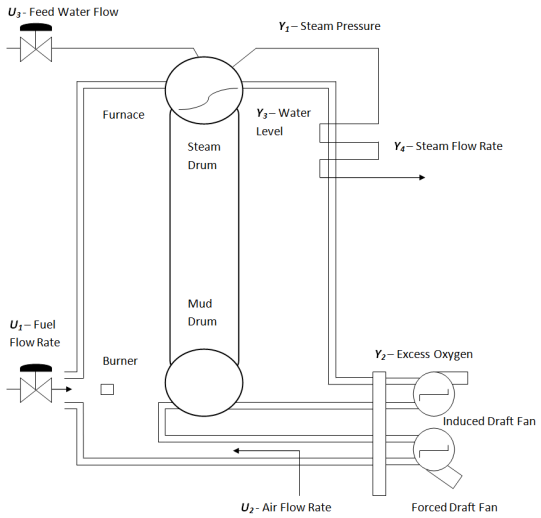

Figure 1. Industrial Steam Generation Plant

Apart from these measurable and deterministic outputs and inputs of the plant, there are certain uncertainties which include *fuel calorific value variations*, *heat transfer coefficient variations*, and *distributed dynamics of steam generation*. The plant also has few constraints like *actuator constraints*, *unidirectional flow rates* and *drum flooding*. *Sensor noise* also makes the recorded plant outputs noisy [2].

While models based on first principle and physical laws are available in the literature, a limited work on steam and boiler modelling based on system identification exists. The objective of this work is to obtain a nonlinear model of steam generator plant directly from test data using the methods of system identification.

Throughout this paper, the following convention is used. Variables in lower case represent scalar quantities. Lower case bold variables represent vector quantities. Upper case bold variables represent matrices.

2 Multivariable Hammerstein identification

Successful identification requires a proper experimental design and choice of a proper model structure. Experimental design involves selection of experimental parameters like sampling time and excitation signal. Several varieties of model structures have been proposed and discussed in the literature. Among these, *block oriented models* have seen great interest among researchers. These are simple models of interconnected blocks where each block represents either a linear dynamic filter or a static nonlinearity. Block oriented models have successfully represented several physical processes like distillation column [3, 4, 5], pH control system [6, 7], and an electrical generator [8].

This work makes use of a popular block oriented model known as the Hammerstein model. The Hammerstein model is composed of a nonlinear memoryless subsystem followed by a linear dynamic one. The flexibility of the Hammerstein model and its structure which separates the nonlinearity from the easily realisable linear parts makes it very popular for modelling physical processes. Hammerstein model has been used to model several industrial processes. These include nonlinear filters [9], control systems [10], biological systems [11], pH neutralisation process [12], a fan and plate process [13], water heater [14], and electrical drive [15].

There are two main approaches used for identification of Hammerstein models, parametric approach, and non parametric approach. Parametric approach models the system with a finite number of variables and the nonlinearity is expressed as a linear combination of finite number of known functions. Some examples of parametric identification include, but are not limited to [16]-[21]. Nonparametric approaches on the other hand represent the system in terms of curves such as step response or bode diagram, obtained from expansion of series like the Volterra series or kernel regression. Significant nonparametric approaches to identify Hammerstein models include [22]-[30].

However, processes having multiple number of inputs and outputs pose several challenges to the task of successful identification using input and output data. Most identification techniques found in the literature fall under the category of prediction error method (PEM), which estimates system parameters by minimising one step ahead output prediction error. And while methods based on PEM have resulted in a well established theory for identification of single input single output (SISO) systems, it faces inherent problems for identification of systems having multiple inputs and multiple outputs (MIMO) [31]. Identification based on PEM is a complicated function of the system parameters, and often get stuck into local minima. PEMs also need an initial estimate for a canonical parametrisation model, i.e. models with minimum number of parameters, which might not be easy to provide. It has been shown in [32] that this minimal parametrisation can lead to several problems. Moreover, PEM generally have to solve nonlinear equations to estimate system parameters. PEM have therefore inherent difficulties with MIMO system identification. Today, more recent studies have shown that techniques based on PEM result in a non-convex optimisation problem in which global optimisation is not guaranteed [33].

