

An Optimal Reference Governor with a Neural Network Combined Model for Hybrid Fuel-Cell/Gas-Turbine

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Abstract—This paper introduces a concept of real-time optimization of hybrid fuel-cell power plants as an alternative distributed generation source that improves the power quality and reliability of the power grid. One of the most important issues of plant operation is the optimal control of the power plant, leading to significant economic and environmental benefits. As a commercialized fuel cell technology, Direct Fuel-Cell with Gas-Turbine (DFC/T) power plant is investigated in this paper. A framework of an optimal reference governor (ORG) is developed to generate optimal control strategies for the local controllers. For the purpose of on-line application, a neural network combined model is built as a state estimator that approximates the plant behaviors, which is compatible with population based real-time heuristic optimization algorithms. The simulation of the optimization result is presented and validated by a comparison with experimental data and simulation result of a mathematical plant model.

Index Terms—Fuel cells, hybrid power plant, fuel-cell/gas-turbine, distributed generation, neural networks, heuristic optimization.

I. INTRODUCTION

FUEL cell has a great potential as an alternative distributed generation (DG) source, which can improve power quality and reliability of the power grid while still able to continue to generate power even when power from a utility is absent. As a part of U.S. DG program and American Recovery and Reinvestment Act [1, 2], fuel cells received extensive attentions because of its high energy conversion efficiency and extra low emissions. Moreover, integration of a fuel-cell stack with a gas turbine has become a convincing technology that can greatly enhance the overall efficiency of power generation. Based on this hybrid structure, a molten carbonate fuel cell (MCFC) with gas turbine system has been developed as a base-load power source for DG. Because of the high operating temperature (up to 600°C), the fuels, *i.e.*, methane and water, can be reformed into hydrogen internally without additional reformations. Thus, this hybrid plant is named as Direct FuelCell with Turbine (DFC/T) power plant.

Fuel optimization is an important issue of an autonomous

control system to improve energy conversion efficiency for modern power plants with advanced technologies. Since the DFC/T plant is expected to run at full load throughout the year, even a small improvement on fuel efficiency will produce significant economic and environmental benefits in the long run. However, the power plant cannot reach high efficiency without a proper control system.

A large-scale nonlinear trajectory planning method [3] and neural network supervisors [4] were introduced to produce optimal setpoints to improve fuel efficiency. However, the trajectory planning method is computationally expensive and not capable of on-line applications. Meanwhile, the neural network supervisor may give invalid result if the operational patterns are not learned during the training phase. Thus, a fast approach for on-line optimization is required for the optimal control of the DFC/T plant. In this paper, an optimal reference governor (ORG) is developed based on modern heuristic optimization algorithms and a neural network combined model, which can provide optimal solutions in real-time and are capable for on-line applications.

II. PROCESS DESCRIPTION

The hybrid DFC/T power plant is a complex multi-input multi-output (MIMO) system, which is expected to run autonomously without supervision and is governed only by the power load demand signal from the central dispatch center. The DFC/T system consists of a direct fuel cell (DFC) system and a gas turbine [5, 6]. The primary feature of this hybrid structure is a high integration of fuel cells, gas turbine, and heat exchangers. The system flow diagram is provided 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 [7].

Meanwhile, the air is injected to the system by an air compressor driven by 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

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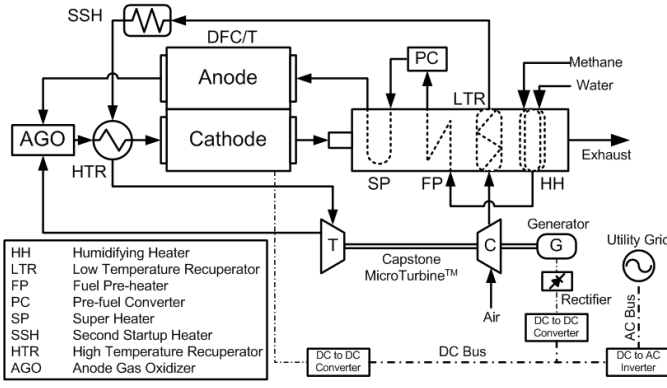
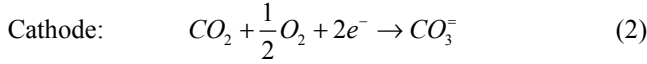
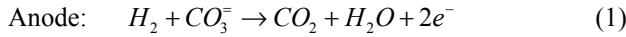


Fig. 1. The flow diagram of the DFC/T Power Plant.

temperature heat recuperator (HTR). The compressed air with high temperature is then expanded in the gas turbine, propelling the air compressor and an AC generator producing extra electric power. The anode off-gas containing a portion of unreacted fuel is fully 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 shown below [7].



