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APPLICATION OF NEURO-FUZZY IDENTIFIER IN THE PREDICTIVE CONTROL OF A POWER PLANT

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Abstract: An adaptive predictive control methodology is applied for a fossil fuel boiler control. The control algorithm takes advantage of a neuro-fuzzy identifier system for prediction of the boiler response in a future time window. An optimizer algorithm based on evolutionary programming technique (EP) uses the identifier-predicted outputs and determines input sequence in a time window. The present optimized input is applied to the plant, and the prediction time window shifts for another phase of plant output and input estimation. The neuro-fuzzy identifier is trained to provide a good estimation of boiler outputs. Neuro-fuzzy rules and membership parameters are trained based on the data log, applying genetic algorithm and back-propagation, respectively. The obtained intelligent control system is highly structural and applicable on different boiler systems. *Copyright ©2002 IFAC*

Keywords: Boilers, Intelligent Control, Predictive Control, Identifiers, Fuzzy Systems, Power Plant Control.

1. INTRODUCTION

Control of a fossil fuel boiler is addressed in classic and modern control approach extensively. It was always a challenge in adaptive and optimal control systems to deal with the Multi-Input Multi-Output (MIMO) characteristic of a boiler system. A wide range of low to high power operation of the power plant complicates the control method based on linear or non-linear model of the boiler. On the other hand, intelligent control methodology has proven to overcome these obstacles. An intelligent control system may be equipped to an appropriate training algorithm that adapts the control system to a wider operating points, and plant changes.

Among the intelligent control systems, model reference control is widely used in different structures (Åström and Wittenmark, 1989). The complexity of this approach and interconnection of plant, identifier and controller in a MIMO system, suggests the need for more portable intelligent control system. Fuzzy control approach overcomes the practical implementation problem due to complexity of the power unit mathematical model (Garduno-Ramirez and Lee, 2000). In addition, optimization techniques, such as Genetic Algorithm (GA) has opened new avenue in training and adapting control systems to the plant variation (Dimeo and Lee, 1995). Predictive control has been applied in process control extensively (Tolle and Ersu, 1992, Saint-Donat, *et al.*, 1994). In this paper, an intelligent adaptive control system is developed by using a highly trainable Neuro-Fuzzy Identifier system (NFI) and Evolutionary Programming Optimizer (EPO) in a boiler control problem and is studied in a wide range of operating condition by training NFI. Boiler measured data are used by GA and error back-propagation methods in this training.

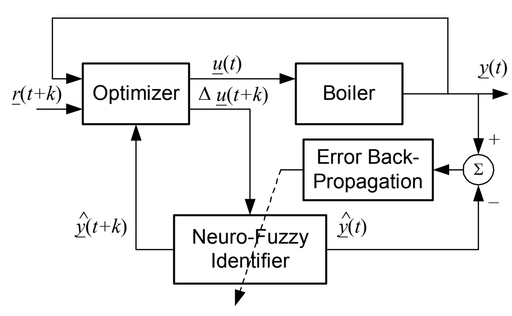

Fig. 1. Neuro-Fuzzy predictive control.

2. INTELLIGENT ADAPTIVE PREDICTIVE CONTROLLER

In predictive control approach, control system anticipates the plant response for a sequence of determined control action in future time horizon (Clarke, 1994). The optimal control action in this time horizon is a good choice to minimize the difference between desired and predicted responses. Model-based Predictive Control (MPC) takes advantage of this prediction. It is originally developed for linear model of the plant that provides the prediction formulation. The MPC was developed for limited classes of nonlinear systems. In some cases, on-line estimation provides parametric estimation of nonlinear process that can be used for an MPC methodology. Neuro-fuzzy system, as universal approximator, may be considered for identification of nonlinear systems. This nonlinear mapping is used for process output prediction in future time horizon.

