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An Integrated Multi-Task Control System for Fuel-Cell Power Plants

Wenli Yang and Kwang Y. Lee, *Fellow, IEEE*

***Abstract*—Development of Smart Grid requires power plants to be more intelligent, efficient, and reliable, which raises new challenges of the control system design for modern power plants. Regarding these requirements, an integrated multi-task control system using artificial intelligence technologies is proposed to improve the efficiency and reliability of a hybrid fuel-cell with gas turbine power plant. The integrated control system consists of a hybrid Neural Network plant model with online learning ability, an Optimal Reference Governor generating optimal setpoints as local control references, and a Fault Diagnosis and Accommodation system to detect internal plant faults and to regulate the plant during plant failures. The three subsystems are integrated to provide compressive management for the power plant. The hybrid fuel-cell power plant is introduced; the structure and strategies of the control system are discussed, and simulation results are presented.**

***Index Terms*—Fuel cells, hybrid power plant, artificial neural networks, heuristic optimization, fault diagnosis, fault accommodation.**

I. INTRODUCTION

Fuel cell is a remarkable alternative energy source with high energy conversion efficiency and extra low emissions. The integration of a fuel-cell stack with a gas turbine has become a convincing technology that can greatly enhance the overall efficiency of the power plant [1]. Based on this hybrid structure, a molten carbonate fuel cell (MCFC), where the fuel can be reformed into hydrogen internally at a high operation temperature, with gas turbine system has been developed as a base-load power source, and is named as Direct FuelCell (DFC) with Turbine (DFC/T). As an intelligent power source in Smart Grid, the DFC/T power plant is expected to run autonomously without supervision and is governed by the power load demand signal from the central dispatch center.

To provide effective and autonomous control for the DFC/T power plant, a comprehensive control system needs to be developed. However, because of the hybrid structure, the DFC/T power plant is a nonlinear system with high complexity, where the electrochemical reactions, thermal dynamics, and thermal mechanical dynamics are highly coupled. Thus, the plant-wide optimization and fault detection are difficult with traditional analytical methods. Nevertheless, as quantitative methods, modern Artificial Intelligence (AI) approaches have shown their potential in solving large scale and complex problems. In this paper, artificial neural networks, fuzzy logic theories, and heuristic optimization algorithms are used to design an integrated multi-task control system to improve the overall efficiency and reliability of the hybrid fuel-cell power plant.

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W. Yang is with Western Digital Corporation, Irvine, CA 92612, USA (e-mail: yangwenli00@gmail.com).

K. Y. Lee is with the Department of Electrical & Computer Engineering, Baylor University, One Bear Place, Waco, TX 76798-7356, USA (phone: 254-710-4817; e-mail: Kwang_Y_Lee@baylor.edu).

II. PROCESS DESCRIPTION OF FUEL-CELL POWER PLANT

The primary feature of this hybrid power plant is an integration of fuel cells and gas turbine that greatly increases the energy conversion efficiency [2]. The gas turbine is not a simple re-utilization of the exhaust heat, but is fully integrated into the heat and mass flow of the fuel-cell system. The flow diagram of the DFC/T power plant is shown in Fig. 1.

A. Gas Flows

The fuels, *i.e.*, methane and water, are introduced to the plant through a humidifying heat exchanger (HH), and heated again by a fuel pre-heater (FP) and a super heater (SH) prior to entering the anode of the fuel-cell stack. These heat exchangers prepare the cold fuel with an appropriate temperature for chemical reactions in the fuel cells and the fuel pre-converter, where the fuel is partially reformed into hydrogen and carbon dioxide in the presence of catalysts.

