



Project Fact Sheet

Advanced Control Modules for Hybrid Fuel Cell/Gas Turbine Power Plants

Contacts:

FuelCell Energy, Inc.
3 Great Pasture Road
Danbury, CT 06813

Project Manager: Hossein Ghezel-Ayagh

Phone: (203) 825-6048; Fax: (203) 825-6273; E-mail: hghezel@fce.com

Principal Investigator: S. Tobias Junker

Phone: (203) 825-6056; Fax: (203) 825-6273; E-mail: tjunker@fce.com

Department of Energy (DOE)

Project Manager: Travis Shultz

Phone: (304) 285-1370; Fax: (304) 285-4638; E-mail: Travis.Shultz@netl.doe.gov

Project Partners:

National Fuel Cell Research Center (NFCRC), Irvine, CA

Carnegie Mellon University (CMU), Pittsburgh, PA

Pennsylvania State University (PSU), State College, PA

Objectives

The overall project goal is to develop advanced and intelligent control algorithms for hybrid fuel cell/gas turbine (FC/T) power plants. The specific objectives are:

- Establish a dynamic modeling environment to facilitate simulation studies, as well as development and testing of control algorithms.
- Increase reliability and availability to extend service life of the components in the hybrid FC/T power plant.
- Develop robust controllers that maintain stable operation and high performance in the presence of disturbances.
- Develop optimal control strategies to improve performance and to accommodate fast response during rapid transients.
- Accommodate measurement errors, as well as sensor and actuator faults to reduce the number of unplanned shutdowns.
- Integrate robust and optimal controllers into an overall supervisory framework.

Introduction

The control system for Fuel Cell/Turbine hybrid power plants plays an important role in achieving synergistic operation of subsystems, improving reliability of operation, and reducing frequency of 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. Figure 1 shows a simplified process diagram of an internally reforming SOFC/T system, which is being studied for development of advanced control algorithms.

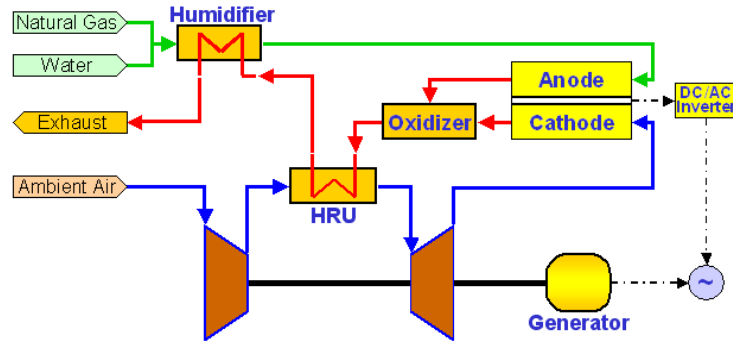


Figure 1: Conceptual process flow diagram for SOFC/T system.

The system is based on an indirectly heated Brayton cycle. The anode exhaust, which contains the remainder of the fuel, is mixed with the cathode exhaust in a catalytic oxidizer, where oxidation of fuel is completed. The hot oxidizer exhaust passes through a heat recovery unit in which it preheats the compressed air before entering the turbine. The hot compressed air is expanded through the turbine section, driving an electric generator.

Dynamic simulation has proven to be a powerful design tool to study the transient behavior of fuel cell/gas turbine hybrid systems. Development of an advanced control strategy is facilitated by using a dynamic model both as a simulation test bed and as part of the controller itself. Components of the advanced control module include a neural network supervisor, robust feedback controllers, and predictive system models. These advanced control components are used in the development and demonstration of an innovative algorithm that optimally controls hybrid power systems, and yet is easily adaptable to the type of fuel used, whether natural gas, coal gas, or digester gas.

Approach

The advanced control module shown in Figure 2 is based on a feedforward/feedback structure.