The structure of intelligent adaptive predictive control is shown in Fig. 1. Prediction system is formed by neuro-fuzzy identifier to generate the anticipated plant output for a future time window, $N_1 \le t \le N_2$. The fuzzy rules and membership functions of this identifier can be trained off-line by the actual measured data of boiler. The future control variable for this prediction stage is determined in an optimization algorithm for the time interval of $N_1 \le t \le N_u$, such that $N_u \le N_2$, minimizing the following cost function:

$$J = \sum_{k=N_1}^{N_2} \left\| \underline{\hat{y}}(t+k) - \underline{r}(t+k) \right\|_R^2 + \sum_{k=N_1}^{N_u} \left\| \underline{\Delta u}(t+k) \right\|_Q^2 + \left\| \underline{y}(t) - \underline{r}(t) \right\|_R^2 \quad ,(1)$$

where $\underline{\hat{y}}(t+k)$ is predicted plant output vector which is determined by NFI for time horizon of $N_1 \le k \le N_2$, $\underline{r}(t+k)$ is desired set-point vector, $\underline{\Delta u}(t+k)$ is predicted input variation vector in time range of $N_1 \le k \le N_u$, $\underline{y}(t)$ and $\underline{r}(t)$ are present plant output and set-point vectors, respectively. The optimization block finds the sequence of inputs to minimize cost function in (1) for future time, but only the first value of this sequence is applied to the plant. This predictive control system is not model-based and is not using the mathematical model of the plant. Therefore, the optimization can not be implemented by conventional methods in MPC. The search engine based on EP is used to determine the optimized control variable for the finite future horizon. The competition search is performed on initial randomly chosen vectors of input deviation in a population and their mutated vectors. The mutation and competition continues to achieve desirable cost value.

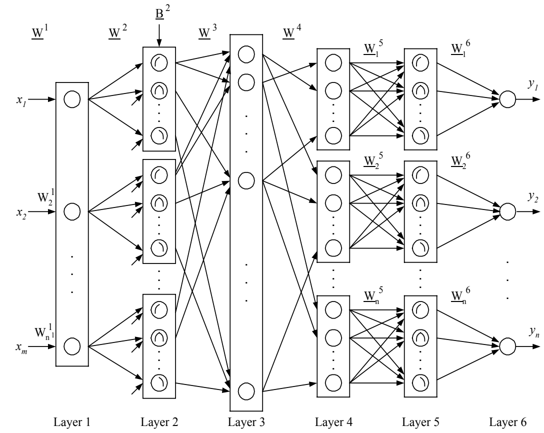

Fig. 2. Structure of neuro-fuzzy identifier

2.1 *Neuro-Fuzzy Identifier*

Neuro-fuzzy identifier technique is chosen for identification in predictive control loop (Ghezelayagh and Lee, 1999). The structure of a MIMO neuro-fuzzy system, with m inputs and n outputs, is shown in Fig. 2. The ith input and the jth output retain p_i and q_j bell-shaped membership functions, respectively. The number of possible rules, with *IF-THEN* format, is $\eta = \prod_{i=1}^{m} p_i$.

The first layer of identifier network represents the input stage that provides the crisp inputs for the fuzzification step. The second layer performs fuzzification with $n^2 = \sum_{i=1}^{m} p_i$. The weights and biases respectively represent the widths and means of input membership functions. Using exponential activation function, the outputs of the second layer neurons are the fuzzified system inputs. The third layer has η neurons. Weighting matrix of the third layer input represents antecedent parts of rules, and is called the *Premise Matrix*. Each row of the premise matrix presents a fuzzy rule such as:

$$R_{Premise} : IF\ x_1\ is\ T_{x_1}^1\ AND ... AND\ x_m\ is\ T_{x_m}^1\ THEN ...$$

where $T_{x_i}^j$ is the jth linguistic term of the ith input. The neuron output is determined by the *min* composition to provide the firing strength of rules.

The fourth layer consists of separate sections for every system output. Each section represents consequent parts of rules for an output, such as:

$$R_{Consequence} : ...\ THEN\ ...\ y_i\ is\ T_{y_i}^1\ ...$$

where $T_{y_i}^j$ is the jth linguistic term of the ith output. Layer 5 makes the output membership functions. Combination of the fifth and sixth layers provides defuzzification method. Weighting matrix of the fifth layer for each output section is a diagonal

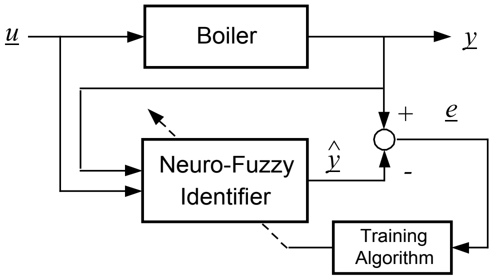

Fig. 2. Series-parallel identification.

matrix that contains width of the output membership functions. The activation value of each neuron provides one summation term in defuzzified output. The linear activation function determines output of each output section. The sixth layer completes defuzzification, and provides crisp output. The weighting vector of each neuron contains means of the output membership functions. The crisp output is derived by using activation function to implement the Center of Gravity approximation.