B. Electrical Power Flows

To feed the electrical power to utility grid, the DC power from the fuel-cell stack and the asynchronous AC power from the permanent magnet generator (PMG) must be synchronized in frequency and phase angle by a power conditioning system (PCS) [8]. The fuel cells usually generate DC power in a low voltage range, which needs to be boosted to a higher voltage for DC bus by DC-DC converters. The AC power from the PMG is rectified into DC power and then boosted to the voltage of the DC bus. A DC-AC inverter is used to convert the DC power to synchronized AC power, which is connected to utility grid. Super capacitors and power filters may be used to eliminate or reduce the undesired harmonics introduced by switching components [8], but not shown in Fig. 1.

C. Control Schemes

The operational status of the plant, such as power, temperature, and rotational speed, must be regulated in order to generate the desired power with smooth and reliable processes. The output power of the plant is determined by the amount of the supplied fuel and the DC current drawn from the fuel-cell stack, which is regulated by feedforward controls. The stack temperature is maintained by the feedback controls on the SSH, LTR, and AGO according to the setpoint of cathode inlet temperature, which is a function of the stack power and is specified by the plant manufacturer. The turbine speed 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 [9].

The DFC/T plant is a large-scale, non-linear, highly coupled system, for which optimization is complicated and difficult. Hence, advanced optimization algorithms and control techniques with appropriate plant model are required to guarantee the efficient operations of the power plant.

III. STRUCTURE OF THE OPTIMAL REFERENCE GOVERNOR

The purpose of the optimal reference governor (ORG) is to find optimal feedforward controls and setpoints that guarantee the reliable operations of the power plant with high energy conversion efficiency. Toward this goal, the ORG is developed as in Fig. 2, where the optimized setpoints and feedforward controls, including fuel cell stack current density (I^2), methane flow rate (n_{CH_4}), turbine speed (RPM), 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.

The core of the ORG is a Multi-objective Optimization Module (MOM) that solves nonlinear optimization problems and generates candidate solutions. The modern heuristic optimizations have been proven to be a powerful tool for solving large-scale optimization problems in power systems [10]. Thus, advanced heuristic optimization techniques will be applied and investigated as the core algorithm of the MOM. The objective functions for the optimization problem include fuel efficiency and tracking errors representing how the output power or temperature follows the demand or setpoints. The operating window provides possible operating ranges for the load-dependent setpoints, serving as the solution space or search space for the heuristic optimization algorithms.

There are three possible phases, *i.e.*, search mode, run mode, and model updating mode, during the operations of the ORG. In the search mode, the candidate setpoints provided by the MOM will be tested by the on-line state estimator, which is realized by neural networks and estimates the outputs of the power plant under the given setpoints. Then, the objective functions will be evaluated based on these estimated outputs, and used by the MOM to refine the setpoints. After several search iterations, the ORG will switch to the run mode, where the optimized setpoints will be given to the local controllers as the references for plant operation. Then, the outputs of the actual plant are compared with the estimated outputs of the online state estimator. If significant errors are detected in the

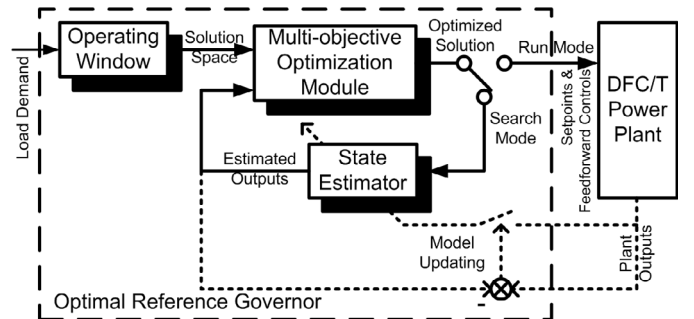


Fig. 2. The structure of the optimal reference governor.

estimated outputs, the ORG will enter the model updating mode, where the on-line state estimator will be re-trained with the newly obtained operating data. After the estimator is updated, the search process will be executed again to ensure the validity of the optimization results. With this structure, the optimal setpoints and feedforward controls can be determined as an optimal control strategy and the plant estimator can be updated as required.

