Neural Network Supervisor for Hybrid Fuel Cell/Gas Turbine Power Plants

Tae-Il Choi, Kwang Y. Lee, *Fellow, IEEE,* S. Tobias Junker, and Hossein Ghezel-Ayagh

Abstract--The neural network (NN) supervisor is developed for online estimation of optimal feedforward (FF) control inputs and setpoints for hybrid fuel cell/gas turbine power systems. The approach consists of determining a neural network structure suitable for predicting FF control inputs and setpoints based on optimal operating trajectories. The optimal trajectories were obtained in a previous study via nonlinear dynamic optimization based on a dynamic power plant model. Determination of the NN structure involves an a priori decision of the type of NN, the overall topology of input/output pairing, definition of a training epoch, as well as an identification of the number of hidden layer neurons and the number of iterations for the training epochs. This allows for straightforward training of the NN using the global training method, which includes all power profiles to define an epoch. In addition to training the NN with all available data, the network's prediction capabilities were tested by training it with all but one dataset and then determining the prediction results based on the untrained dataset. Results from eighteen case studies show that the developed NN supervisor is capable of predicting the optimized FF and setpoint trajectories satisfactorily.

***Index Terms*—Fuel cell, MCFC, hybrid fuel cell turbine power plants, dynamic optimization, neural network supervisor, setpoints, feedforward control, scheduling.**

I. Introduction

FUEL Cell/Gas Turbine (FC/GT) systems embody an approach to using fossil fuels efficiently, cleanly, and affordably for production of electricity [1]. The FC/GT power plants are expected to have negligible emissions while achieving projected efficiencies of 75% based on the fuel's lower heating value (LHV) for natural gas [2]. As an alternative to natural gas, these systems can also be configured to operate on fuels such as coal gas or biomass derivatives (e.g., from wood gasification or waste-water treatment plants) [3].

FC/GT hybrid systems have a high degree of coupling between fuel cell, gas turbine, and heat recovery units. The overall dynamics are nonlinear with varying degrees of inter-dependencies among the processes. The design of an FC/GT hybrid power plant has to address the operational constraints and details of the component performance characteristics [4].

Dynamic simulation has proven to be a powerful design tool for the study of the transient behavior of FC/GT hybrid systems [5]. Additionally, dynamic modeling provides a platform for investigating the advanced control algorithms and dynamic optimization routines during the design phase. The utility of dynamic simulation of fuel cell systems in the design of various fuel cell power plants has been explored elsewhere [6].

The dynamic operation and control of FC/GT hybrid power plants requires a synergy of operation among subsystems, increased reliability of operation, and reduction in maintenance and downtime. The control strategy plays a significant role in system stability and performance as well as ensuring the protection of equipment for maximum plant life [7,8]. In particular, optimal control of load changes is required for dynamic scheduling of setpoints and feedforward control inputs for the system controllers, as well as estimation of disturbances and data reconciliation.

A nonlinear programming framework was developed to determine optimal operating policies for hybrid fuel cell/gas turbine power systems [9,10]. Formulation of the dynamic optimization problem was focused on determination of optimal operating trajectories for tracking power plant load variations. Efficiency measures were also included to maximize efficiency while tracking the desired load profile. Results from eighteen case studies show that the dynamic optimization can be performed quickly – albeit not in real-time – with excellent results.

The primary objective of this paper is the development, implementation/solution, and documentation of a neural network (NN) supervisor for FC/GT hybrid power plants. Because dynamic optimization is computationally expensive, it is not feasible for real-time optimization of FC/GT systems. Instead, a neural network will be trained with data provided by the dynamic optimization. Once trained, the NN supervisor will be able to provide FF control inputs and setpoints to the power plant almost instantaneously. Due to the interpolation/extrapolation properties of neural networks, the NN supervisor will also be able to provide operating data for previously untrained trajectories.

A. Process Description

FC/GT systems are combined cycles composed of integration of a high temperature (>873 K) fuel cell, either a Molten Carbonate Fuel Cell (MCFC) or Solid Oxide Fuel Cell (SOFC), and a gas turbine. The FC/GT cycle based on a variant of MCFC technology with internal reforming capability (under the trade names Direct FuelCell®/Turbine and DFC/T®) has taken a lead in responding to the recent

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demands for increased fuel-to-electric power conversion efficiency. Recently, the factory tests of an Alpha DFC/T hybrid power plant, fabricated by integration of a 250kW Direct FuelCell® (DFC®) stack with a 60kW Capstone MicroTurbine™, was successfully concluded with a near record setting performance [11]. The Alpha DFC/T hybrid power plant achieved a power generation level of greater than 320 kW at 56% (LHV) while operating on natural gas. Figure 1 shows a simplified process flow diagram.