Meanwhile, the air is injected to the system by an air compressor connected to a common shaft with a gas turbine. The cold air is subsequently heated by a low temperature heat recuperator (LTR), a secondary start-up heater (SSH), and a high temperature heat recuperator (HTR). The compressed air with high temperature is then expanded in the gas turbine, propelling the air compressor and a permanent magnet generator (PMG) producing extra electric power. The anode off-gas containing a portion of un-reacted fuel is fully

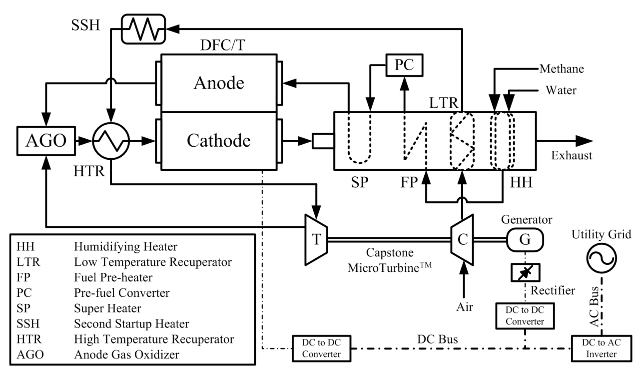

Fig. 1. The flow diagram of the DFC/T Power Plant.

oxidized in an anode gas oxidizer (AGO), producing extra heat to drive the gas turbine. The oxidized gas finally enters the cathode of the fuel-cell stack as a reactant of the electrochemical reactions [3].

B. Local Control Schemes

The output power of the plant is determined by the amount of the supplied fuel (n_{CH4}) and the DC current (I_{stk}) drawn from the fuel-cell stack, which is regulated by feed-forward controls. The stack temperature (T_{stk}) is maintained by the feedback controls on the SSH, LTR, and AGO according to the setpoint of cathode inlet temperature (TCI_{set}), which is a function of the stack power and is specified by the plant manufacturer. The turbine speed ($N_{turbine}$) is controlled by the PMG and a speed controller according to the speed setpoint. Moreover, the plant is operating at constant pressures regulated by two pressure controllers with constant setpoints determined by the fuel-cell stack design [4].

III. THE STRUCTURE OF THE MULTI-TASK CONTROL SYSTEM

The proposed multi-task control system consists of local controllers, a hybrid plant model, an optimal reference governor (ORG), and a fault diagnosis and accommodation (FDA) system. The block diagram of the integrated system is shown in Fig. 2. The local controllers regulate local plant variables according to the setpoints provided by the ORG and fault accommodation system. A hybrid plant model is provided by combining a mathematical model and a Neural Network (NN) augmenter.

During normal operations, the ORG uses a multi-objective optimization framework to generate optimal setpoints based on the power load demand signal. The setpoints are applied to the local controllers without modifications. The output of the hybrid model serves as a reference for the fault diagnosis system to calculate the residuals between the actual plant and the simulation model. A fault accommodation system will be activated if significant residuals are detected.

When internal faults are detected, the fault accommodation system will regulate the whole system by modifying the setpoints to avoid marginal operating status or even instabilities. Then it will try to recover the supplied power under a faulty condition. These actions give human operators time to perform further fault analysis and make decisions.

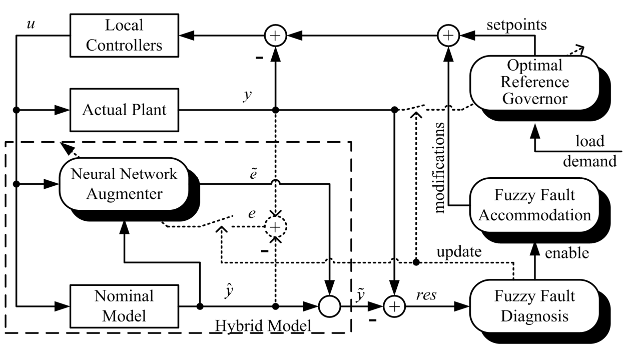

Fig. 2. Block diagram of the integrated multi-task control system.

Moreover, the residuals are possibly caused by the inaccuracy of the model other than actual plant faults. In this case, the fault diagnosis system will give a model update signal to retrain the NN augmenter with the new operational data, and the plant model in the ORG is also updated simultaneously.

IV. HYBRID NEURAL NETWORK MODEL

A nonlinear mathematical model of an MCFC stack was first developed by Lukas, Lee, and Ghezel-Ayagh [3] based on principles of energy and mass component balances and thermo-chemical properties. Then, a plant-wide model of the DFC power plant was built and simulated [5]. The theoretical model of the hybrid DFC/T plant is finally obtained with the integration of a gas turbine model and the plant-wide DFC model [2]. However, due to the assumptions of the nominal model and the uncertainties of the actual plant, the discrepancies between the simulation and the experimental data are non-negligible. Thus, controllers or algorithms designed based on the nominal model may become degraded or inapplicable to the actual plant.