Identification process may not perform desirably if it does not include the input/output interaction. For this purpose, series-parallel configuration (Narandra and Parthasarathy, 1990) is chosen as it is drawn in Fig. 3. This identification structure considers the past output states in conjunction with the present inputs to determine the present output. The identifier with augmented inputs is represented by

$$\underline{\hat{y}}(k+1) = \hat{f}\Big(\underline{y}(k), ..., \underline{y}(k-i)\, ; \underline{u}(k), ..., \underline{u}(k-j) \Big), \quad (2)$$

such that $\underline{\hat{y}}(k)$ is the estimated output at time step k, $\hat{f}$ is identifier function, $\underline{u}(k)$ and $\underline{y}(k)$ are plant input and output vectors, respectively, at time step k.

2.2 Adaptive Neuro-Fuzzy Identifier

Adaptation of neuro-fuzzy identifier to a boiler system is essential to extract an identifier that truly models the boiler. Training algorithms enable identifier to configure fuzzy rules and adjust membership functions to model a boiler with certain error penalty. Training of neuro-fuzzy identifier is taking place in two phases of *configuration* and *tuning*. Configuration phase determines fuzzy rules automatically based on available data from the boiler operation. For this purpose Genetic Algorithm (GA) training is chosen (Goldberg, 1989), because of specific structure of the neuro-fuzzy identifier. Fuzzy membership functions are adjusted during tuning to reduce modeling error. Error back-propagation method is used for this tuning.

In the start of training, the identifier is initialized with default input/output membership functions and

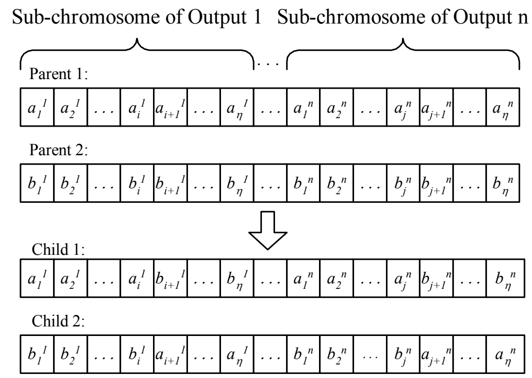

Fig. 4. Compound chromosome and GA crossover operation.

fuzzy rules. Positions of '1's in the premise and consequence weighting matrices of the third and fourth layers define fuzzy rules. These matrices are encoded in the form of GA chromosome. We recall that the fourth layer consists of several sub-sections because of multiple outputs. Therefore, a GA chromosome has a compound structure with n sections as the number of boiler outputs. Fig. 4 shows a compound chromosome that is different from simple chromosome in standard GA. The number of genes in each section is equal to the rule number η. Each section encodes the premise and consequence matrices with an integer value of *allele*, θ^i_j, that belongs to the alpha-numeric set of $\theta^i_j \in A = \{0, 1, ..., q_i\}$, for $j = 1, \ldots, \eta$. Therefore, GA with non-binary alphabet (Mason, 1991) will be the training method. Alpha-numeric size of each section is equal to the membership function number of corresponding output. The value of θ^i_j represents the row position of '1' in each column of the consequence matrix. The GA will act separately on these sub-chromosomes to find the best fit. Having a set of experimental input/output plant data points, GA can be applied to find optimal set of fuzzy rules. The fitness function, based on the least squares principle, provides evaluation of population individuals. To complete the GA iteration, it is necessary to prepare the next generation of population with applying three GA operators: selection, crossover and mutation. The weighted roulette wheel is used as selection operator that assigns a weighted slot to each individual (Dimeo and Lee, 1995). Crossover operator generates two offspring strings from each pair of parent strings, chosen with probability of p_c. Crossover takes place in every sub-chromosome of parents. Crossover points are determined randomly with uniform distribution. Mutation operator changes value of a gene position with a frequency equal to mutation rate p_m. The new value of a chosen gene will be randomly determined with uniform distribution.

