# Learning Based Control of a Fuel Cell Turbine Hybrid Power System

[Extended Abstract]

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## ABSTRACT

Increased demands for energy are driving development of new technologies for power generation with high efficiency. Direct fired fuel cell turbine hybrid systems are one such development, which promise to drastically increase power generation efficiency, respond to transient loads quickly, and offer fast start up times. However, traditional control techniques are inadequate in these hybrid energy systems because of high nonlinearities and coupling between system parameters, as well as the lack of an accurate system model. In this work, we evolve a neural network controller for a hybrid fuel cell turbine system. In order to allow for neuroevolution to be computationally tractable, we develop a computationally efficient simulator based on real plant data. Results demonstrate that the proposed controller can accurately control plant parameters such as the fuel cell inlet flow rate to within 0.04% of a desired setpoint, and is robust to noise in both system sensors and plant actuators.

## Categories and Subject Descriptors

I.2.1 [**Computing Methodologies**]: Artificial Intelligence —Applications

## Keywords

Neuro-evolutionary Control, Neural Networks

## 1. INTRODUCTION

Due to ever increasing demands for electricity, there is a strong desire for energy sources which are thermally efficient and flexible to rapidly changing load demands, such as daily load spikes. Novel power plant designs are being developed to meet these needs, but multiple challenges exist in the design of new plants. For example, the US Department of Energy's Hybrid Performance Project (HyPer) is a hybrid power plant incorporating both gas turbine power cycles and solid oxide fuel cells, in which control of the power plant is the limiting factor in future development of the technology.


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HyPer is an experimental power plant which incorporates a Solid Oxide Fuel Cell (SOFC) in conjunction with a Brayton cycle gas turbine in a direct fired hybrid configuration. This hybrid design has many benefits including drastic increase in efficiency, fast response times to transient loads, quick plant start up times, and extended fuel cell lifespan. However, traditional control methods have been inadequate for control of this plant due to high nonlinearities, inaccurate models, or limited empirical transfer functions [2].

Neuroevolutionary control offers a robust, model-free solution to controlling HyPer, since it has been shown to be successful in highly dynamic, nonlinear, and noisy control problems such as micro air vehicle flight [1]. However, neuroevolutionary algorithms require a large number of calls to a fitness function. The HyPer plant operates in real time and existing empirical models of HyPer are both limited in scope and run slower than real time, due to the computational cost of simultaneously solving energy and momentum equations. Neither the physical HyPer plant or the existing empirical models allow for fast evaluation of controllers. Thus, in order to develop a neuroevolutionary controller for HyPer, a fast fitness assignment operator is required.

In this paper, we develop a neuroevolutionary controller for the HyPer facility. In order to conduct an evolutionary algorithm, we developed a fast neural network based model of the HyPer plant, based on actual measured plant data, which is capable of simulating hours of plant runtime in seconds. We demonstrate the ability of the controller to accurately guide the plant to desired setpoints using a bypass air valve. Further, we demonstrate that the controller is robust to sensor and actuation noise, and rejects disturbances within the system.

## 2. METHODS

In order to evolve a controller for the plant, a fast running simulation of the plant is needed to assign fitness to the controller. A neural network approximation of the plant state is learned from real plant data using error backpropagation. The cold air valve characterization data has a wide range of plant states and control actions, and thus describes a wide operation regime of the power plant. The simulation maps current plant state and control action to the plant state at the next step. The resulting learned simulation of the plant is both fast to evaluate and captures the dynamics of the power plant to within 0.115% with a maximum error of approximately 5% at any particular time step, allowing it to be used as for fitness approximation in the evolutionary algorithm.

Since an accurate simulation of the plant is now available which can be evaluated quickly, neural network controllers can be evolved. Controllers are evolved for across a variety of state setpoints found in the data. Inputs to the neural network controller are the 19 plant state variables in the data, and the desired setpoint for each variable, network output is a control decision for the cold air valve actuation and fuel flow valve. Fitness is assigned to the network based on the sum squared error between the desired setpoint of the fuel cell flow rate and the simulated output for multiple setpoints across all time steps. Control networks have 19 inputs, 15 hidden units, and 2 outputs. A population of 100 networks are initialized random weights with values drawn from a Gaussian distribution with mean of 0.0 and standard deviation of 0.75. Mutation occurs by adding a random value drawn from a Gaussian distribution with standard deviation of 1.0 for 30 of the network weights. Once a controller is evolved, system response to a step input is observed.