A. Structure of Neural Network Augmenter

Removing the basic assumption of the fundamental model will greatly increase the model complexity, and modeling the uncertainty of the plant also has considerable difficulty. Hence, an augmenter based on neural networks is employed to enhance the model only with input and output data of the simulation and the actual plant [6].

The whole plant is divided into 10 subunits (8 units listed in Fig. 1 plus fuel-cell stack and gas turbine). The augmentation algorithm is implemented for each subunit as the Hybrid Model in Fig. 2, where a particular subunit of the nominal model is simulated with the same inputs as the actual plant. The simulation result $\hat{y}$ differs from the experimental output y due to the existence of the model error e, which is used for the training of the NN. The augmented result of the hybrid model $\tilde{y}$ follows the relationships below:

$$\tilde{e} \to e = y - \hat{y} \text{ and } \tilde{y} = \hat{y} + \tilde{e} \to y \tag{1}$$

With the training process, as the estimated error by NN augmenter goes to the actual model error, the compensated simulation output will go to the real output of the actual power plant. Thus, the model accuracy can be improved.

B. Validation of the Hybrid Neural Network Model

The Neural Network Augmenters were trained using experimental data of the DFC/T power plant from standby mode to a full power load. The simulation results of the fundamental model and the hybrid model using the exactly same inputs as the experiment are compared with the operational data and the average relative errors are calculated for each subunit in Table I, where it can be seen that the relative error of the hybrid model is significantly reduced by the NN augmenters.

TABLE I

RELATIVE ERRORS OF THE ORIGINAL AND HYBRID MODELS

Subunits	Original Model Relative Error [%]	Hybrid NN Model Relative Error [%]
FC Stack	3.7	0.18
Gas Turbine	12.9	0.89
HH	1.8	0.24
LTR	4.3	0.31
FP	1.3	0.08
PC	1.8	0.35
SP	1.3	0.06
SSH	8.4	0.68
HTR	2.9	0.11
AGO	2.7	0.71

V. OPTIMAL REFERENCE GOVERNOR

To improve the fuel efficiency of the DFC/T power plant, the proposed ORG applies heuristic optimization algorithms to find optimal feedforward controls and setpoints that guarantee high energy conversion efficiency of the power plant [7, 8]. Toward this goal, the ORG is developed as in Fig. 3, where the optimized setpoints and feedforward controls, including fuel cell stack current (I_{stk}), methane flow rate (n_{CH4}), turbine speed ($N_{turbine}$), heating power of the second-startup heater (Q_{SSH}), LTR control move (u_{LTR}), and AGO control move (u_{AGO}), are determined based on a given load demand.

A. Structure of the Optimal Reference Governor

The proposed ORG consists of a Multi-objective Optimization Module (MOM), a state estimator, and an operating window. In this paper, heuristic optimization techniques [9] are applied and investigated with the MOM. The state estimator works as a plant model that estimates plant states and outputs based on the given setpoints. The operating window provides possible operating ranges for the load-dependent setpoints and serves as the solution space for the optimization algorithms.

The ORG has three possible statuses, *i.e.*, search mode, run mode, and updating mode. In the search mode, the candidate setpoints provided by MOM are evaluated by the state estimator, which can be implemented by any plant model with online updating abilities [8]. Then, the objective functions are calculated and used by MOM to refine the solutions. After a certain number of search iterations, the ORG will switch to the run mode, where the optimized setpoints will be given to local controllers as the references for plant operation. In the meantime, if significant model error is detected, the ORG will enter the model updating mode, where the state estimator will be re-trained with the newly obtained operating data.

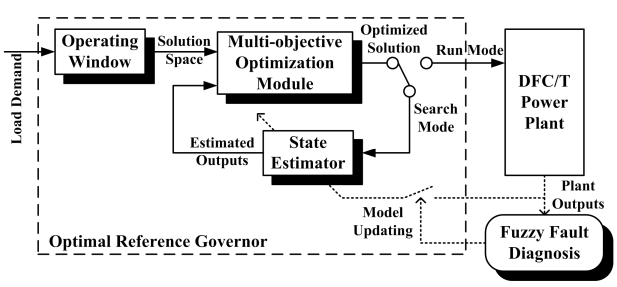

Fig. 3. The structure of the proposed ORG.

