Intelligent Washing Machine: A Bioinspired and Multi-objective Approach

Rasoul Mohammadi Milasi, Mohammad Reza Jamali, and Caro Lucas

Abstract: In this paper, an intelligent method called BELBIC (Brain Emotional Learning Based Intelligent Controller) is used to control of Locally Linear Neuro-Fuzzy Model (LOLIMOT) of Washing Machine. The Locally Linear Neuro-Fuzzy Model of Washing Machine is obtained based on previously extracted data. One of the important issues in using BELBIC is its parameters setting. On the other hand, the controller design for Washing Machine is a multi objective problem. Indeed, the two objectives, energy consumption and effectiveness of washing process, are main issues in this problem, and these two objectives are in contrast. Due to these challenges, a Multi Objective Genetic Algorithm is used for tuning the BELBIC parameters. The algorithm provides a set of non-dominated set points rather than a single point, so the designer has the advantage of selecting the desired set point. With considering the proper parameters after using additional assumptions, the simulation results show that this controller with optimal parameters has very good performance and considerable saving in energy consumption.

Keywords: Genetic algorithm, identification, intelligent control, washing machine.

1. INTRODUCTION

Acquisition of adequate system knowledge is often problematic or impractical due to system complexity and the fact that the structure and parameters in many systems change in significant and unpredictable ways over time. Moreover, to reduce design complexity control designers often utilize less detailed models for control than what they have access to. To address the control demands of such highly complex and uncertain systems one can enhance today's control methods using intelligent control systems and techniques. The area of Intelligent Control including fuzzy logic, neural network and emotional learning methods is a fusion of a number of research areas in Systems and Control, Computer Science and Operations Research among others, bringing together, merging and expanding in new directions and opening new horizons to address the new problems of this challenging and promising area. There are several techniques used for intelligent control and utilized in challenging industrial application domains where those methods provide particularly useful solutions [1-6].

Several attempts have been made to model the emotional behavior of human brain [7,8]. In [9] the computational models of amygdala and context processing were introduced. Based on the cognitively motivated open loop model, a new controller architecture called BELBIC (Brain Emotional Learning Based Intelligent Controller) was introduced [10]. After that the controller was applied to many applications [11-15] and the results showed that this controller had good performance, but there were still some problems that posed difficulties. The first problem was its large control signal. In [16,17] a method to overcome this problem was introduced and applied to Washing Machine and results showed that this controller provided very good energy consumption. The second problem was its undefined controller gains which had to be decided via past experience and expert knowledge or trial and error to gain the best performance.

From recorded documents it can be found out that the notable improvements in Washing Machine technology belonged to 1990s and 2000s. In [18] and [19] sensing devices and new motors were introduced for Washing Machine. The new method proposed remote sensing of pressure inside the wash load of domestic Washing Machine via a wireless data

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acquisition system [20]. Intelligent and fuzzy logic based controllers for Washing Machines were also successfully introduced since the 90's and quickly gained sizable market share [2]. Besides, many other works have been done in design and control of Washing Machine electromotor [21-23]. In 1990 the first fuzzy controller for Washing Machine was introduced by Matsushita Company. They used fuzzy controller for auto-adjusting motor cycle versus amount and kind of dirt and cloth volume. In fact the fuzzy control system had three inputs and one output using optic sensors for measuring inputs [2], [24]. Later, intelligent Washing Machines gained popularity all over the world. Hitachi Washing Machines used fuzzy controllers with amount of cloth and quality of cloth as inputs and automatically set the wash cycle for the best use of power and water [2]. In [25] and [26] a rather sophisticated finite element model of Washing Machine were presented. On the other hand, in [16] a lumped model for Washing Machine was introduced. In that work a Locally Linear Model Tree (LOLIMOT) neuro-fuzzy algorithm [27-29] was used for modeling the Washing Machine based on previously extracted data. Next the modified brain emotional learning based intelligent controller (Modified BELBIC) was applied on the model of Washing Machine.

As it was mentioned above, one of the main problem of BELBIC controller is its undefined parameters. In this work, the modified BELEBIC parameters [16] are tuned via Multi Objective Genetic Algorithm (MOGA) for obtaining the best performance. The performance is defined based on two objectives: energy consumption and washing process. Optimization based on multiple objectives [30-32] provides a range of solutions, due to trade off between objectives, rather than one solution. Finally, simulations show that the energy consumption can be reduced considerably more than that in manual tuning.