# 3. RESULTS

The evolved controller for fuel cell mass flow rate control with cold air valve actuation can bring the flow rate to within 0.04% of the setpoint with little overshoot for large step input as can be seen in Figure 1. This evolved neural network controller is also robust to noise in the plant far exceeding the true noise in the system and errors in its own control decisions. This suggests that learning based controls could allow for the use of inexpensive sensors and actuators, decreasing the cost of the overall plant.

Figure 2 shows results when 10% noise is applied to the input of the network. In our neural network controller noisy inputs are averaged out since the output depends on all plant state variables. The control decision is robust to the noise in the plant. Plant output is still noisy, but 10% sensor noise maps to less than 2% noise in the true output of the plant at the worst. This demonstration shows the noise rejection capabilities of the neural network controller to be far greater than needed in the plant. Implemented in the plant, this controller would receive filtered data with noise far below 5%. In addition to sensor noise, network output is robust to 5% actuation noise producing similar results to Figure 2.

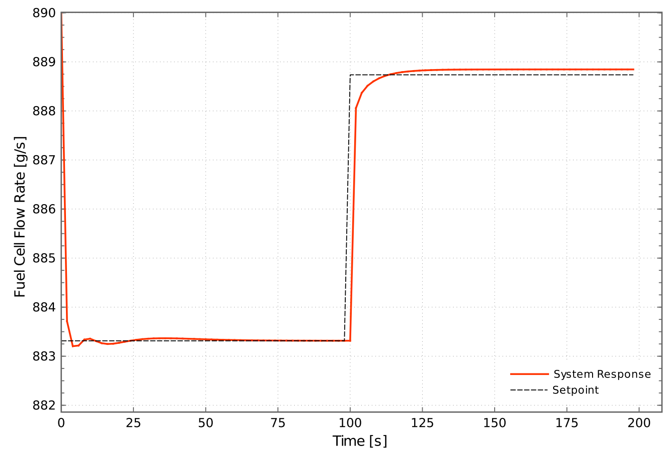


Figure 1: Control of fuel cell flow rate with the cold air valve response to step input in control. Initial step down shows small controller overshoot, the step up shows lightly damped behavior.

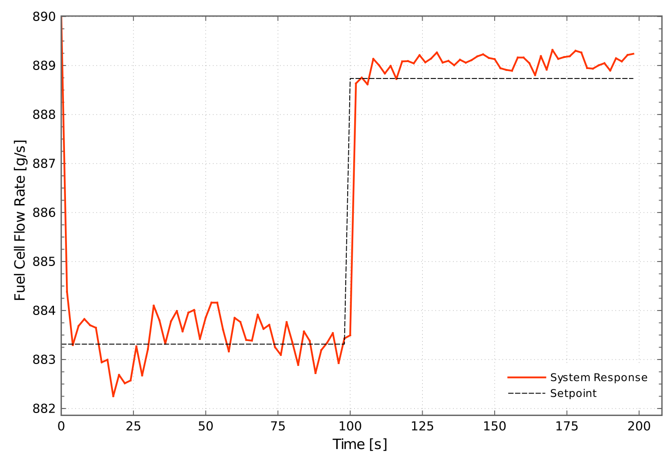


Figure 2: Evolved neural network controller response to 10% sensor noise. Notice that 10% sensor noise is larger than the commanded control step input.

# 4. DISCUSSION

In this work, we developed a neural network controller for the HyPer facility using a neuroevolutionary algorithm. The evolved neural network controller results in accurate setpoint tracking, is robust to sensor and actuator noise, and can accurately control individual plant states across a wide operational regime.

In order to evolve a controller for HyPer, a fast neural network simulator was developed. HyPer is a hardware plant, and thus runs in real time. Analytical models of HyPer run at or slower than real time, due to the computational time associated with simultaneously solving partial differential equations numerically. Evolving a controller for HyPer requires a fast simulation, due to the need for large numbers of calls to a system evaluation function to assign fitness during evolution. Using real data from HyPer experiments, we trained a neural network with backpropagation to model the HyPer facility. This network was then used to assign fitness in the neuroevolutionary control algorithm.

Future work on control for this plant will focus on the expansion of the simulation to include control of several variables across the plant, developing multiobjective controllers for the plant, and validating the control methods in hardware.

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# 5. REFERENCES

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