IV. NEURAL NETWORK COMBINED MODEL AND OPERATING WINDOWS

The MOM needs to work with a plant model that estimates the steady-state outputs of the system under given setpoints. Since most heuristic optimizations are population based, the state estimator should be able to process and evaluate multiple sets of setpoints simultaneously. However, the original mathematical model [5-7], which was built based on the rules of energy and material conservations and represented by differential equations, is a "series" model, where the system states must change continuously, and only one set of setpoints can be tested at a single time. Thus, the mathematical model is not suitable for the state estimator of the ORG. Therefore, a special model has to be developed to work with the MOM.

The state estimator is realized by artificial neural networks (ANN) in this paper as a simplified plant model that fulfills the requirements of the MOM and the ORG framework. The ANNs are non-linear statistical modeling tools, and have been playing an important role for system modeling and control system design in the area of power systems [11, 12]. Because the neural network (NN) model depends only on the input and output data, not the structure of the system, it is flexible and can easily be adapted to different types of power plants and control systems. Here, NN models are developed and trained for each subsystem of the power plant, and then a neural network combined model (NNCM) [12] is obtained as the state estimator by integrating the subsystem NN models.

A. Definition of Subsystems

It can be seen from Section II that the DFC/T power plant is highly complicated and can hardly be modeled with a single NN. The system inputs consist of 6 series of setpoints, and the outputs include gas components, temperatures, and power of each subunit. To reduce the complexity of the state estimator, the whole system in Fig. 1 is divided into 7 subsystems, for each of whom, a neural network model will be built. These subsystems are HH, LTR-SSH, FP-PC-SP, Stack, Turbine-Compressor, HTR, and ORG systems. The subunits connected in a row are combined into one subsystem to reduce the total number of the neural networks to be trained.

B. Training of Neural Networks

1) Training data

The NN model for each subsystem needs to be trained with either operational data or simulation data containing the dynamic behaviors of the power plant. In this paper, due to the limitation of the operational data, the NN models are trained

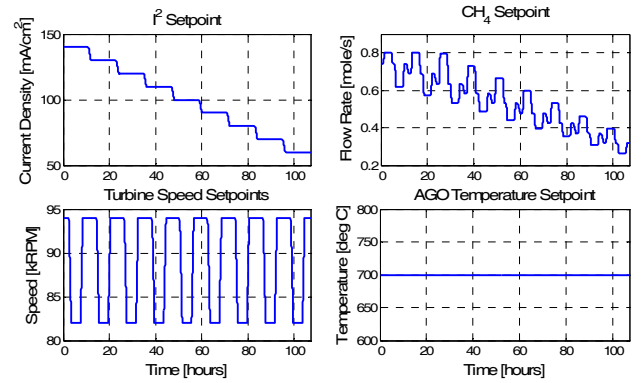


Fig. 3. The designed inputs for the simulation to generate training data.

with the data generated by the mathematical model [5-7]. The data used for NN training should possess as much system characteristics as possible, so that the NN model would learn sufficient information and operational patterns to achieve better performance. Hence, the inputs of the simulation should be carefully designed.

The designed inputs for simulation are shown in Fig. 3, which covers the operational status from full load to half load. The current density setpoint I^2 steps from 140 down to 60 mA/cm² with 10 mA/cm² decrements. The CH_4 setpoint and the turbine speed setpoint change repeatedly according to different current density levels, and attempt to cover most operational regions. The AGO temperature setpoint keeps constant, in which case the AGO control move will have a broad operational range because of the closed-loop PI controller and the variations of other setpoints. Meanwhile, the setpoint changing rates are limited to avoid operational or computational difficulties.

2) Neural networks design

Since most subsystems are static heat exchangers, the feedforward neural networks (FNN) are used for these subsystems, except for the fuel-cell stack, AGO, and gas turbine, which contain dynamic behaviors and need recurrent or diagonal recurrent neural networks (DRNN) [12, 13]. The FNN realizes a static mapping with a simple structure, which is capable of modeling static systems, but it cannot represent a dynamic response in the time domain. Nevertheless, the DRNN can naturally represent dynamic systems and needs fewer weights and neurons than the fully-connected recurrent neural network (FRNN). Hence, the static subsystems are modeled with FNN, while the dynamic subsystems are modeled with DRNN. With this assignment, the state estimator can preserve the dynamic characteristics of the system, while maintaining a low complexity.