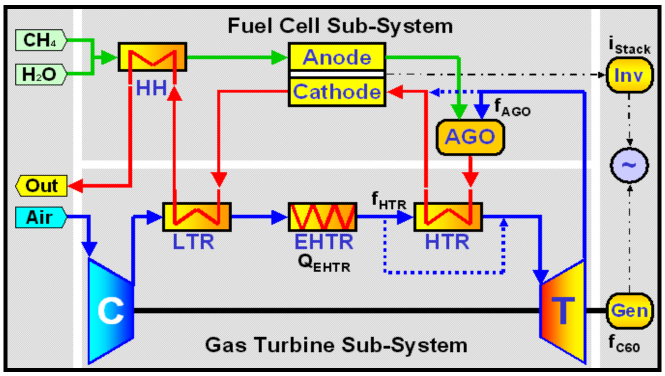


Fig. 1. Flow diagram of FuelCell Energy's Direct FuelCell/Turbine® (DFC/T®) hybrid system.

The key feature of this process is a high level of integration between the fuel cell subsystem and the turbine subsystem. The turbine provides process air to the fuel cell, while the fuel cell provides heat to the turbine. Both subsystems produce electric power. Power from the turbine is produced in a high-speed generator; DC power from the fuel cell is inverted to AC prior to being sent to the utility grid.

In the fuel cell subsystem, feed water humidifies natural gas in a humidifier/heat exchanger (HH) prior to entering the fuel cell anode. In the anode methane is reformed into hydrogen and carbon dioxide and its chemical potential is converted to electrical energy. The anode exhaust, which contains some unreacted fuel, is mixed with hot air and oxidized completely in the anode gas oxidizer (AGO). An oxidizer bypass (dotted line) facilitates temperature control of the oxidizer. Hot effluent from the oxidizer heats the turbine inlet, enters the fuel cell cathode, preheats the compressor outlet, and finally provides heat to the humidifier [12,13].

In the turbine subsystem, ambient air is first compressed and then preheated in a low temperature recuperator (LTR) using fuel cell waste heat. The compressed hot air is heated further using a high temperature recuperator (HTR) located between oxidizer and fuel cell cathode. An HTR bypass (dotted line) facilitates temperature control of the cathode inlet temperature. Hot air leaving the HTR is expanded through the turbine section before being sent to the AGO. The turbine drives both the compressor and a permanent magnet generator. During system startup additional heat is provided by an electric heater (EHTR) and the generator works as a motor as long as the turbine cannot provide sufficient torque to operate the compressor.

B. Overview

The organization of this paper is as follows; Section II gives a summary of the previously performed dynamic optimization studies for FC/GT power systems. Based on the optimization results, a NN supervisor is developed in Section III and NN structures are explained in detail. Section IV presents simulation results obtained using developed NN structures, and conclusions are drawn in Section V.

II. Summary of Dynamic Optimization Results

To enable dynamic optimization of hybrid FC/GT systems, a simultaneous problem formulation was implemented and coupled to a large-scale nonlinear programming algorithm [9,10]. A generalized optimization framework for off-line trajectory planning was implemented. The optimization is constrained by the plant dynamics, as well as input and output constraints. This problem formulation was considered for two types of dynamic optimization problems for optimal process operation. First, in power tracking, we determined control inputs so that desired load trajectories are tracked. We have determined control inputs for both ramp and step profiles over various power regimes.

Second, we maximize efficiency while tracking load changes. To facilitate this task, we have included an efficiency measure into the objective function, and we track the same load profiles as in the previous cases. The effect of the efficiency measure is controlled via the weight □. Maximization of efficiency can be turned off by setting $\varepsilon = 0$. For a value of $\varepsilon = 10^{-3}$, the best trade-off between maximizing efficiency and tracking the desired power is achieved [10].

III. Development of NN Supervisor

Development in the control area has been fueled by three major needs: the need to deal with increasingly complex systems, the need to meet increasingly demanding design requirements, and the need to attain these requirements with less precise advanced knowledge of the plant and environment [14]. Increasingly complex dynamic systems with significant uncertainty have led to a revolution from conventional control methods. The importance of studying neural networks-based control architectures is revealed in fundamental difficulties of the current adaptive control techniques.

The recent revival in neuroengineering research, which started in the early 1980's, has focused mainly in the field of pattern recognition and signal processing. Only a few efforts have dealt with applications to control engineering [15]. It is well known that the ability to learn is one of the main advantages that make the neural networks so attractive. Neural networks (NNs) can also provide, in principle, significant fault tolerance, since damage to a few links need not significantly impair the overall performance. The massive parallelism, natural fault tolerance and implicit programming of neural network computing architectures suggest that they may be good candidates for implementing real-time controllers for large-scale, nonlinear dynamic systems [16].

Several neural network models and neural learning schemes were applied to system controller design during the last three decades, and many promising results are reported. Most people used the feedforward neural network (FNN), combined with tapped delays, and the backpropagation training algorithm to solve the dynamic problems; however, the feedforward network is a static mapping and without the aid of tapped delays it does not represent a dynamic system mapping. On the other hand, recurrent neural networks have important capabilities not found in feedforward networks, such as attractor dynamics and the ability to store information for later use. Of particular interest is its own natural temporal operation. Thus the recurrent neural network (RNN) is a dynamic mapping and is better suited for dynamic systems than the feedforward network.