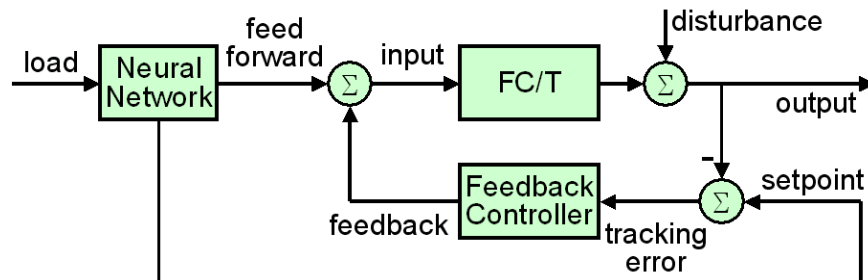


Figure 2: Advanced control module comprising neural network supervisor and robust feedback controller.

It consists of a combined robust controller and a neural network supervisor that together manipulate the actuators to optimally control the hybrid system during load ramps. The feedforward controller will provide optimal dynamic scheduling based on the prescribed load profile and trends. Because the optimization routines are computationally too intensive for real-time application, they are carried out off-line. The resulting data is then used to train a neural network supervisor. The feedforward controller performance depends strongly on the accuracy of the model employed to tune it. A feedback control strategy is utilized to compensate for setpoint deviations caused by imperfect feedforward control moves and to counteract process

disturbances such as variations in fuel composition and ambient temperature. The feedback controller will be designed to be robust to modeling errors and process disturbances.

Results

Modeling

A comprehensive set of component models has been developed and implemented in MATLAB/Simulink. The models include software programs (modules) for internally reforming DFC and SOFC stacks, microturbine, and balance-of-plant equipment. Integrated system models were developed for both SOFC/T and DFC/T systems based on the component-level models. The modular nature of the computer models in Simulink allows for flexibility in development of integrated system models, as shown in the DFC/T example of Figure 3.

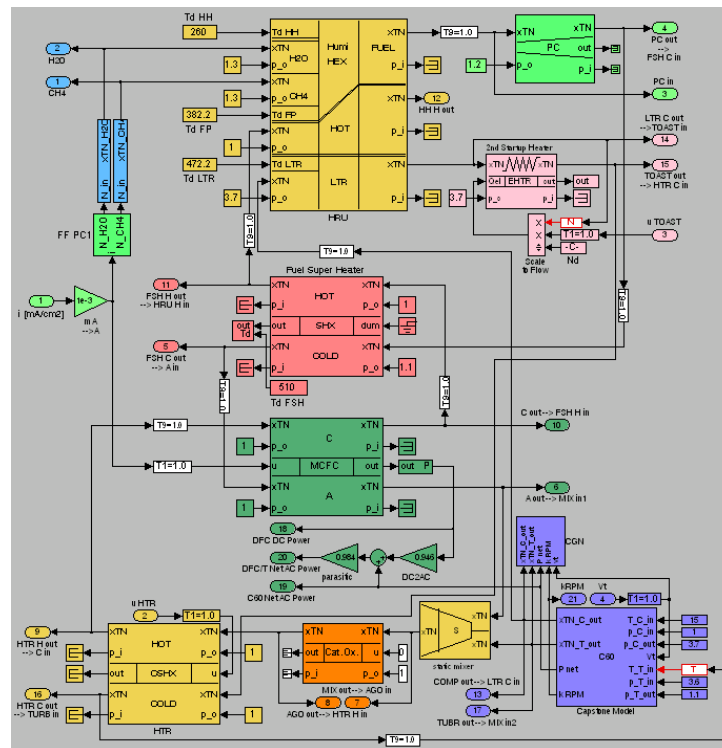


Figure 3: DFC/T dynamic simulation model in MATLAB/Simulink.

The integrated dynamic system models were utilized to refine the control strategy of the DFC/T system for start-up of the microturbine and fuel flow, as well as for control of the cathode inlet temperature throughout the operating range. The underlying principle for the developed control strategy is optimization of the waste heat recuperation to maximize the turbine inlet temperature and power generation. The strategy was implemented in the dynamic models to simulate and verify start-up and load operations of a sub-MW class hybrid power plant. The dynamic simulation studies have resulted in improvements of the control system design. As an example, thermal management of the fuel cell stack was improved by manipulating the microturbine speed.