The rest of paper is as follow: in Section 2 and Section 3, the modeling of Washing Machine using Locally Linear Neuro-Fuzzy Modeling (LOLIMOT) and Brain Emotional Learning Based Intelligent Controller (BELBIC) will be discussed respectively. The Multi Objective Genetic Algorithm will be represented in Section 4 and finally, the Washing Machine Controller will be designed and simulated in Section 5.

2. IDENTIFICATION OF WASHING MACHINE

The network structure of a Local Linear Neuro Fuzzy Modeling is depicted in Fig. 1. Each neuron realizes a Local Linear Model (LLM) and an associated validity function that determines the region of validity of the LLM. The network output is calculated as a weighted sum of the outputs of the local linear models, where the validity function is interpreted as the operating point dependent weighting factors. The validity functions are typically chosen as normalized Gaussians.

The local linear modeling approach is based on a divided-and-conquer strategy. A complex Washing Machine model divided into a number of smaller and thus simpler sub-problems, which are solved independently by identifying simple linear models [16,17,27-29]. The most important factor for the success of such an approach is the division strategy for the original complex problem this will be done by an algorithm named LOLIMOT (Locally Linear Model Tree). LOLIMOT is an incremental tree-construction algorithm that partitions the input space by axis-orthogonal splits [27]. In each iteration, a new rule or local linear model is added to the model and the validity functions that correspond to the actual partitioning of the input space are computed, and the corresponding rule consequence are optimized by a local weighted least squares technique. In [16] the Locally Linear Neuro Fuzzy Modeling (LLNF) method is used to identify Washing Machine based on previously extracted data. As shown in Fig. 2, the proposed model of Washing Machine has four inputs and two outputs. The inputs are motor speed, heater temperature, detergent and water volume, while the

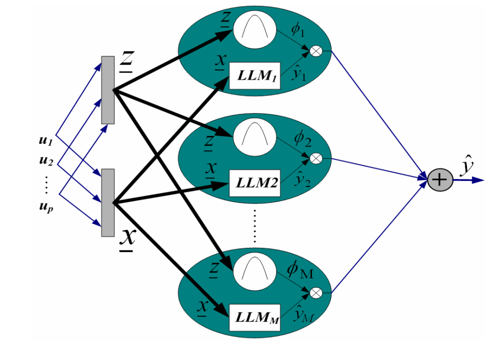

Fig. 1. Network structure of a local linear neuro-fuzzy model.

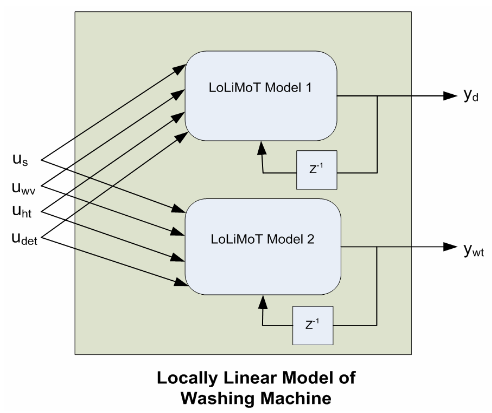

Fig. 2. Configuration of proposed Washing Machine.

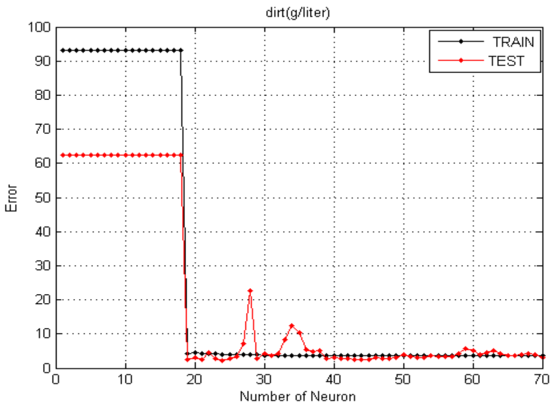

Fig. 3. The variation of sum square error of dirt [16].

outputs are water temperature and cloth dirt.

An examination of the empirical data suggests first order models for the amount of cloth dirt dissolved in Washing Machine water and water temperature are needed as a minimal model [16].