The desire for a simple RNN and a shorter training time for the neural network model has led to the development of diagonal recurrent neural networks (DRNN) [18]. It can be shown that the DRNN model is a dynamic mapping in a way the fully connected recurrent neural network (FRNN) is dynamic [19]. Since there are no interlinks among neurons in the hidden layer, the DRNN has considerably fewer weights than the FRNN and the network is simplified considerably. The DRNN was used successfully for nuclear reactor temperature control, load forecasting, and synchronous machine control [17-19]. In view of the complexity of the hybrid fuel cell/gas turbine system, we adopt the DRNN as a possible candidate architecture for the neural network controller.

A. *Neural Network Supervisor*

The NN supervisor is proposed to mimic the function of the nonlinear dynamic optimization function block in generating the setpoint profiles and FF control inputs for the FC/GT. The high computational cost of dynamic optimization can be avoided by replacing it with a NN supervisor for fast on-line computations. The NN supervisor can be trained offline with dynamic optimization data. Once the network is trained it can be used for real-time application. Based on the power profile, the NN supervisor computes the required outputs almost instantaneously. The output includes the setpoints of the system and FF control inputs for the plant.

In addition to the speed of the computation, another key advantage of neural networks is their learning ability and their interpolation/extrapolation properties. In contrary to dynamic optimization which needs to be performed for all possible loads, the NN supervisor can provide output for a load which may not have been included in the training data set [20-22].

The NN supervisor will provide two kinds of outputs, the setpoints and the FF control inputs for a corresponding load profile. Various NN structures will be explored to determine suitable structures for the NN supervisor. After finding optimal values, NNs are trained and performances are evaluated.

B. *Determination of Setpoints and FF Control Inputs*

In a first step, the setpoints and feedforward control inputs to be predicted by the NN supervisor have to be determined. The following data are required for operation of the FC/GT power plant [10]:

1) The plant setpoints are:
   a. Anode gas oxidizer (AGO) outlet temperature, T_{AGO} in [°F]
   b. Micro-turbine speed, N in [kRPM]
   c. Stack power, P_{stack} in [kW].
   d. Cathode inlet temperature, TCI in [°F]
2) The feedforward control inputs are:
   a. Stack current, i_{Stack} in [mA/cm^2],
   b. Split fraction for the high temperature recuperator, f_{HTR}
   c. Split fraction for anode gas oxidizer, f_{AGO}
   d. Split fraction of for the micro-turbine, f_{C60}
   e. Methane flowrate in [mol/s]

The number of items in this list can be reduced by recognizing that the cathode inlet temperature setpoint and methane flow FF control input can directly be computed from available look-up tables as a function of stack current [10]. This reduces the problem size to three setpoints and four inputs.

A total of eighteen power profiles is available from the dynamic optimization. Each nine profiles with and without optimization of efficiency: Five ramp rates {0.5, 2, 10, 20, 40} kW/min and four step profiles {[5,75], [75,150], [150,225], [225,300]} kW.

C. *Design of NN Structures*

The NN supervisor provides two kinds of outputs for a given load profile: setpoints and FF control inputs. Various neural network structures were explored to determine suitable structures for the NN supervisor. If a single NN with one input (power profile) and seven outputs (three setpoints and four FF control signals) is used, the performance result is not satisfactory due to the complexity of the NN computation. Since the NN supervisor requires two outputs, it was found that better results can be obtained by employing two simpler neural networks instead as shown in Figure 2.

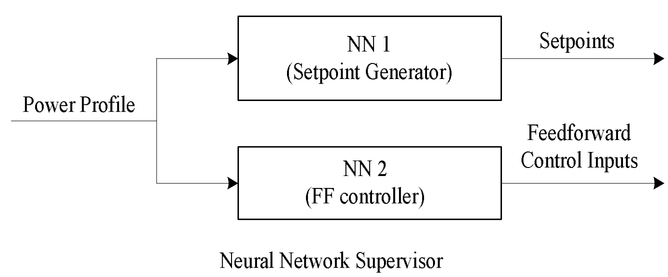


Fig. 2. Structure of the NN Supervisor.

The first NN generates setpoints and the second NN generates feedforward control signals according to the power profile as discussed in subsection B above. Both NNs were investigated separately to determine the best configuration for each NN structure.

D. *Data Preparation and Evaluation Criteria*

Since input and output data contain variables of different magnitudes, they need to be scaled prior to designing and training the NNs. Input and output data $X_{i,j}$ are normalized in the range [–1, 1], according to:

$$X_{i,j}^{n} = 2 \cdot \frac{X_{i,j} - X_{i,j}^{\min}}{X_{i,j}^{\max} - X_{i,j}^{\min}} - 1$$

$$X_{i,j}^{\min} = \min(X_{i,j})$$

$$X_{i,j}^{\max} = \max(X_{i,j})$$

where $i \in [1,18]$ are the eighteen datasets obtained from dynamic optimization and $j \in [1,7]$ are the seven setpoints and FF control inputs discussed in subsection B above.