Robust Decentralized and Centralized Control Design

For the conceptual SOFC/T system shown in Figure 1, analyses of the relative gain array of the system at several operating points have given insight into input/output pairing for decentralized control [1]. To control the stack temperature during transient load changes, a cascade control structure was developed to accommodate the large time constant of the fuel cell stack in rapid load following applications. Inferential sensing of the fuel composition was implemented using voltage as an indicator of varying fuel concentrations. This algorithm was implemented to manipulate the fuel flow, which resulted in making the SOFC/T system robust to varying fuel compositions. The resulting system control approach has transient load-following capability over a wide range of power, ambient temperature, and fuel concentration variations.

To improve control performance, a centralized linear quadratic regulator (LQR) including state estimation via Kalman filtering (KF) was developed [1]. The controller was augmented by local turbine speed control and integral system power control. This control structure offers improved control of fuel cell temperature and improved rejection of variations in fuel composition when compared to the de-centralized controller (Figure 4). However, the decentralized controller achieved better control of the oxidizer temperature. Because rejection of fuel variations and maintenance of cell temperature are more important than tight control of the oxidizer temperature the new controller is an improvement over the current state of the art.

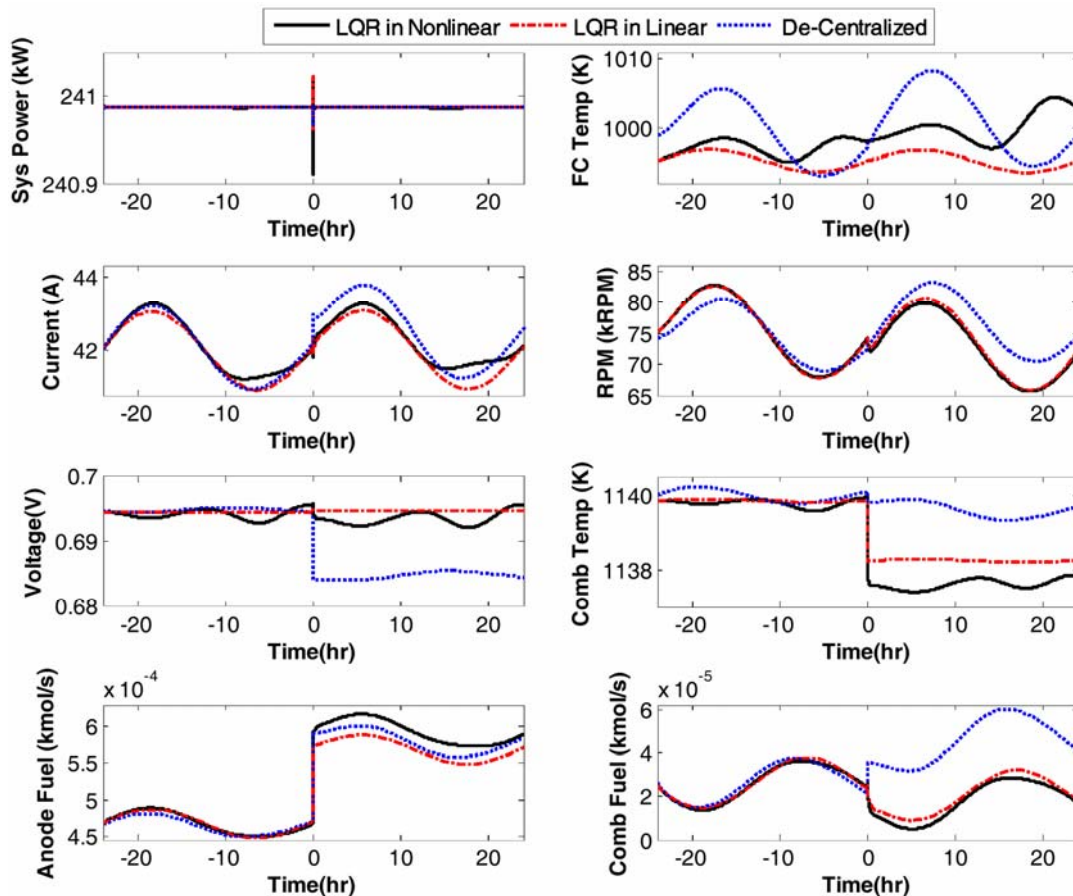


Figure 4: Performance comparison of centralized LQR controller (using linear and nonlinear models) with previously developed decentralized controller.

Optimal Dynamic Scheduling