The NN applied here has a simple structure of two layers: a hidden layer and an output layer. The input/output specifications of a NN are the same as the corresponding subsystem. The numbers of hidden neurons are assigned to twice of the number of inputs plus one. In order to guarantee the modeling accuracy, some subsystems have slightly higher numbers of hidden neurons. The NNs are trained by the backpropagation method with the Levenberg-Marquardt

algorithm [14, 15], which needs fewer training iterations and less time for convergence. The parameters of the NNs and the training/testing results are listed in Table I, where it can be seen that the NN models can estimate the outputs of the power plant accurately with the designed structure.

TABLE I
PARAMETERS AND PERFORMANCE OF THE NEURAL NETWORK MODELS

Subsystem	# of inputs	# of outputs	# of hidden neurons	Training Epochs	Mean Square Error
HH	7	2	15	55	1.1×10^{-4}
LTR-SSH	9	2	24	60	4.6×10^{-3}
FP-PC-SP	8	6	17	11	8.7×10^{-3}
Stack	11	12	25	30	5.8×10^{-4}
Turb.-Comp.	7	6	18	45	7.8×10^{-3}
HTR	7	2	15	35	8.9×10^{-4}
ORG	7	5	15	28	2.4×10^{-4}

C. Neural Network Combined Model

Once the NN models for each subsystem are successfully trained, they will be combined to compose a NN-based combined model (NNCM) [12], where the individual NN models are connected in series, in parallel, or in loops. The outputs of a specific NN model may be the inputs of other NN models, or be part of the outputs of the combined model. The 7 NN models are connected according to the input/output relationships in Fig. 4, and then an overall plant model is achieved. Because of the structure of the power plant, several subsystems are connected in loops, which will cause computational difficulties due to the algebraic loops formed by interconnecting the subsystems.

1) The algebraic loops

After the individual NNs are joined into a combined model, multiple algebraic loops are developed as the dashed arcs in Fig. 4. An algebraic loop has a computational problem in simulation that the input of a system is determined by the output of itself. For example, in loop 2, the input and output of the Stack are the output and input of the FP-PC-SP, respectively. These algebraic loops will create computational difficulties in simulation. First, the system states and outputs are hard to determine because they are self-dependent. Second, the simulation errors will propagate and accumulate through the loops during simulation.

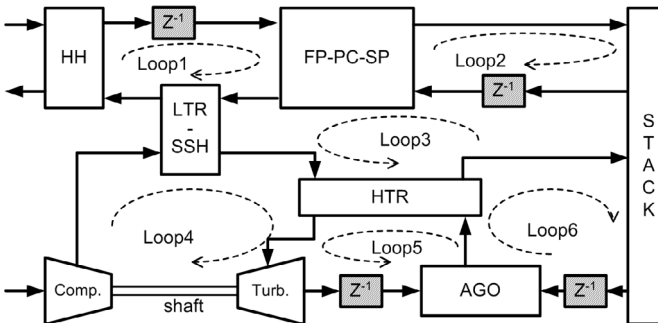


Fig. 4. The NN combined model with algebraic loops and unit delays.

2) The unit delays

The typical technique to eliminate the algebraic loops is adding a small delay as a memory unit in the loop. Since the NN models are discrete, unit delays (*i.e.*, Z^{-1}) are added. These delays should remove all the loops from the system, and should be as few as possible to minimize the complexity of the combined model. In addition, one algebraic loop should only contain one unit delay; otherwise, the convergence rate would be slow. One possible solution is shown in Fig. 4, where 4 unit delays in grey blocks are applied to break the algebraic loops.

Moreover, the initial values for these delay units are also required to start the simulation. To determine the initial values, two NN starters are developed to estimate the initial conditions based on the given setpoints. One NN starter estimates the initial values of the outputs of the fuel cell stack. The other NN starter initializes other delay units. With these unit delays and NN starters, the simulation of the combined model can be started and processed successfully.

D. The Operating Windows

Given a certain power load demand, there are many combinations of setpoints that can satisfy the power demand, but each setpoint should be bounded in a particular range, which is called an operating window. The operating windows for these setpoints need to be determined as the solution space in the MOM. Operating windows are physically realizable operating ranges, constrained by physical limitations such as actuator limits, power limits, temperature limits, etc. Some limitations are easy to determine, such as the split ratios of heat exchangers and the maximum power of electric heaters, but others need to be found from the plant operational data.