This problem can be solved by Identification of state-space models using the methods of subspace identification. Subspace identification methods (SIM) do not need to solve nonlinear equations to find optimum solutions, rather these methods use reliable numerical tools such as QR decomposition and singular value decomposition (SVD) which lead to numerically efficient implementations. Moreover, there is no need for imposition of a canonical form on the system.

Subspace methods therefore do not suffer from the inconveniences encountered in applying PEM to MIMO system identification. Hence, these methods are fast as well as accurate [34].

This work uses state-space model to model the linear dynamic subsystem of the Hammerstein model, and Radial basis function neural network (RBFNN) to estimate the nonlinearity at the input.

3 Identification Structure

The RBFNN is trained using Particle Swarm Optimisation (PSO) technique, while parameters of the state-space model are determined using the numerical algorithm for state-space system identification (N4SID) proposed in [35, 32]. A novel heuristic algorithm is formulated which updates the parameters of both these models one by one. The input nonlinearities in a MIMO Hammerstein model can either be combined together or separate [27, 36]. Figures 2 and 3 show two Hammerstein models, both having p inputs and r outputs. In the first system, each nonlinearity is separate from the other. This Hammerstein system has p inputs, p intermediate variables, and r outputs at every sampled time instant t. Every nonlinearity is therefore approximated by a separate RBF network. Thus, the j^{th} nonlinear output $v_j(t)$ depends only on $u_j(t)$. Given that a separate set of weights

$$\mathbf{w}_j = [w_{1j} \quad w_{2j} \cdots w_{nj}], \tag{1}$$

and a separate basis vector

$$\boldsymbol{\phi}_j(t) = [\phi\|u_j(t) - c_1\| \cdots \phi\|u_j(t) - c_n\|] \tag{2}$$

exist for that nonlinearity, the output of the j^{th} nonlinear function is given by

$$v_j(t) = \mathbf{w}_j \boldsymbol{\phi}_j^T(t), \tag{3}$$

where n is the number of neurons in the hidden layer, c_i is the centre for the i^{th} neuron of that layer, ϕ is the radial basis function, and $\|.\|$ denotes norm.

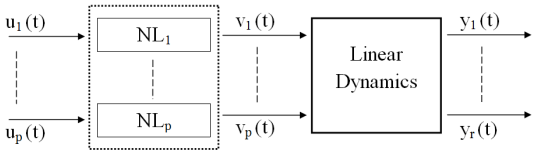

Figure 2. Hammerstein model with separate nonlinearities

In the second Hammerstein system, the nonlinearity is combined at the input which reflects the effect of all the inputs on every output of the nonlinear function. Such

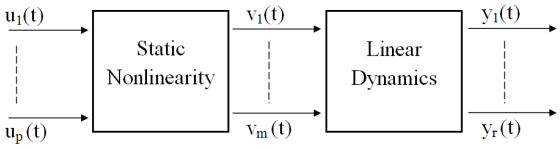

Figure 3. Hammerstein model with combined nonlinearities

a Hammerstein system has p inputs, m intermediate variables, and r outputs at every sampled time instant t. Unlike the system with separate nonlinearities, a single RBF network approximates the nonlinear block. Thus while all nonlinear outputs have a unique set of weights, they have a single basis function vector defined by

$$\boldsymbol{\phi}(t) = [\phi\|\mathbf{u}(t) - \mathbf{c}_1\| \cdots \phi\|\mathbf{u}(t) - \mathbf{c}_n\|]. \tag{4}$$

The j^{th} nonlinear output $v_j(t)$ is defined as:

$$v_j(t) = \mathbf{w}_j \boldsymbol{\phi}^T(t). \tag{5}$$

Notice that for this case, the input to the RBF network at time instant t is the vector $\mathbf{u}(t) \in \Re^{p\times 1}$ instead of a scalar value. Vector $\mathbf{c}_i \in \Re^{p\times 1}$ is the centre vector for i^{th} neuron. The RBF neural network takes the system inputs $\mathbf{u}(t)$ and transforms it to intermediate variables $\mathbf{v}(t)$. The centres of the RBFNN are kept fixed, and thus, the only adjustable parameters in the RBFNN are the weights of its output layer. This set of intermediate variable, $\mathbf{v}(t)$ is fed to the linear subsystem. Considering p equal to m, the output equations for the linear subsystem for both the cases are given by