In case of locally linear identification, the most imperative concern is the number of neurons. It is desirable that the number of neurons be as small as possible. The number of neurons has been obtained based on sum of squared error curve. The number of outputs determines the number of Locally Linear Neuro-Fuzzy networks, so the proposed model of Washing Machine has two parallel LLNF network. As shown in Fig. 3, the optimal number of neurons for the first LLNF network, which has dirt as output, is about twenty. More neurons does not effect in significant reduction of error. Similarly, for the second LLNF network, which has the water temperature as output, the number of neurons is 13 neurons. Next, using the Locally Linear Model Tree algorithm, a model is fitted to the data. Below are the brief five basic steps to identify the Washing Machine model [16,28-30]:

1. Start with an initial model of Washing Machine,
2. Find worst Locally Linear Model that has maximum local loss function.
3. Check all hyper-rectangles to split (through).
   - (3a) Construction of the multi-dimensional Fuzzy Membership Functions for both hyper-rectangles.
   - (3b) Construction of all validity functions.
   - (3c) Local estimation of the rule consequent parameters for both newly generated LLMs.
   - (3d) Calculation of the loss functions for the current overall model.
4. Find best division (the best of the alternatives checked in Step 3, and increment the number of LLMs: M → M+1).
5. Test for convergence.

3. BRAIN EMOTIONAL LEARNING BASED INTELLIGENT CONTROLLER

There are many studies that have been carried out for modeling emotional learning. A computational model of brain was proposed in [7-9]. Later, this model was used as a controller and called BELBIC [10]. BELBIC was not only a simple controller but also an adaptive controller with good performance [15-17].

BELBIC is divided into two main parts, very roughly corresponding to the amygdala and the orbitofrontal cortex, respectively. The amygdaloid part receives inputs from the thalamus and from cortical areas, while the orbital part receives inputs from the cortical areas and the amygdale only. The system also receives reinforcing signal. As shown in Fig. 4, there is one A node for every stimulus S including one for the thalamic stimulus. There is also one O node for each of the stimuli except for the thalamic node. There is one output node in common for all outputs of the model, called E. The E node simply sums the outputs from the A nodes, then subtracts the inhibitory outputs from the O nodes. The result is the output from the model. The E' node is sums the outputs from A except A_{th} and then subtracts from inhibitory outputs from the O nodes.

$$E = \sum_i A_i - \sum_i O_i \quad (\text{include } A_{th}) \tag{1}$$

$$E' = \sum_i A_i - \sum_i O_i \quad (\text{not include } A_{th}) \tag{2}$$

The thalamus connection to A_{th} is calculated as the maximum over all stimuli S.

$$S_{th} = \max(S_i) \tag{3}$$

Unlike other inputs to the amygdala the thalamic input is not projected into the obitofrontal part and cannot be inhabited.

The emotional learning occurs mainly in amygdala. With definition of $[x]^+ \equiv \max(0, x)$, the learning rule of amygdala is given as follow:

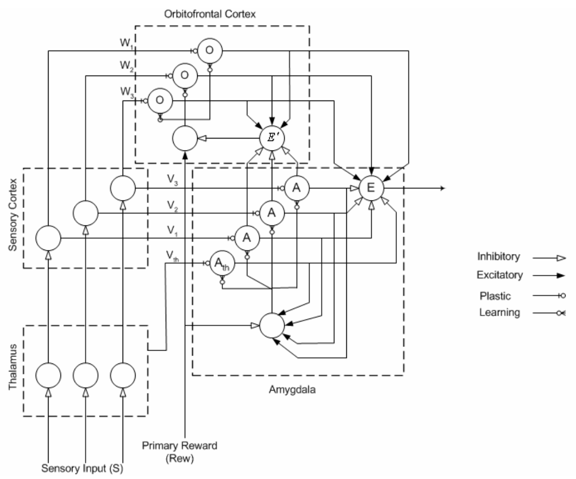

Fig. 4. A graphical depiction of the BELBIC [7-9,16].

$$\Delta V_i = k_a (S_i [R_w - \sum_j A_j]^+), \tag{4}$$

where k_a is adjusting term for learning speed, R_w is reinforcing signal and V_i is plastic weight of each A_i (including A_{th}).

Similarly, the learning rule in orbitofrontal cortex is calculated as the difference between the E' and the reinforcing signal R_w.

$$\Delta W_i = k_o (S_i (E' - R_w)), \tag{5}$$

where W_i is the gain in orbitofrontal connection and k_o is learning rate factor in orbitofrontal.