The results of training were evaluated based on the following indices for the normalized values:

- Mean Absolute Error:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| , \quad \hat{y}_i : \text{predicted value}$$

- Mean Square Error:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 , \quad \hat{y}_i : \text{predicted value}$$

E. Optimal Number of Hidden Layer Neurons

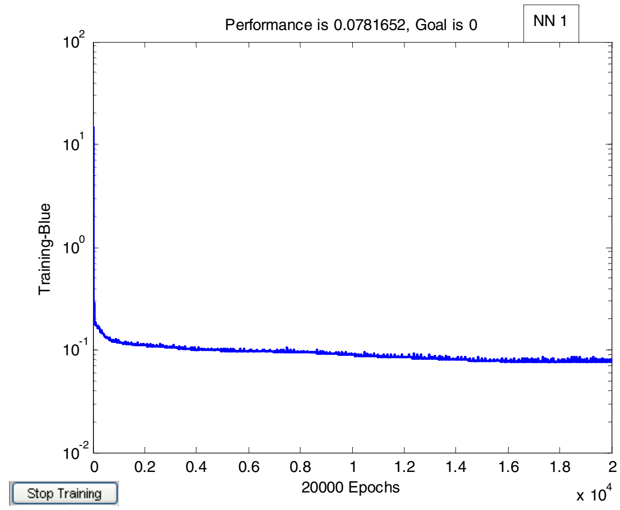
In the neural network structure, more hidden neurons are needed as the function being fitted increases in complexity [23]. To determine the best number of hidden neurons, the prediction error was plotted as a function of the number of neurons. Four different cases with different numbers of iterations {100, 200, 300, 500} are tested. As the number of iterations is increased from 100 to 500, performance results improve slightly, showing different values according to the number of hidden layer neurons. The best performance is achieved with, 70 hidden neurons for NN1 and 75 hidden neurons for NN2.

F. Optimal Number of Iterations for an Epoch

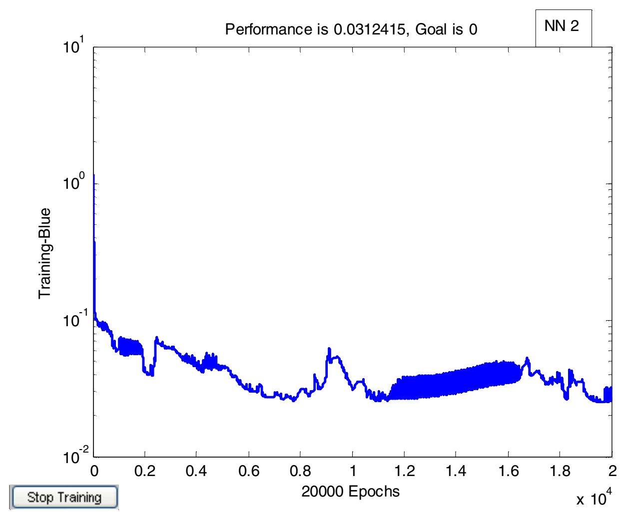
An epoch is one sweep through all the records in the training set. The eighteen profiles determined by dynamic optimization will be divided into two sets {A,B}, the first one for data with zero efficiency weight ($\varepsilon = 0$), the second one for data with nonzero efficiency weight ($\varepsilon = 10^{-3}$). If only one power profile is used as an input, the NN can generate accurate output. However, if all nine power profiles of one set are used, the sequence training data affects the performance.

Initially, random sequences of power profiles were used for the global training [18]. However, the quality of training results varied depending on the random sequence. Therefore, all 9 power profiles are used to define an epoch, i.e., one epoch consists of nine power profiles and the performance results were improved regardless of training sequences.

Fig. 3 shows the performance trajectories of training error (MSE) for both NNs. The error performances converge fast within the first 500 iterations for both cases, and thus 500 iterations could be used to reduce the computational time. However, the simulation results of AGO temperature setpoint and control input for 0.5 kW/min power profile were not satisfactory. Therefore, the number of iterations was increased to 20,000 until performances of AGO temperature setpoint and control input became satisfactory (Fig. 7).



(a) Training of NN1.



(b) Training of NN2.

Fig. 3. Performance trajectories of error with 20,000 iterations, $\varepsilon = 0$.

IV. Simulation Results

Using predetermined optimal NN structures, both NNs were trained and performances were evaluated with trained and untrained data. For the evaluation with trained data, all 9 power profiles were used for training. For the evaluation with untrained data, only 8 power profiles were used for training, and the evaluation was made with the untrained power profile.

A. Evaluation with Trained Data

Both NNs were trained with an epoch consisting of all nine power profiles of each set {A,B} and the trained NNs were evaluated for each power profile. Training data with efficiency weight ($\varepsilon = 10^{-3}$) show more variations than those with zero efficiency weight ($\varepsilon = 0$), and worse performance results were obtained as shown in Table I. The evaluation results are compared in Figure 4 for each output. It shows that the setpoint of stack power (P_{stack}) and control inputs of stack current (i_{stack}) and HTR split fraction (f_{HTR}) perform better than other outputs.