$$\begin{aligned} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{v}(t) + \mathbf{s}(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{v}(t) + \mathbf{z}(t), \end{aligned} \tag{6}$$

where $\mathbf{v}(t) \in \Re^{p\times 1}$ and $\mathbf{y}(t) \in \Re^{r\times 1}$ are the vectors for p inputs and r outputs of the linear subsystem observed at discrete time instant t. Vector $\mathbf{z}(t) \in \Re^{r\times 1}$ is called the measurement noise and $\mathbf{s}(t) \in \Re^{n\times 1}$ is called the process noise. Both $\mathbf{z}(t)$ and $\mathbf{s}(t)$ are zero mean, white noise sequences, which have covariance matrices given by

$$E\left[\begin{pmatrix} \mathbf{s} \\ \mathbf{z} \end{pmatrix} \begin{pmatrix} \mathbf{s}^T & \mathbf{z}^T \end{pmatrix} \right] = \begin{bmatrix} \mathbf{Q} & \mathbf{S} \\ \mathbf{S}^T & \mathbf{R} \end{bmatrix} \delta_{pq}, \tag{7}$$

where E denotes expected value and δ_{pq} denotes kronecker delta which is explained in [35, 32].

If $\mathbf{y}(t) = [y_1(t) \cdots y_r(t)]^T$ denotes the vector for original outputs of the sampled data, $\hat{\mathbf{y}}(t) = [\hat{y}_1(t) \cdots \hat{y}_r(t)]^T$ denotes the vector for the outputs of the estimated system, then $\mathbf{e}(t) = \mathbf{y}(t) - \hat{\mathbf{y}}(t)$ denotes error vector, then a cost function based on the square of output

error is sought to be minimized. This cost function is given by

$$I = \sum_{t=1}^{l} \mathbf{e}^T(t)\mathbf{e}(t), \quad (8)$$

where l denotes total number of data points.

4 Training Algorithm

4.1 Particle Swarm Optimisation

PSO is a heuristic search optimisation algorithm which works on the principle of swarm intelligence [37]. It imitates the behaviour of animals in a swarm which work collaboratively to find their food or habitat. In PSO the search is directed, as every particle position is updated in the direction of the optimal solution. PSO is robust and fast and can solve most complex and nonlinear problems. It generates better solutions within lesser time as compared to other evolutionary algorithm (EA) based methods and exhibits stable convergence characteristics. In this work, PSO is used to train the RBFNN. Each particle of the swarm represents a candidate value for the weight of RBFNN output layer. The fitness of the particles is the reciprocal of the cost index given in equation 8. Hence, the smaller the sum of output errors, the more fit are the particles. Based on this principle, PSO updates the position of all the particles moving towards an optimal solution for the weights of RBFNN.

Each particle of the swarm is represented in a D-dimensional space with

$$X_i = [x_{i1} \quad x_{i2} \cdots x_{iD}] \quad (9)$$

Particle best positions providing the most optimum solutions are given as

$$P_i = [p_{i1} \quad p_{i2} \cdots p_{iD}] \quad (10)$$

The change in the position of each particle, or the velocity of each particle is given by

$$V_i = [v_{i1} \quad v_{i2} \cdots v_{iD}] \quad (11)$$

The velocity and position updating of the particles is the core of PSO, and involves some very important parameters like the constriction factor, inertia weight, and cognitive and social parameters.

$$V_i(n+1) = \chi[wV_i(n) + c_1 * r_{i1}(n) * \{P_i(n) - X_i(n)\} + c_2 * r_{i2}(n) * \{P_g(n) - X_i(n)\}] \quad (12)$$

$$X_i(n+1) = X_i(n) + x * V_i(n+1) \quad (13)$$

In the above equations, c_1 and c_2 are the *cognitive* and *social* parameters respectively, and are both positive constants. w is the *inertia weight* and χ is called the *constriction factor*. Both of these parameters were later added to the original PSO algorithm in [38] to overcome the inefficient behaviour of the algorithm, especially in the neighbourhood of global minimum.