B. Problem Formulation

The optimal control can be formulated as a multi-objective nonlinear optimization problem, which can be solved by MOM. The problem is described as:

Find the six setpoints that minimize the three objective functions:

$$F_1 = \frac{1}{M}\sum_{i=1}^{M}\left(P_{load}^{(i)} - P_{net}^{(i)}\right)^2 \tag{2}$$

$$F_2 = \frac{1}{M}\sum_{i=1}^{M}\left(TCI_{set}^{(i)} - TCI_{act}^{(i)}\right)^2 \tag{3}$$

$$F_3 = \frac{1}{M}\sum_{i=1}^{M}\frac{P_{csm}^{(i)}}{P_{net}^{(i)}} \tag{4}$$

The first objective function is defined on the power load, where $P_{load}^{(i)}$ is the power load demand of the *i*-th sample point, $P_{net}^{(i)}$ is the net output power in steady state provided by the state estimator, and M is the total number of sample points for power load. The second objective function is defined on the cathode inlet temperature error to maintain the temperature of the fuel-cell stack, where $TCI_{act}^{(i)}$ and $TCI_{set}^{(i)}$ are the actual value and the setpoint of cathode inlet temperature, respectively. The third objective function is defined on efficiency. Here, $P_{csm}^{(i)}$ is the consumed power, including the chemical potential of fuel and the heating power Q_{SSH} used by SSH [2].

The state estimator serves as a nonlinear function that maps the 6 setpoints to the plant states of interest:

$$[P_{net} \quad TCI_{act}] = f_{SE}\left(I_{stk}, n_{CH_4}, N_{turbine}, Q_{SSH}, u_{LTR}, u_{AGO}\right) \tag{5}$$

C. Optimization Results

Particle Swarm Optimization (PSO), a stochastic, population-based heuristic optimization algorithm, is selected as the first approach for MOM, because it has high

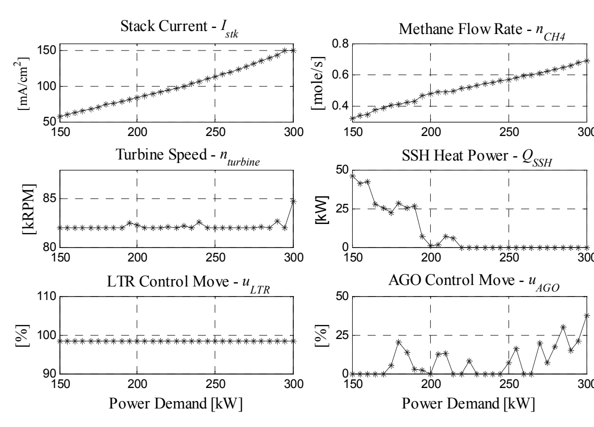

Fig. 4. Optimal setpoints generated by the ORG.

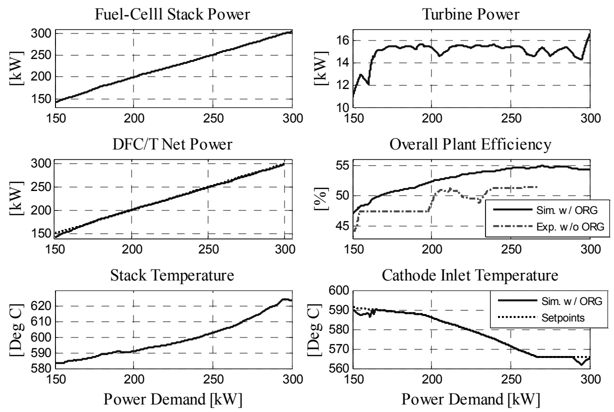

Fig. 5. System responses under the optimized setpoints from ORG.

convergence rate for large-scale problems and low implementation complexity [10, 11]. Both Pareto optimal theory and weighted aggregation have been investigated [7], but due to the space limitation, only the second approach is presented. The aggregation weights are selected based on the importance of the three objective functions in (2)-(4), to which the weights factors of [0.4, 0.4, 0.2] are assigned, respectively.