TABLE I
EVALUATION WITH TRAINED DATA

Error Criteria		NN1 (setpoints)			NN2 (FF control inputs)			
		T_{AGO}	N	P_{stack}	i_{Stack}	f_{HTR}	f_{AGO}	f_{C60}
MA	$\varepsilon = 0$	0.2266	0.3223	0.1481	0.1477	0.2091	0.4916	0.3011
E	$\varepsilon = 10^{-3}$	0.2534	0.3592	0.1815	0.1628	0.2265	0.4959	0.3331
MS	$\varepsilon = 0$	0.0653	0.4067	0.0209	0.0262	0.2316	0.3982	0.3088
E	$\varepsilon = 10^{-3}$	0.2735	0.6393	0.1566	0.0315	0.2928	0.4095	0.3827

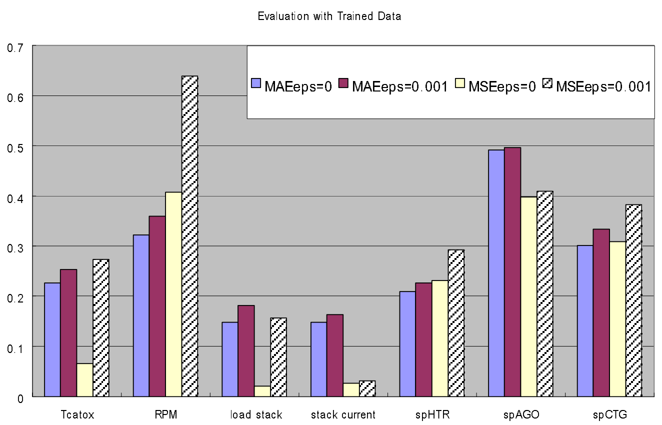


Fig. 4. Evaluation with trained data.

B. Evaluation with Untrained Data

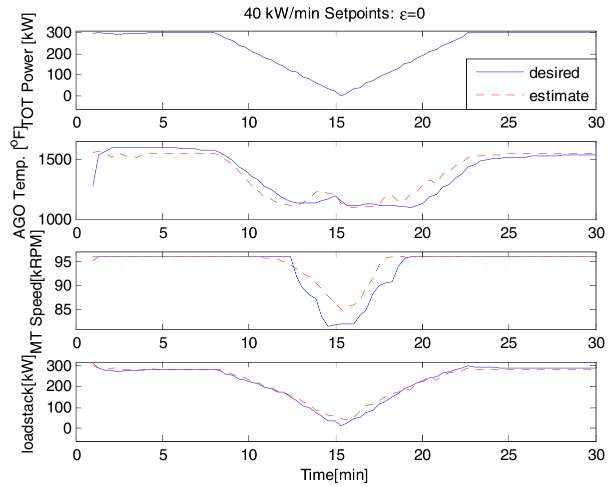
For the evaluation with untrained data, both NNs are trained with an epoch which consists of all eight power profiles except one for each set. The trained NNs are then evaluated for the untrained power profile. For instance, eight power profiles except ramp 40 kW/min for evaluation are used for training, and the untrained ramp 40 kW/min power profile is used for evaluation in Figure 5.

As in the evaluations using the trained data, two cases of data were tested: Case A for data with zero efficiency weight ($\varepsilon = 0$) and Case B for data with nonzero efficiency weight ($\varepsilon = 10^{-3}$). Case A is quite similar to the case with the trained data. Case B is slightly worse than Case A as summarized in Table II. In most cases, evaluation results with untrained data show quite similar results as with trained data. Only the untrained [5,75] step power profile overpredicts the MT speed setpoint, caused by the lack of training data with lower power level.

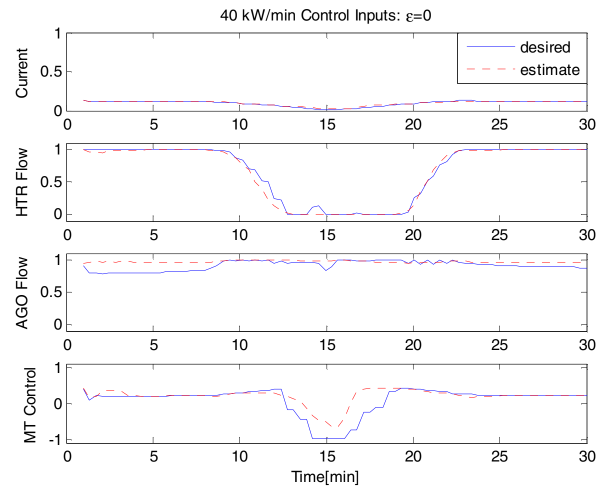
TABLE II
EVALUATION WITH UNTRAINED DATA

Error Criteria		NN1 (setpoints)			NN2 (FF control inputs)			
		T_{AGO}	N	P_{stack}	i_{Stack}	f_{HTR}	f_{AGO}	f_{C60}
MA	$\varepsilon = 0$	0.3084	0.4301	0.1451	0.1269	0.1142	0.5031	0.562
E	$\varepsilon = 10^{-3}$	0.3352	0.6712	0.2023	0.1809	0.2907	0.5542	0.686
MS	$\varepsilon = 0$	0.2392	0.4957	0.0353	0.0261	0.0371	0.5099	0.536
E	$\varepsilon = 10^{-3}$	0.2966	0.7187	0.0592	0.0483	0.3029	0.5472	0.766