Tuning the parameters of fuzzy membership functions completes training of the neuro-fuzzy system. Adjusting the membership function increases the accuracy of the identifier, since the initial membership functions have been chosen in the beginning of the training. Error back-propagation is used for training self-organized NFI. Let $D_k = \{\underline{\beta}(k), \underline{\gamma}(k)\}$ be a set of given pair of desired system input/output, such that $\underline{\beta}(k) \subset \Re^n$, $\underline{\gamma}(k) \subset \Re^m$. If $\underline{\hat{y}}(k)$ is the output of the neuro-fuzzy system in response to the input $\underline{\beta}(k)$, the squared error is defined as the following

$$E = \tfrac{1}{2}[\,\underline{\gamma}(k) - \underline{\hat{y}}(k)\,]^T [\,\underline{\gamma}(k) - \underline{\hat{y}}(k)\,]\,. \tag{3}$$

The training set contains the mean and width of the input-output membership functions. The sixth layer's weighting factor $w^6_{i,j}$ is updated by

$$w^6_{i,j}(k+1) = w^6_{i,j}(k) - \nu\,(\,\partial E / \partial w^6_{i,j}\,)\big|_k\,, \tag{4}$$

where ν is the learning rate. The error rate is derived from (3) as in the following:

$$\partial E / \partial w^6_{i,j} = -[\,y_i(k) - \hat{y}_i(k)\,]\,(\,\partial \hat{y}_i / \partial w^6_{i,j})\big|_k\,, \tag{5}$$

such that rate of the neuro-fuzzy output is derived by

$$\partial \hat{y}_i / \partial w^6_{i,j} = I^6_{i,j} / \sum\nolimits_{l=1}^{n_i^5} I^6_{i,l}\,. \tag{6}$$

In a way similar to the derivation of (3)-(6), the width and the mean of the membership functions in all other layers can be derived. The learning rates should be chosen appropriately. A small value of learning rate provides slow convergence. Moreover, stability may not be achieved with using large learning rate. Training ends after achieving specified error or reaching the maximum iteration number. Mean and width of the input/output membership functions are updated with final values of weighting matrices and bias vectors.

2.3 Control Input Optimizer

Optimized control input vector is determined in future time horizon by Evolutionary Programming (EP) technique (Fogel, 1991). Generations of input vectors are formed and selected by means of probability transition rules. Each individual in a generation competes with some of the other individuals in a combined population of the old and mutated generations. The competition results are valued by using a probabilistic rule. The winners of combined population constitute the next generation for evaluation of input vectors.

Initial population is produced randomly by individuals such as the following ith individual:

$$\Delta U_i = [\underline{\Delta u}_1^i \quad \underline{\Delta u}_2^i \quad \ldots \quad \underline{\Delta u}_m^i]\,,\ \text{for}\ i = 1,2,\ldots,N_p \tag{7}$$

where N_p is population size, m is number of inputs, $\underline{\Delta u}_j^i$ is the ith vector as in the following

$$\overline{\Delta u_i}^{\,j} = [\Delta u_i^j(1) \quad \Delta u_i^j(2) \quad \cdots \quad \Delta u_i^j(n_y)]^T \tag{8}$$

such that n_y is the number of steps in predictive discrete-time horizon for boiler output estimation that is defined by $n_y = N_2 - N_1$. The individuals of input vector variation belong to the limited range of $\Delta u_i^j(l) \in [\Delta u_{\min}^j, \Delta u_{\max}^j]$.

The fitness function of the ith individual in population is defined by (1). Based on this fitness function, the maximum, minimum, sum and average of the individual fitness should be calculated for further statistical process.

Each individual of the population derives a new individual as in the following:

$$\Delta u_j^{i+Np}(l) = \Delta u_j^i(l) + \mathrm{N}\left(0, \sigma^2\right) \tag{9}$$

where $\mathrm{N}(0,\sigma^2)$ represents Gaussian random variable with zero mean and variance σ^2. The variance is chosen to be a function of fitness value of the ith individual. The generated new individuals and old individuals produce a new combined population with size of $2N_P$. Each member of the combined population competes with some other members to determine which one is valued to survive to next generation. To select the survived individual, a weight value is assigned to each individual by