The simulation used for NN training is used to determine the operating windows. In Fig. 5, the simulation data is sorted and plotted in grey against the net output power. The special patterns of the simulation data are caused by the pre-designed input for the simulation. It can be seen that, for a particular output power, all setpoints are bounded in certain ranges and the envelopes of operational data are selected as the operating windows, which define the search space or the solution space

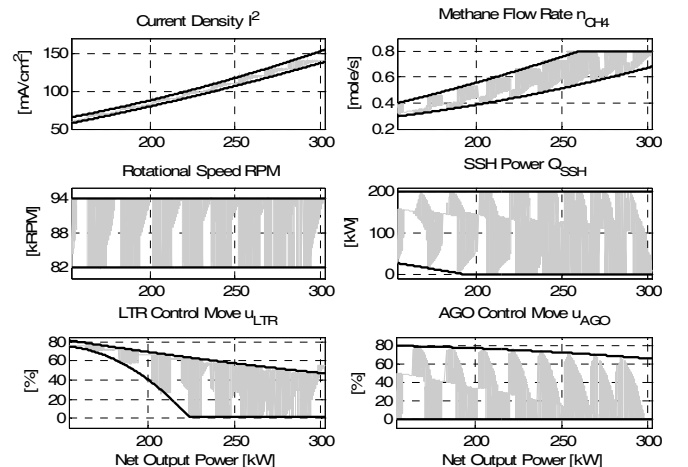


Fig. 5. The operating windows of the DFC/T power plant.

for the MOM and are marked with bold lines in Fig. 5.

V. PROBLEM FORMULATION

The optimal control problem for the DFC/T power plant can be formulated as a multi-objective nonlinear optimization problem, which can be solved by the MOM. The problem is described as:

Find the 6 setpoints that minimize the 3 objective functions:

$$\min\{F_1, F_2, F_3\} \quad (3)$$

where

$$F_1 = \sum_{i=1}^N (P_{load} - P_{net})^2 \quad (4)$$

$$F_2 = \sum_{i=1}^N (TCI_{set} - TCI_{act})^2 \quad (5)$$

$$F_3 = \sum_{i=1}^N \frac{P_{csm}}{P_{net}} \quad (6)$$

The first objective function is defined on the power load, where P_{load} is the power load demand, and P_{net} is the net output power of the power plant. This objective function forces the generated power to follow the power demand. The second objective function is defined on the cathode inlet temperature, an important control variable for plant operation to maintain the temperature of the fuel-cell stack. The cathode inlet temperature setpoint, TCI_{set} , is determined by the current density according to the manufacturer's requirement, while TCI_{act} is the actual cathode inlet temperature. The third objective function is defined on efficiency, where P_{csm} is the total consumed power by the power plant, including the chemical potential contained in the fuels and the power used by the electric heater. Minimizing this objective function will maximize the plant efficiency.

The NNCM in the problem serves as a nonlinear function (7) that maps the 6 setpoints to the operational variables of interest. Here, the net output power and the cathode inlet temperature are selected as the outputs of the NNCM. The objective functions will be calculated from the selected outputs and the given setpoints.

$$[P_{net} \quad TCI_{act}] = f_{NNCM}(I^2, n_{CH_4}, RPM, Q_{SSH}, u_{LTR}, u_{AGO}) \quad (7)$$

The constraint of the optimization problem is that each setpoint searched by the PSO must belong to its operating window given in Fig. 5.

VI. OPTIMIZATION RESULTS

To verify the validity and performance of the ORG framework and the NNCM, the particle swarm optimization (PSO) is applied as the core optimizer for the MOM. The PSO is a stochastic, population-based heuristic optimization algorithm, which has high convergence rate for large-scale problems and low implementation complexity [16-18]. Static weighted aggregation method [19] is used to select the optimal