Figs. 5-10 and Table III show the performance results for evaluation with trained data using 20,000 iterations for an epoch. Figs. 5-7 show the performance results for ramp power profiles and Figs. 8-10 show the ones for step power profiles. Training data with efficiency weight ($\varepsilon = 10^{-3}$) show more variations than the ones with zero efficiency weight ($\varepsilon = 0$), and worse performance results were obtained as compared in Table 3.

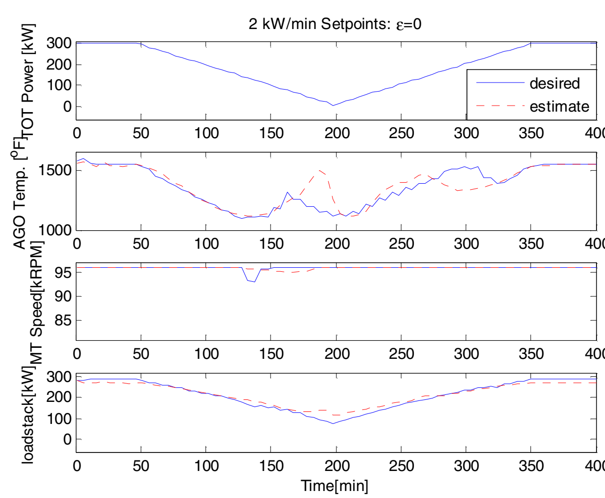


(a) Setpoints.

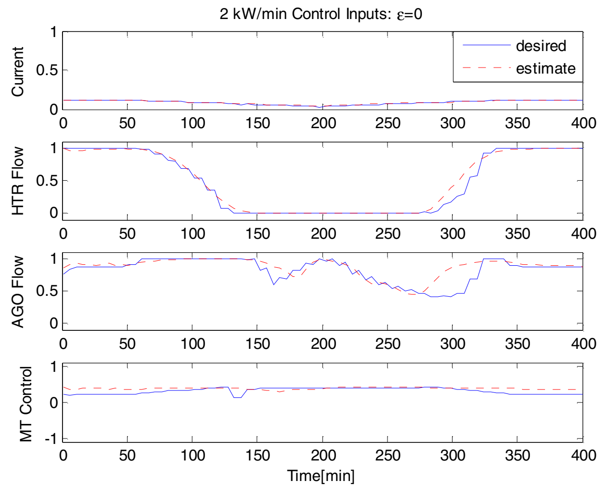


(b) Control inputs.

Fig. 5. Evaluation with ramp 40 kW/min.

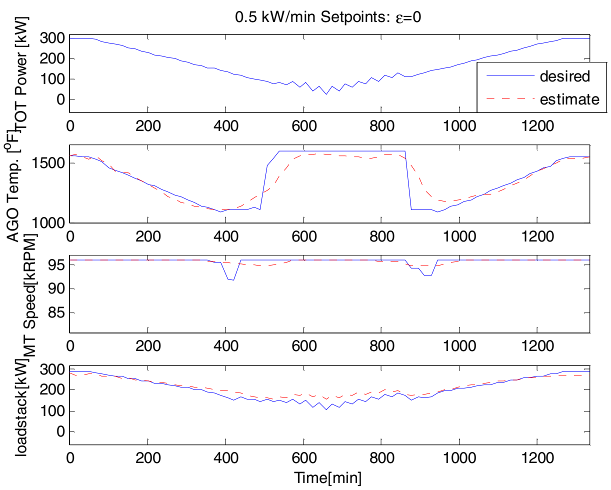


(a) Setpoints.

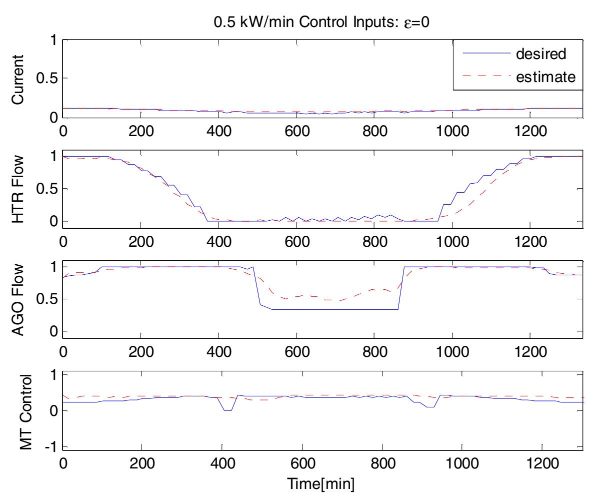


(b) Control inputs.