As it is evidence, the orbitofrontal learning rule is very similar to the amygdaloid rule. The only - but essential - difference is that the orbitofrontal connection weight can both increase and decrease as needed to track the required inhibition.

Finally the node values calculated as follow:

$$A_i = S_i V_i, \tag{6}$$

$$O_i = S_i W_i. \tag{7}$$

Note that since amygdala does not have the capability to unlearn any emotional response that it ever learned, inhabitation of any inappropriate response is the duty of orbitofrontal cortex. In other words, this system works at two levels: the amygdaloid part learns to predict and react to a given reinforcer. This subsystem can never unlearn a connection; once learned, it is permanent, giving the system the ability to retain emotional connections for as long as necessary. The orbitofrontal system tracks mismatches between the base systems predictions and the actual received reinforcer and learns to inhibit the system output in proportion to the mismatch.

The reinforcing signal R_w comes as a function of others signal which can be supposed to be an instantaneous cost function validation i.e., award and punishment are applied based predetermined defined cost function.

$$R_w = J(S_1, S_2, ..., S_n, E, PO_1, ..., PO_m), \tag{8}$$

where PO_i is one of the outputs of plant.

Similarly, the sensory inputs must be a function of plant outputs and controller outputs as follows:

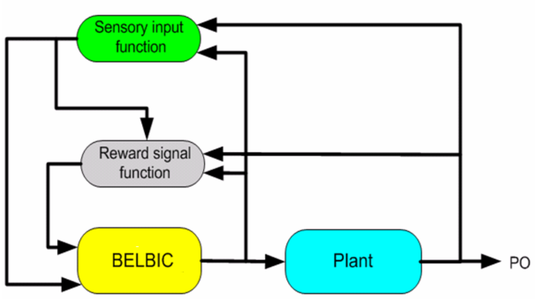

Fig. 5. Control system configuration using BELBIC.

$$S_i = f(E, PO_1, ..., PO_m). \tag{9}$$

In Fig. 5 the block diagram of these control method is depicted.

4. MULTI-OBJECTIVE GENETIC ALGORITHMS

Genetic algorithms (GA's) are search procedures based on the evolutionary process in the nature. Most GA's have been used for single objective problems, although several multi-objective schemes have been proposed [30]. Fonseca and Fleming [31] have used an approach called the multi-objective genetic algorithm (MOGA), which is an extension on an idea by Goldberg [32]. This formulation maintains the genuine multi-objective nature of the problem, and is essentially the scheme used here. Further details of the MOGA can be found in Fonseca and Fleming [33,34]. The idea behind the MOGA is to develop a population of Pareto-optimal or near Pareto-optimal solutions. The aim is to find a set of solutions which are non-dominated and which satisfy a set of inequalities. An individual j with a set of objective functions $\varphi^j = (\phi_1^j, ..., \phi_n^j)$ for maximizing all of objectives is said to be *non-dominated* if for a population of N individuals, there are no other individuals' k from 1 to n and $k \neq j$ such that:

a) $\phi_i^k \leq \phi_i^j$ and for all $i = 1,2,\ldots,n$

b) $\phi_i^k < \phi_i^j$ for at least one i.

Genetic algorithms are naturally parallel and hence lend themselves well to multi-objective settings.