$$v_i = \sum_{k=1}^{p} v_k \tag{10}$$

where p is the number of members to compete with, and $v_k \in \{0,1\}$ is determined as in the following by randomly choosing the kth individual with uniform distribution:

$$v_k = \begin{cases} 1 & if\ \lambda_k < \dfrac{f_k}{f_k + f_i} \\ 0 & otherwise \end{cases} \tag{11}$$

such that $\lambda_k \in [0,1]$ is a randomly selected number with uniform distribution, and f_k is fitness of the selected individual. The N_P individuals with the highest competition weights are selected to form the next generation of population. This newly formed generation participates in next iteration. To determine the convergence of the process, the difference of maximum and minimum fitness of the population is checked against the desired number. If this convergence condition is met, then the individual with the highest fitness is selected as sequence of n_y input vectors for the future time horizon. The first vector is applied to the plant and the time window shifts to the next prediction phase. In order to eliminate the offset error in boiler response, a proportional gain is placed after the controller output.

3. BOILER CONTROL IMPLEMENTATION

To simplify simulation, actual boiler data is obtained from a boiler model that is developed by Bell and Åström (Åstrom and Bell 1987). The model is a nonlinear 4th order, derived by physical and empirical methods, as in the following:

$$d\,x_1 / d\,t = (u_3 - x_1)/20\,, \tag{12}$$

$$d\,x_2 / d\,t = (3.55\,w_s - x_2)/20\,, \tag{13}$$

$$d\,p / d\,t = -0.0018\,u_2\,p^{9/8} + 0.9\,u_1 - 0.15\,u_3\,, \tag{14}$$

$$d\,\rho_f / d\,t = (141 u_3 - w_s)/85\,, \tag{15}$$

$$L = 0.05\,(\,0.13073\,\rho_f + 100\,\alpha_{cs} + q_e/9 - 67.975\,)\,, \tag{16}$$

$$w_s = (\,1.1 u_2 - 0.19\,)\,p\,, \tag{17}$$

$$\alpha_{cs} = \frac{(1 - 0.001538\,\rho_f\,)\,(\,0.8\,p - 25.6\,)}{\rho_f\,(1.0394 - 0.0012304 p\,)}\,, \tag{18}$$

$$q_e = (\,0.85 u_2 - 0.147\,)\,p + 45.6 u_1 - 2.5 u_3 - 2.1\,, \tag{19}$$

where p is drum steam pressure (kg/cm^2), x_1 and x_2 are state variables for water swell and shrink effects, w_s is steam mass flowrate (kg/s), L is water level deviation about mean (m), ρ_f is fluid density (kg/m^3), u_1, u_2 and u_3 are normalized fuel, steam, and feedwater valve positions, α_s is steam quality (mass ratio), and q_e is evaporation rate (kg/s).

The actuator dynamics of control valves are also modeled to limit rate of change in valve positions:

$$\left|\,d\,u_1 / d\,t\,\right| \le 0.007 \quad /\sec \quad 0.0 \le u_1 \le 1.0\,, \tag{20}$$

$$-1.0 \le d\,u_2 / d\,t \le 0.1 \quad /\sec \quad 0.0 \le u_2 \le 1.0\,, \tag{21}$$

$$\left|\,d\,u_3 / d\,t\,\right| \le 0.05 \quad /\sec \quad 0.0 \le u_3 \le 1.0\,. \tag{22}$$

Before closing the control loop, NFI is trained to represent the boiler identifier. Training data is saved by simulation of this boiler model. A set of valve position inputs is chosen to excite boiler model. The input vector of the identifier includes inputs of boiler, drum pressure and steam flowrate state variables. Every inputs and outputs of NFI has seven membership functions. The training engine evaluates rule set candidates and finds the final set. The plant data is obtained from boiler simulation in three power ranges. The crossover and mutation rates are chosen to be p_c = 0.7, p_m = 0.005 in GA training. Fig. 5 depicts the comparison of the identifier response and the boiler data in response to the fuel deviation sequence in low power range. After training NFI, it is placed in the closed loop of the predictive control as in Fig. 1. The prediction time window is selected to be N_1=50 sec, N_2=130 sec, N_u=70 sec with prediction time step of $\Delta t = 10$ sec, while the simulation time step is 0.1 sec. Population size is N_P=10. The boiler response to ramp change of power from low to medium power is shown in Fig. 6. The set-points of steam flowrate and pressure steam rise up in ramp for this power change, while the water level set-point is kept constant. Steam pressure, in Fig. 6-(a), follows the ramp variation and settles to constant reference input after 25 prediction steps. The transient response shows an overshoot that suppresses after two prediction cycles due to anticipation of set-point in future time. Steam mass flowrate of the same test in Fig. 6-(b) accepts similar transition in the beginning and end of the ramp. Moreover, it settles to the final reference value faster than steam pressure due to faster dynamic of the flowrate that is performed by NFI. Boiler drum water level is shown in Fig. 6-(c), and it stays almost constant during the ramp power up. To improve the transient response, a larger prediction time may be chosen to consider the future set-point values earlier in optimization of control action. In addition, increase of population size in EPO improves the transient and settling performance of the outputs because optimizer will be able to search between more candidates, obtaining an optimized input vector.