A nonlinear programming framework has been developed to determine optimal operating policies for hybrid FC/GT power systems. The approach consists of a dynamic model of the system, reformulated as an index 1 DAE [2]. The system model was discretized with an implicit Runge-Kutta method and formulated in the AMPL modeling environment. This allowed for the straightforward solution of a dynamic optimization problem using large-scale nonlinear programming solvers; the IPOPT solver was used for this project [3]. The computer model was utilized in the optimization of operating trajectories, including ramping the entire power range at various speeds as well as local stepping studies at various power levels. Optimization studies were performed and feedforward control moves and setpoints were provided to Matlab/Simulink to visualize and interpret the results. Eighteen case studies showed that the dynamic optimization could be performed quickly with excellent results.

The optimization problem was augmented by an efficiency measure. Because of its built-in flexibility, the program was easily adapted to maximize efficiency. The ramping and stepping studies were repeated, with higher efficiencies achieved while tracking the desired profiles. Results show that it is possible to operate the power plant as desired while simultaneously enhancing efficiency. Figure 5 shows the achieved efficiency improvement for a load stepping study by comparing the results with and without the inclusion of the efficiency measures in the optimization's objective function.

Finally, the optimization framework's applicability to parameter estimation and inferential control was demonstrated. Case studies, using the developed algorithms, verified that accurate estimation of variations in fuel composition is feasible, allowing for compensation of fuel flow and resulting in increased reliability of operation.

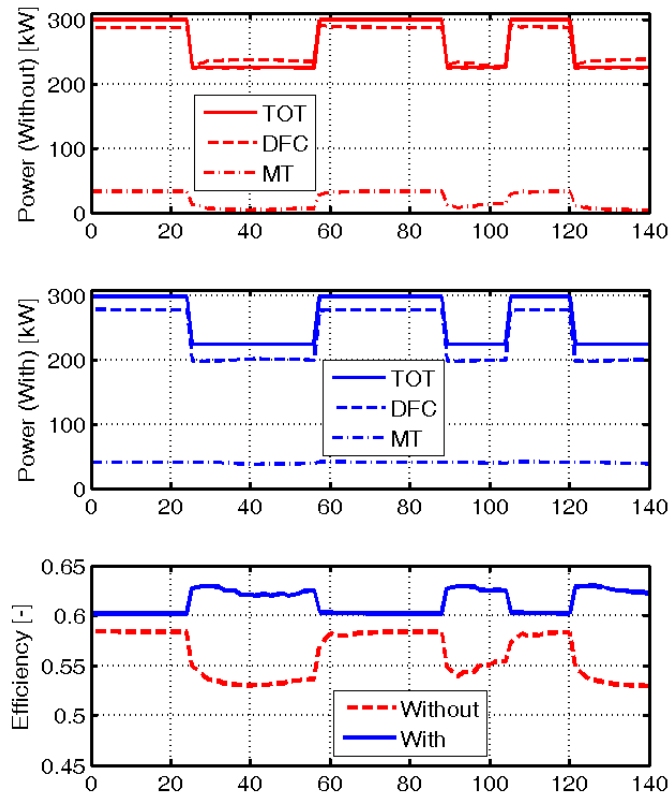


Figure 5: Trajectory planning for step profile with and without the inclusion of efficiency in the objective function.