4.1.1 Conginitive and Social parameters

The value of c_1 signifies a particle's attraction to a local best position based on its past experiences. The value of c_2 determines the swarm's attraction towards a global best position. The values of c_1 and c_2 are adjusted after several tries such that c_1 is kept slightly larger than c_2 but with $c_1 + c_2 \leq 4$ as proposed in recent literature [39]. This enables the swarm to trust local best solutions and move slowly towards a global best.

4.1.2 Constriction factor

The value of the constriction factor is kept close to 1. This enables slow convergence with better exploration.

4.1.3 Number of particles and swarm size

Assuming separate nonlinearities at the input, a set of 4 neurons is selected at each input to estimate the nonlinearity. This accounts to 16 neurons for all the inputs, and thus 16 synaptic weights. The number of particles is therefore taken 16. A swarm population size of 50 is selected and the optimisation process is run for 100 iterations. These parameters provide excellent learning for the RBFNN.

4.2 Subspace numerical algorithm

The proposed algorithm makes use of N4SID numerical algorithm for estimation of state-space matrices. The algorithm was proposed in [32, 35]. The objective of the algorithm is to determine the order n of the system, and the system matrices $\mathbf{A} \in \Re^{n \times n}$, $\mathbf{B} \in \Re^{n \times p}$, $\mathbf{C} \in \Re^{r \times n}$, $\mathbf{D} \in \Re^{r \times p}$, $\mathbf{Q} \in \Re^{n \times n}$, $\mathbf{R} \in \Re^{r \times r}$, and $\mathbf{S} \in \Re^{n \times r}$, and the Kalman gain matrix $\mathbf{K}$ (if required), without any prior knowledge of the structure of the system. This is achieved in two steps

- Determination of model order n and a Kalman filter state sequence estimates
  $\hat{\mathbf{x}}_i, \quad \hat{\mathbf{x}}_{i+1}, \quad \cdots \quad \hat{\mathbf{x}}_{i+j}$ by first projecting row spaces of data block Hankel matrices, and then applying a singular value decomposition.

- Solution of a least squares problem to obtain the state space matrices. Mathematical details of the these steps follow in [32, 35].

4.3 PSO/Subspace hybrid algorithm

Based on minimisation of output error given in equation 8, the hybrid PSO/Subspace identification algorithm is defined below

1. Estimate state-space matrices **A**, **B**, **C** and **D** from original non linear data using N4SID (initial estimate).

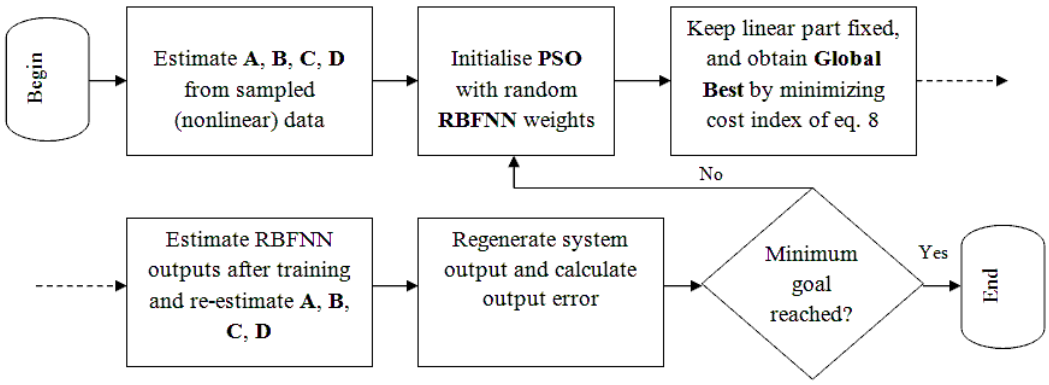

Figure 4. PSO/Subspace algorithm

2. Initialise PSO with random population of possible RBFNN weights.
3. Keeping the state-space matrices fixed, obtain a global best set of weights which minimises the cost index given in equation 8.
4. Estimate set of RNFNN outputs **v** once optimum weights are obtained.
5. Estimate state space matrices **A**, **B**, **C** and **D** from the new set of neural network outputs **v** and original system outputs **y**. This estimate of state-space model would be an improvement on the previous estimate.
6. Regenerate output $\hat{\mathbf{y}}$ from the new estimate of the complete system.
7. If a minimum goal of cost function is not achieved, keep repeating steps 2 to 6.