The optimal control setpoints generated by the ORG are shown in Fig. 4 for the power loads from 150kW to 300kW with 5kW increments. The steady system responses of the power plant under the optimal setpoints given in Fig. 4 are simulated and presented in Fig. 5. The plant efficiency after optimization is also compared with the operating data without ORG in dash-dot line showing the improvement.

VI. Fault Diagnosis and Accommodation

Efficiency optimization is not sufficient for an autonomous control system. Since local controllers have limited information, incorrect control behavior may take place due to system faults. When fault occurs, the control system should detect the fault at an early stage and react properly to avoid damage or degradation. A fault diagnosis and accommodation system is introduced in this section.

A. Fuzzy Fault Diagnosis

1) Definition of Fuzzy Faults: Internal faults can occur anywhere in the power plant at any time. However, it is impossible and unnecessary for a control system to identify the exact locations of all minor faults. On the other hand, the ability of locating faults at a subunit level will be sufficient. Since temperature control is the most important control scheme, fault diagnosis is designed to aim at temperature control failures [12].

In this paper, six fault patterns are defined on temperature control failures at the six major heat exchangers as below.

- Humidifier/Heat exchanger (HH) fault
- Fuel Pre-Heater (FP) fault
- Low Temperature Recuperator (LTR) fault
- High Temperature Recuperator (HTR) fault
- Anode Gas Oxidizer (AGO) fault
- Second Start-up Heater (SSH) fault

To provide more information about the temperature failures, two faulty styles are defined for each fault pattern according to fault symptoms:

- The first style is "P-fault," which represents the case that the actual output temperature is higher than expected.
- In contrast, the second style is "N-fault," which represents the case that actual output temperature is lower than expected.

Although these faulty styles are defined on heat exchangers, they can also represent a series of faults having similar symptoms, such as failures in sensors, actuators, and other parts of control loops or gas flows.

2) Diagnosis Algorithm: The fault diagnosis algorithm usually includes two steps: residual generation and decision making. In this paper, the analytical redundancy method [13] is applied. The hybrid NN model works as a reference of nominal operations without any fault. The outputs of the power plant are compared with the estimated outputs of the model. The discrepancies between the plant and model serve as the residuals used for decision making. The residual res_i of the *i-th* subunit is calculated from the output y_i of the actual power plant and the estimated output $\tilde{y}_i$ of the plant model, as shown in Fig. 6.

A number of decision making methodologies have been investigated by researchers [14-17]. In this work, fuzzy logic is selected, because it is an effective tool in processing the ambiguous relationships of fuzzy faults. Both the residual and its integral are taken as the inputs of the fault diagnosis logic. The integral of residual contains more information about the time history and is more important for fault diagnosis than only the residual [18]. However either a large residual or a small residual can be accumulated to the same integral values as time elapses. The small residual could be caused by the inaccuracy of the model but not the system fault. Thus, the residuals of each subunit are also taken into consideration.

Slow plant degradations, such as fouling and corrosion, are not considered as system faults at the beginning since their effects are small. These slow degradations will be learned by the NN augmenter and compensated by the hybrid model. As

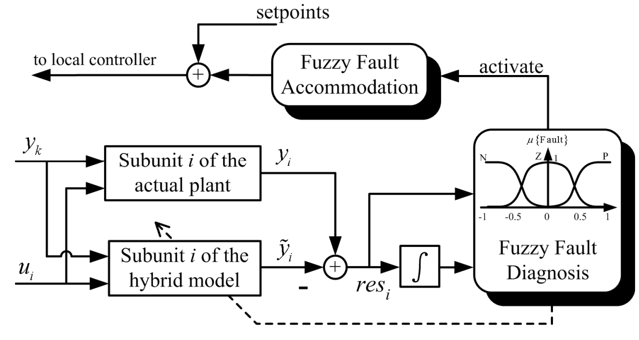

Fig. 6. The structure of the fault diagnosis and accommodations system.

the fouling or corrosion grows, the plant degradations are accumulated by the NN augmenters and build up a large augmentation signal. At this time, the diagnosis system will give out a warning signal indicating maintenance is required for one or multiple subunits.