5. MULTI-OBJECTIVE GENETIC ALGORITHMS WASHING MACHINE CONTROLLER DESIGN AND SIMULATION

Intelligent washing machines have in recent years won sizable market share in an already competitive environment. Our interest in developing superior control mechanisms also stems from the fact that intelligent washing machines provide one of the most promising application areas for new electromotor technologies (switched reluctance and permanent magnet). Our past research has shown that bioinspired control systems achieve excellent performance in motion centric processes. We further conjecturize that bounded rationality approaches to machine intelligence can be adopted for finding the proper balance between different objectives using limited resources in an uncertain environment. These objectives, it was thought, can be achieved via BELBIC for intelligent control of washing machine. Emotion, in biological realm serves as experience-based cues for making decisions with bounded rationality. Likewise, in artificial systems, our past research has shown that BELBIC can achieve the same goals especially in motion centric appliances like washing machines. To test that conjecture, we need to conduct experiments with a real washing machine. As a first step, we replace the real washing machine with a publicly available simulator for which it is easy to introduce changes in system dynamics or add disturbances. We assume we do not know the system dynamics and so the latter must be identified based on input-output data obtained from the simulator (which, in the next step, can be obtained from the real washing machine). We used a LOLIMOT identifier for that task. The existence of LOLIMOT will be even more crucial during the stage of actual experimentation with the proposed washing machine. Without it, MOGA cannot be run in reasonable execution time. Dirt, derivative of dirt, and Determination of water temperate are the output of the washing machine model and they are feedback to control the inputs, speed, heater temperature, detergent. Water volume is dependant on the amount of clothes to be washed and can be determined by inverse dynamic method. At first, a little water is let into washing tub, and the motor is powered on, thereby turning the rotor in the tub and causing the water and clothes to start rotating. This turns the motor into dynamo, which generates a small amount of electrical power. The length of time during which power is generated in this way is measured, and the measurement is used as an indicator of the amount of cloth: a larger amount produces greater inertia, leading to longer generation time. Thus the amount of water can be inferred from amount of clothes [2,24]. We consider amount of cloth and thus water volume constant and assumed 15 liter. Therefore, the initials values for inputs are zero except the initial value of water volume which is 15.

Brain Emotional Learning Based Intelligent Controller (BELBIC) was used as a controller for Washing Machine, and it was shown that BELBIC controller can have better performance than fuzzy controller [16]. Although BELBIC worked well, its parameters were adjusted using trail and error rather than using an optimal approach. For passing over this drawback, in this work, a Multi-Objective GA (MOGA) is employed for tuning BELBIC parameters (k_o,k_a).

Two depended objectives (cost functions) are considered as objectives of MOGA. Three BELBIC are employed for three different inputs, so there are six parameters which must be set. The proposed cost functions are as followed:

$$\text{Objective 1:}\ \ (4 - dirt(t)), \tag{10}$$

$$\text{Objective 2:}\ (w_1 S^2 + w_2 HT^2 + w_3 D^2), \tag{11}$$

$$w_1 = 0.1,\ w_2 = 0.8,\ w_3 = 0.45,$$

where D, S, and HT respectively are abbreviation of Detergent, Speed, and Heater Temperature. As it is clear from Fig. 6, after optimization using MOGA, there are a set of optimal parameters rather than specific optimal parameter. In other words, the dimension of optimal set is always one dimension less than number of objectives. In this case the optimal set is a line in the plane of two objectives.

For obtaining the best point in the above set, we consider additional assumptions. We expect these parameters satisfied two conditions: first, the washing process has to be finished, i.e., the clothe dirt has to be removed. Second, Objective 2, which actually is energy consumption, must be minimized.

In Table 1, the best parameters which are obtained from optimization algorithm (MOGA+Additional Assumptions) are shown. Note that k_a and k_o are learning rate factors.

With considering the above parameters and using MATLAB SIMULINK, the control of Washing Machine has been simulated. The variation of Washing Machine's and BELBIC's inputs and outputs are depicted in Figs. 7, 8, and 9.

In Fig. 7, the variations of Washing Machine's outputs are shown. As it is evident, the dirt reaches its steady state values. Note, the water dirt increase is considered to be the index for the progress in the washing process. Therefore, the cloths have been completely washed and the washing process is ceased after 31 minutes. The derivative of dirt is also depicted to show the variation of dirt more precisely.

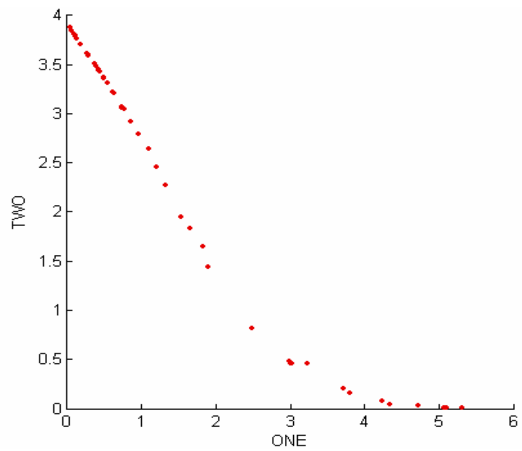

Fig. 6. The trade-off between optimal points for the two objectives (the x-axis shows the first objective and the y-axis shows the second objective).