5 Simulation Results

A data set for the plant containing 9600 samples obtained at a sampling rate 3 seconds is taken from [40]. Out of these, 5000 samples are used for training, while 4600 samples are left aside for validation. The centres of the RBFNNs are uniformly distributed in the data intervals. PSO/Subspace algorithm identifies the boiler plant. The normalised mean squared error at the output converges to a final minimum value within a few iterations of the algorithm.

The dynamics of the system are identified by an 8^{th} order state-space model. The obtained model is simulated with the remaining 4600 samples of the data set. The results show remarkable concordance with actual measured data. Figures 5 and 6 show Drum pressure and Oxygen level predicted with fair accuracy. Figures 7 and 8 show Drum water level and Steam production rate. The accuracy of prediction in simulation is encouraging.

6 Conclusion

The identified model has accurately predicted process outputs making it highly reliable for predictive controller design. Combined advantages of subspace methods and ability of particle swarm to obtain global minimum have effectively estimated a mathematical model that caters to system dynamics as well as plant nonlinearities using data from the plant which contained disturbances as well as noise.

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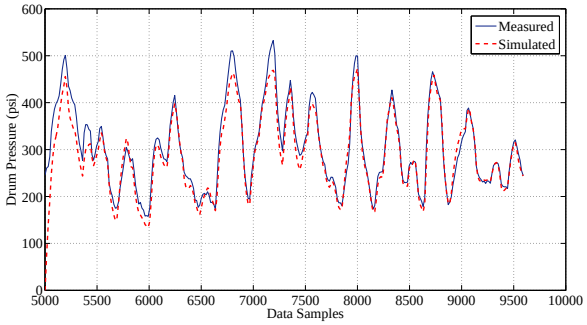

Figure 5. Plot of simulated and measured drum pressure

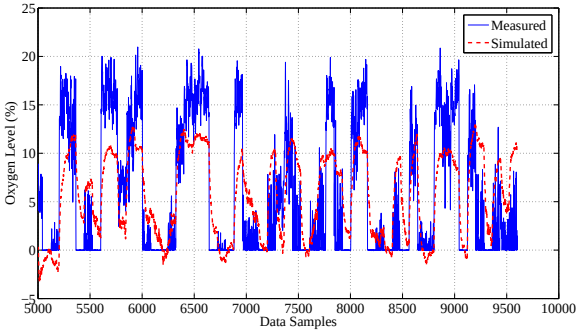

Figure 6. Plot of simulated and measured excess oxygen

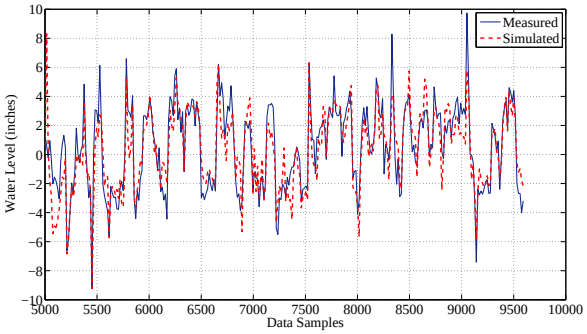

Figure 7. Plot of simulated and actual drum water level

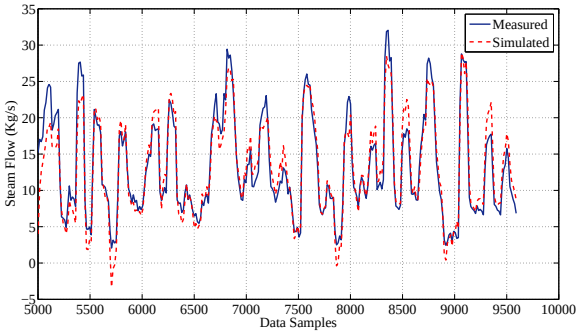

Figure 8. Plot of simulated and measured output steam