Fig. 6. Evaluation with ramp 2 kW/min.

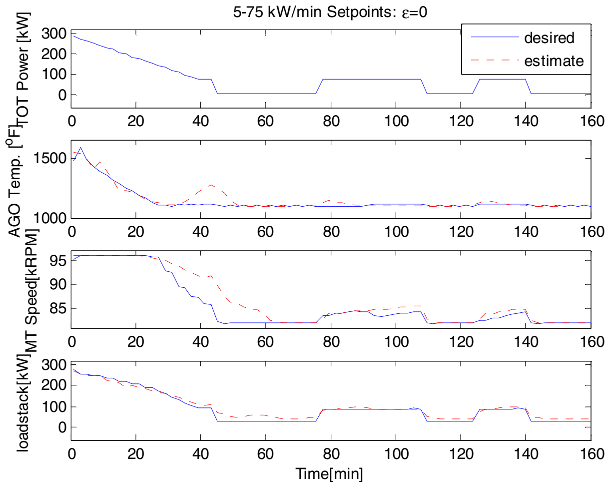


(a) Setpoints.

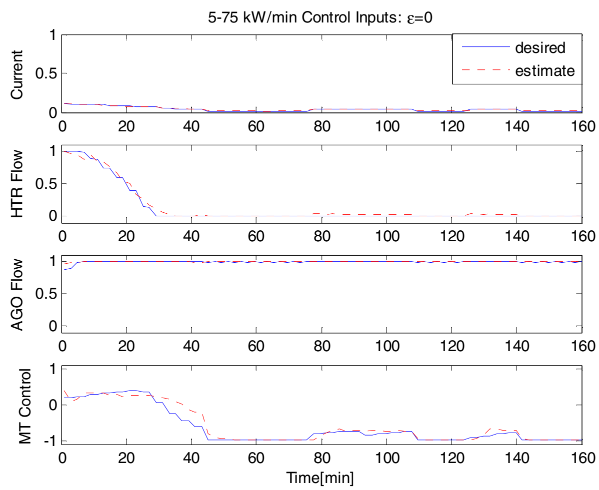


(b) Control inputs.

Fig. 7. Evaluation with ramp 0.5 kW/min.

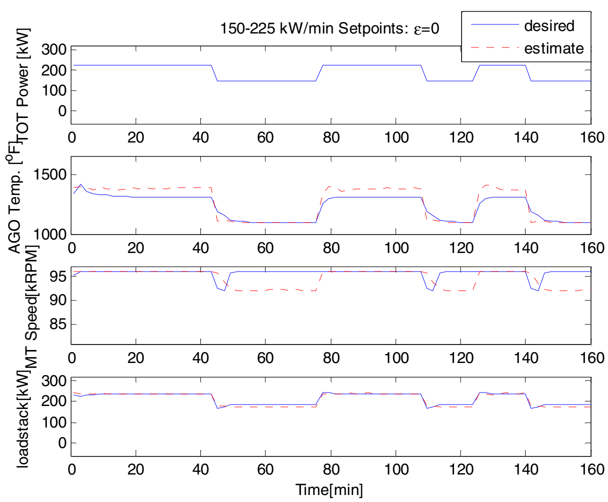


(a) Setpoints.

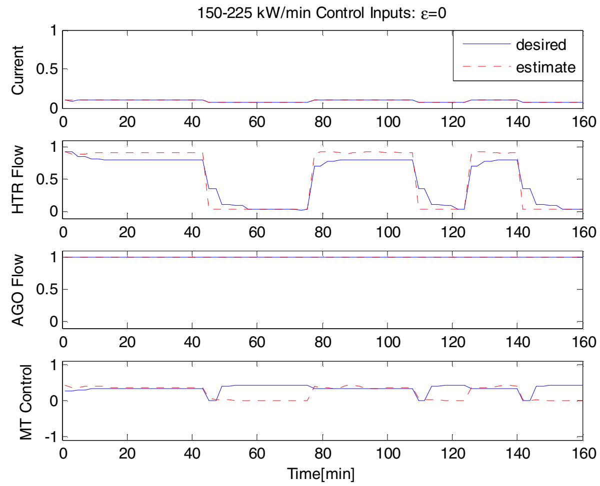


(b) Control inputs.

Fig. 8. Evaluation with step 5-75 kW.