3) Fuzzy Rules: The major fuzzy rules for fault diagnosis can be concluded as below:

- If the integral of the residual is high/low and the residual is high/low, then a “P”/“N” fault exists.
- If the integral of the residual is high or low and the residual is not high or not low, then model error exists.

The first rule defines the condition for the existence of a “P” or “N” fault, and second rule defines the condition for the existence of model error. The degree of high or low is represented by the degree of truthfulness that a variable belongs to a particular fuzzy set, *i.e.*, “high” or “low.”

B. Fault Accommodation

Detecting faults alone is not sufficient, though it is necessary for a control system. When a fault occurs, the plant needs to be regulated to prevent from entering critical or even unstable operating regions before the fault is cleared or human takes over the control system. Due to the high complexity of the DFC/T power plant and the random nature of faults, it is difficult to design specific and detailed regulators to accommodate the system with very limited information on the causes and consequences of the faults. Nevertheless, fuzzy logic, as a qualitative scenario, is a powerful tool that has low complexity and less difficulty in designing the fault accommodation system [19].

*1) Accommodation Strategies: M*aintaining the electro-chemical reactions smooth and stable is the primary goal of the control system either under normal situations or during system failures. During system failures, the local control schemes may become weak, not functional, or even broken. On the other hand, the stack temperature is determined by the energy contained in the fuel. Thus, the stack temperature still can be maintained by adjusting the amount of the fuel and the amount of the fresh air. The output power can be regulated by adjusting the stack current.

The control strategies can be described as follows:

- If the stack temperature is higher/lower than normal, then decrease/increase the fuel flow rate n_{CH4} and increase/decrease the compressor speed $N_{turbine}$;
- If the output power is higher/lower than demand, then decrease/increase the stack current I_{stk}.

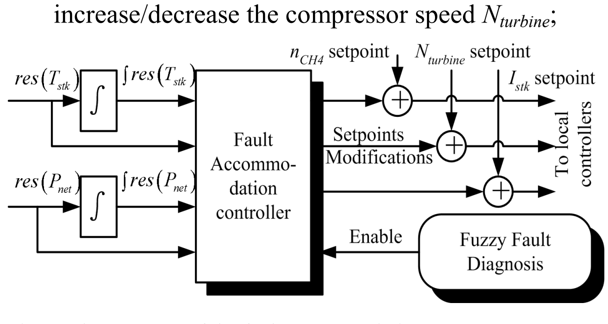

Fig. 7. The structure of the fault accommodation system.

2) Accommodation Structure: According to the compensation strategies, the control scheme in Fig. 7 is implemented for the FDA system. The input signals are the residuals of the two variables that need to be regulated, *i.e.*, the stack temperature T_{stk} and the net output power P_{net}. Both the residuals and their integrals are introduced to the accommodation controller for the same reason as in the diagnosis system. The outputs of the controller are setpoint modifications, which will compensate the original setpoints to take effect. The modified setpoints are restricted to the operational limitations to prevent instability and damages.

C. Simulation Results

An SSH-N fault is simulated under a power demand of 150kW. At such low power, the SSH serves as an electric heater to provide additional heat, and the generator works as an electric motor to provide additional torque. As a possible failure mode, an SSH-N fault is simulated at $t = 0$s, such that no additional heat is provided.

Fig. 8 shows the vector of the diagnosis result, where each element of the vector provides the likelihood index for the existence of each fault pattern. The solid lines indicate the results without measurement noise. The SSH result steps to -0.8 within 3 seconds indicating the existence of an SSH-N fault, while other outputs remain at zero. The dotted lines show the diagnosis results with Gaussian White Noises ($\mu = 0$, $\sigma = 5$ °C for temperature, $\sigma = 0.1$ mole/s for gas flow rate) in measurement data. Although the results are disturbed by the noise, the SSH fault can still be distinguished from others because of its magnitude and response time.