Neural Network Development

A neural network (NN) supervisor was developed that mimics the function of the nonlinear dynamic optimization function block in generating setpoint profiles and feedforward (FF) control inputs. To avoid the high computational cost, the dynamic optimization could be replaced with a NN for fast on-line computations. Based on structural considerations, a diagonal recurrent neural network structure [4] was developed for prediction of the optimal setpoint and FF inputs.

It was observed that dividing the supervisor into two separate NNs, one for setpoints, and one for FF inputs, resulted in better predictions. Several NN structures were tested to find an optimal structure for the available data. It was demonstrated, as shown in Figure 6, that the NN supervisor is suitable to generate outputs for an arbitrary load, even though, the load was not used for the network training.

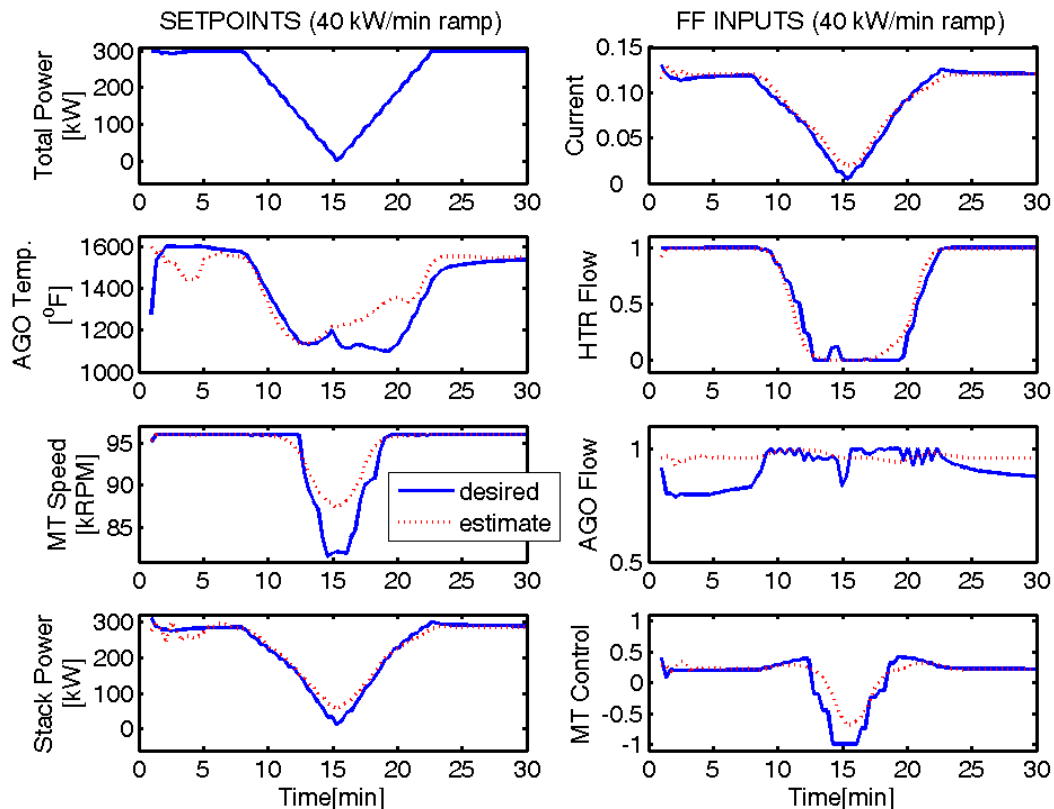


Figure 6: Neural network performance evaluation for a 40 kW/min power ramp.