Table 1. BELBIC optimal parameters.

	k_a	k_o
BELBIC(I)	0.00253	0.02088
BELBIC(II)	0.100	1,663
BELBIC(III)	1.091	0.736

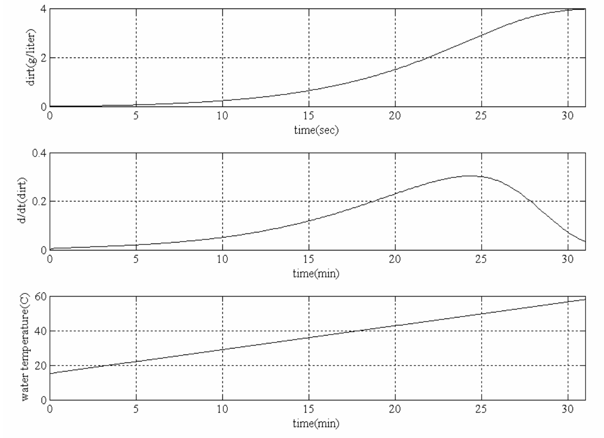

Fig. 7. Variation of Washing Machine outputs.

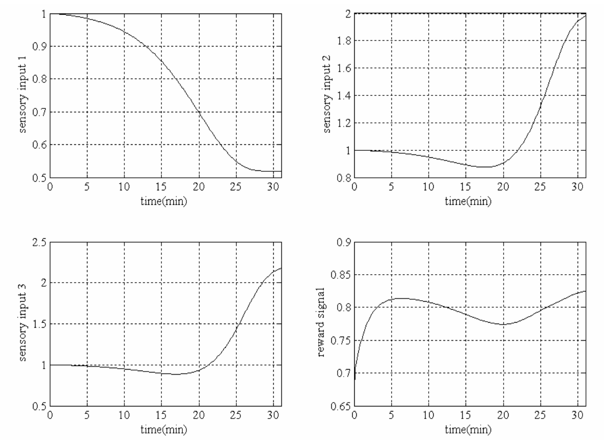

Fig. 8. Variation of sensory inputs and reward function.

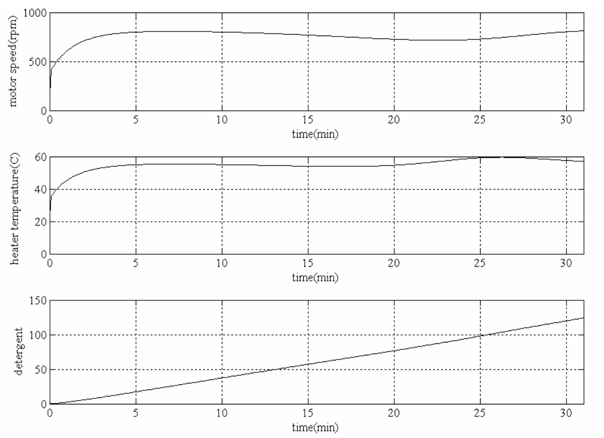

Fig. 9. Variation of Washing Machine inputs (controller signals).

The last graph of this figure shows the water temperature. Water temperature varies from almost 17 ^{o}C to 59^{o}C which is reasonable range for a real washing machine.

In Fig. 8, the variation of R_{ew} and S_i of each BELBIC are depicted. The variation of R_{ew} is rather smooth meaning that it is no need to punish or award the controller more than its current condition. Finally, in Fig. 9 the variation of Washing Machine inputs (BELBIC outputs) are depicted. It is clear that this controller provides reasonable control signals, moving in safe and reasonable levels of motor speed, heater temperature, and detergent.

With considering optimal parameters, it is found out that the cost function can be reduced more than 40% percent which it is very important in Washing Machine control.

6. CONCLUSIONS

Pareto based multi-objective Genetic Algorithm (MOGA) is used for obtaining the set of optimal parameters of Brain Emotional Learning Based Intelligent Controller (BELBIC) and a designer can select any desired member of this set. Two dependant cost functions are proposed and minimized. Due to their dependence, there must be a tradeoff between these cost functions. Considering other assumptions, the best parameters are obtained, and the simulation results done using MATLAB SIMULINK show the effectiveness of the proposed controller. It is shown that the proposed controller not only provides the desired outcome but gives the reasonable and smooth control signals which are very important in control problems.

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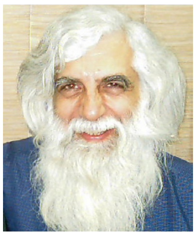

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