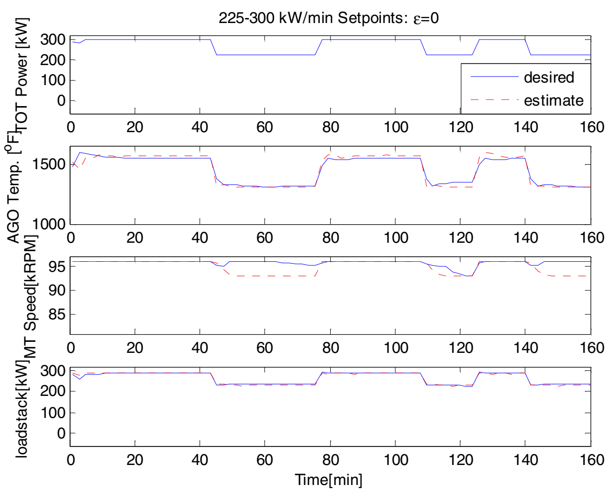


(a) Setpoints.

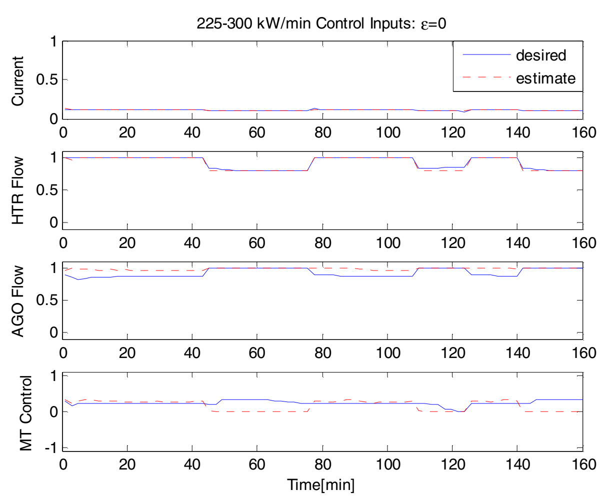


(b) Control inputs.

Fig. 9. Evaluation with step 150-225 kW.



(a) Setpoints.



(b) Control inputs.

Fig. 10. Evaluation with step 225-300 kW.

TABLE III
EVALUATION WITH 20,000 ITERATION OF AN EPOCH

ε = 0				ε = 0.001			
NN1		NN2		NN1		NN2	
MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
0.2371	0.2578	0.3207	0.3271	0.3650	0.3493	0.3597	0.3904

V. CONCLUSIONS

Based on structural considerations, a diagonal recurrent neural network (DRNN) was selected to model the NN supervisor for FC/GT hybrid systems. Furthermore, rather than designing a single NN for the three setpoints and the four FF control inputs, it was found that dividing the supervisor into two separate NNs, one for setpoints, and one for FF control inputs, resulted in better predictions. Several NN structures were tested to find the optimal number of hidden layer neurons and the number of iterations for an epoch. After finding optimal values, NNs were trained and performances were evaluated.

The NN supervisor has been developed to reduce the computational cost inherent to the dynamic optimization. Despite the limited data from the optimization studies, the performance results of the developed NN supervisor showed their potential for real-time application. As demonstrated, the NN Supervisor can generate outputs for an arbitrary load which was not used for training. When the plant experiences disturbances or change in plant parameters, the output of the system may not match the setpoint profile generated by the NN supervisor. In this case, the NN supervisor trained off-line can be trained adaptively for real-time adjustment.

Future improvements of the NN supervisor are possible by generating additional nonlinear optimization results with input profiles which would generate richer information than the ones used in this study. In addition, the training can be improved by training the NNS online together with the dynamic model.

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VIII. Biographies

Tae-Il Choi received his B.S. degree in Electrical Engineering from Hanyang University in Seoul, Korea, in 1982. He received his M.S. degree in Electrical Engineering from the Pennsylvania State University in May 1993. He has worked for Korea Electric Power Corporation as an engineer from 1982 until 1988, and section chief in distribution automation department since 1991. He is currently a Ph. D. candidate in Electrical Engineering at the Pennsylvania State University. His research interests include distribution automation, artificial intelligence, and distributed generation.

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S. Tobias Junker received his Diploma and Ph.D. in Chemical Engineering, respectively, from the Aachen Institute of Technology, Germany, in 1998 and the University of Delaware in 2004. He is currently employed by FuelCell Energy, Inc., Danbury, CT, where he is conducting research on advanced process control concepts for DFC/T and SOFC/T power plants. He is involved with the development of detailed dynamic process models of fuel cells and associated processing equipment and is developing control strategies for DFC/T and SOFC/T power plants.

Hossein Ghezel-Ayagh received his B.S. degree from Abadan Institute of Technology, in 1971, and his M.S. and Ph.D. degrees from the Illinois Institute of Technology, respectively, in 1977 and 1981, all three in chemical engineering. Dr. Ghezel-Ayagh is the project manager for the development of Direct FuelCell/Turbine® Power Plant under a Vision 21 Cooperative Agreement with DOE. He has been involved in research activities related to fuel cell development, process design and simulation at FuelCell Energy, Inc., Danbury, CT. He has also been engaged in evaluation, testing and design of power plant systems using various types of fuels such as natural gas, coal gas and heavy hydrocarbons.