4. CONCLUSIONS

Structure of intelligent adaptive predictive control is studied and used in control of a fossil fuel boiler. This control approach is equipped to a neuro-fuzzy identifier to foresee a sequence of fuel, air and steam valve positions in future time window. This sequence of plant inputs is optimized, determined with evolutionary programming technique. The first input vector of the sequence is used to excite the boiler valve position at each time. The time window shifts for another time step and the prediction phase repeats to determine the next input. The neuro-fuzzy identifier is highly structural and trainable, and can be adapted to the boiler-measured data. Genetic algorithm and error back-propagation methods are used to train fuzzy rules and fuzzy membership function parameters, respectively. This neuro-fuzzy identifier makes the predictive control process to be non-model based, and provides an intelligent control methodology that is adapted to boiler operating conditions and changes.

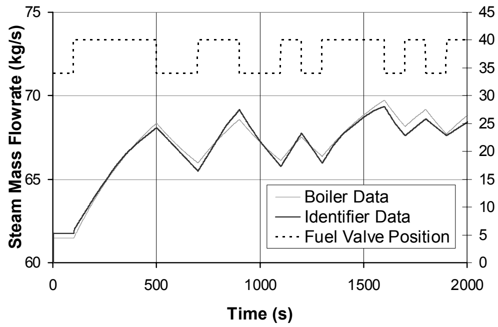

Fig.5. Steam mass flowrate of identifier and boiler in response to fuel valve deviation in low power.

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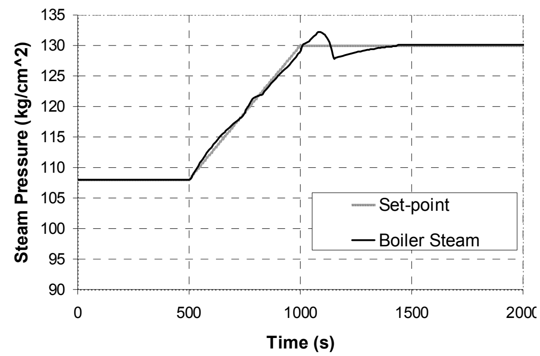
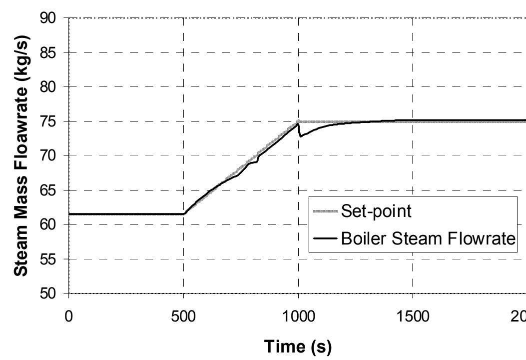


(a)



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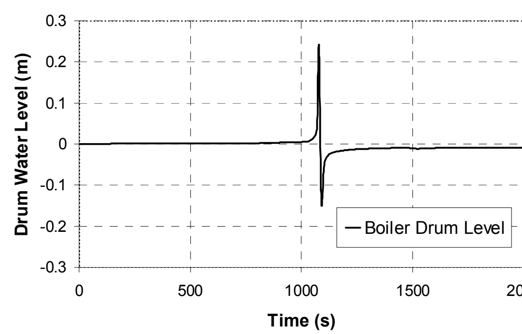

(c)

Fig. 6. Transient response to ramp variation of low to medium power (a) steam pressure (b) steam mass flowrate (c) drum water level.

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