References

1. S. Skogestad and I. Postlethwaite, *Multivariable Feedback Control – Analysis and Design*, John Wiley & Sons, New York, 1996.
2. S. E. Mattsson and G. Söderlind, *Index Reduction in Differential-Algebraic Equations Using Dummy Derivatives*, SIAM J. Sci. Comp. 14:677–692, 1993.
3. A. Wächter and L. T. Biegler, *On the Implementation of a Primal-Dual Interior Point Filter Line Search Algorithm for Large-Scale Nonlinear Programming*, Math. Program., 106: 25-57, 2006.
4. C. C. Ku and K. Y. Lee, *Diagonal Recurrent Neural Network for Dynamic Systems Control*, IEEE Transactions on Neural Networks, 6:144-156, January 1995

Publications & Conferences

1. H. Ghezal-Ayagh, M. D. Lukas and S. T. Junker. "Dynamic Modeling and Simulation of a Hybrid Fuel Cell/Gas Turbine Power Plant for Control System Development", Proceedings of ASME/Fuel Cell Science, Engineering and Technology Conference 2004, ASME FuelCell2004-2488.
2. H. C. Maru and H. Ghezal-Ayagh, "Direct Carbonate Fuel Cell – Gas Turbine Combined Cycle Power Plant", Presented in European Fuel Cell Forum, Lucerne, Switzerland, July 5-8, 2005.
3. S. Kameswaran, D. Ko, L.T. Biegler, S.T. Junker, and H. Ghezal-Ayagh, *Optimal Off-Line Trajectory Planning for Load Ramping of Hybrid Fuel Cell/Gas Turbine Power Generating Plants*, AIChE Annual Meeting, Cincinnati, OH, November 2005.
4. F. Mueller, F. Jabbari, J. Brouwer, and R. A. Roberts, *Control design for a Bottoming Solid Oxide Fuel Cell Gas Turbine Hybrid System*, 4th ASME International Conference on Fuel Cell Science, Engineering and Technology, Irvine, CA, June 2006.
5. R. Roberts, J. Brouwer, F. Jabbari, T. Junker, and H. Ghezal-Ayagh. *Control design of an atmospheric solid oxide fuel cell/gas turbine hybrid system: Variable versus fixed speed gas turbine operation*, Journal of Power Sources 161(1), pp. 484–491, Oct. 2006
6. F. Mueller, F. Jabbari, J. Brouwer, S. T. Junker, and H. Ghezal-Ayagh. *Linear Quadratic regulator for a Bottoming Solid Oxide Fuel Cell Gas Turbine Hybrid System*, Proceedings of the 7th International Colloquium on Environmentally Preferred Advanced power Generation (ICEPAG), Newport Beach, CA, Paper No. ICEPAG2006-24018, September 5–8, 2006.
7. S. Kameswaran, L. T. Biegler, S. T. Junker, and H. Ghezal-Ayagh. *Optimal off-line trajectory planning of hybrid fuel cell/gas turbine power plants*, AIChE Journal, 53(2), 460–474 (2007).
8. F. Mueller, F. Jabbari, J. Brouwer, R. Roberts, S. T. Junker, and H. Ghezal-Ayagh. *Control Design for a Bottoming Solid Oxide Fuel Cell Gas Turbine Hybrid System*, Accepted for Publication in the Journal of Fuel Cell Science and Technology, scheduled for May 2007.
9. T.-I. Choi, K. Y. Lee, S. T. Junker, and H. Ghezal-Ayagh. *Neural Network Supervisor for Hybrid Fuel Cell/Gas Turbine Power Plants*, IEEE Power Engineering Society (PES) General Meeting, Tampa, FL, June 24–28, 2007.

Acronyms

AMPL	A Mathematical Programming Language
BOP	B alance- O f- P lant
DFC/T [®]	D irect F uel C ell/ T urbine [®]
DRNN	D iagonal R ecurrent N eural N etwork
GT	G as T urbine
IPOPT	I nterior P oint O PTimization
KF	K alman F ilter
LQR	L inear Q uadratic R egulator
NLP	N onlinear P rogramming
NN	N eural N etwork
PLC	P rogrammable L ogic C ontroller
RGA	R elative G ain A rray
SOFC/T	S olid O xide F uel C ell/ T urbine