The simulation results of the accommodation system are shown in Fig. 9, where the upper two plots show the dynamic system responses under the accommodation actions in the lower three plots. Three control methods, *i.e.*, PI controller (in dotted lines), fuzzy controller (in solid lines), and fuzzy-neural network (in dashed lines) [12], are implemented with the fault accommodation strategies and framework in Fig. 7. The dash-dot lines denote the system response without

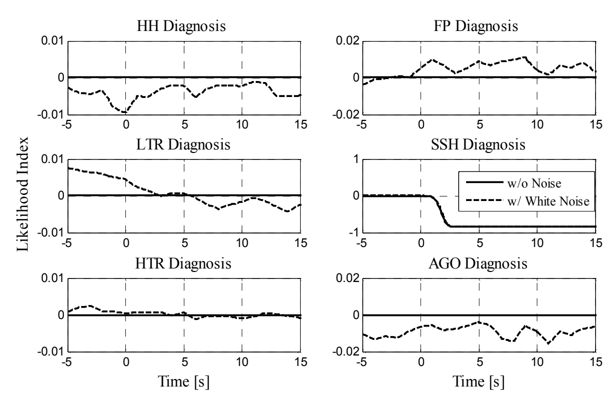

Fig. 8. Diagnosis results during SSH-N fault @ 150 kW.

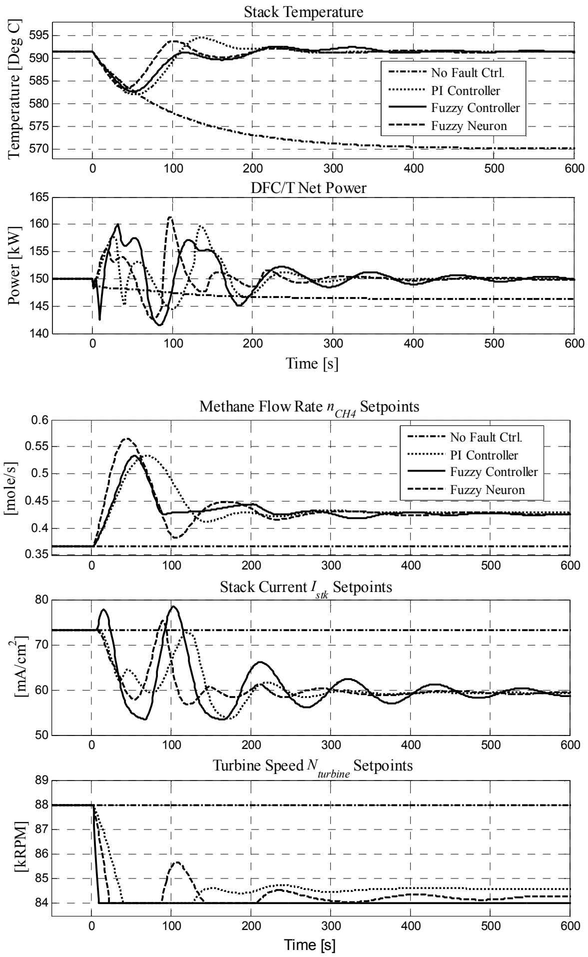

Fig. 9. DFC/T response during SSH-N fault @ 150 kW.

fault accommodation.

Without the FDA system, although the output power drops by only 4kW, the stack temperature drops by 20°C to 570°C, which is sufficiently low to stop all electrochemical reactions. Once the plant is shut down, it may take days to restart and may cause significant offline time. When the FDA system is applied, the system is driven to a steady working status in 300 seconds with a temperature drop of 10°C. The fuzzy controller has less overshoot and the fuzzy-neural network is faster than the traditional PI controller in regulating the stack temperature. The three controllers have comparable disturbances of 10kW in power control, but the fuzzy controller has slightly more oscillations as time elapses.

VII. Conclusion

In this paper, an integrated multi-task control system is proposed for the hybrid fuel-cell and gas turbine power plant. The integrated control system consists of a hybrid plant model, an ORG, and a FDA system, and provides comprehensive plant-wide management for the hybrid power plant. The hybrid model is an adaptive plant model with high accuracy and on-line updating ability. The ORG optimizes plant operations by generating optimal control references. The FDA system monitors the actual plant and plant model to report plant faults and model errors, and regulates the power plant if any internal fault is present. The overall system is not a simple combination of the individual control systems, but is an integrated system that each part cooperates with each other. With the integrated system, the efficiency and reliability of the DFC/T power plant can be considerably improved and the performance of the entire control system is upgraded.

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