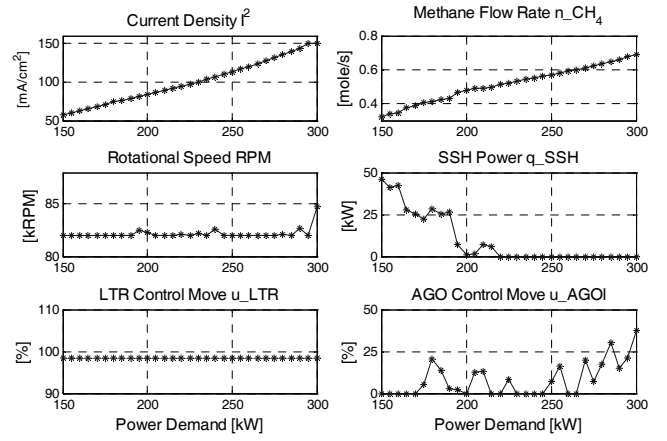


Fig. 6. Optimal setpoints generated by the ORG.

solution. The aggregation weights should be selected according to the requirements of specific applications. Here, without losing generality, the three objective functions are combined to a scalar function as:

$$F = 0.4F_1 + 0.4F_2 + 0.2F_3 \quad (8)$$

The optimal control setpoints are generated by the ORG in Fig. 6 for the power loads from 150kW to 300kW with 5kW increments. The sample points are marked with asterisk. The current density and methane flow rate increase monotonically with the power demand. The turbine speed keeps at the lowest limit, so that less cold air will be injected to the system. The SSH power decreases and stays at zero when the power load reaches a certain level. The LTR control stays at the highest value to maximize heat recuperation. The AGO control goes around zero to transfer more heat to the turbine, and increases at high power load to maintain the cathode inlet temperature.

The simulation results of the NNCM and the original mathematical model are shown and compared in Fig. 7. The net power generated by the DFC/T can follow the power demand very well, and the cathode inlet temperature is correctly controlled. The estimation result of the NNCM can approximate the behavior of the hybrid power plant well with acceptable errors. Based on the simulation result, the DFC/T

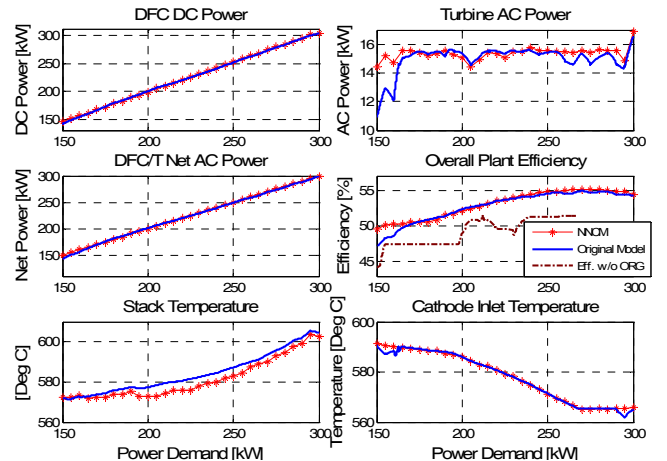


Fig. 7. System response with optimized setpoints given by the ORG.

efficiency increases when the load demand is rising, until it reaches the maximum efficiency of 55% at 270kW. Then, the efficiency slightly drops if the power goes higher. The optimized efficiency is also compared with the actual operating data in dash-dot line, where the experiment was conducted without the ORG. It can be seen that the simulation result with the optimized setpoints and feedforward controls shows higher fuel efficiency than the operation data without the ORG. Thus, the optimization results provided by the ORG are valid for the optimal operations of the DFC/T to improve fuel efficiency.

VII. CONCLUSION

The presented optimal reference governor utilizes the neural network combined model and heuristic optimization algorithms to generate optimal setpoints and feedforward controls to improve fuel efficiency of the DFC/T power plant. The ORG applies a neural network combined model to approximate the behaviors of the hybrid power plant and to serve as a state estimator, which estimates the plant outputs according to the given setpoints, and is compatible with population based heuristic optimizers. The PSO algorithm is investigated with the ORG framework to verify its validity. The simulation results and the comparison with the operational data validate the solution of the optimization problem and demonstrate the performance of the NNCM as a state estimator.

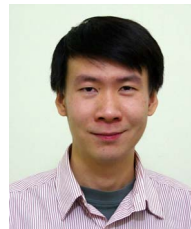
The proposed ORG with NNCM provides a multi-objective optimization framework, which is not only valid for the DFC/T power plant, but also capable of the optimization problems for the operations of any power plants or power systems. Meanwhile, different optimization algorithms and system modeling method can also be investigated with this framework. Further improvement with higher performance can be expected in future work.

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IX. BIOGRAPHIES



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