# Optimized Anticipatory Control Applied to Electric Power Systems

T. E. Fieno D. T. Bargiotas* L. H. Tsoukalas

Purdue University, School of Nuclear Engineering,
West Lafayette, IN 47907-1290 – USA
fieno@.ecn.purdue.edu , tsoukala@.ecn.purdue.edu

*Technological Educational Institute of Chalkis
Department of Electrical Engineering,
Psachna, Evia 34400 – Greece
bargiotas@teihal.gr

**Abstract**
A new anticipatory control algorithm is presented to address an important challenge emerging in deregulated power systems, that is, matching power demand in a local area grid with the power delivered by a (local) power plant. A neural network anticipatory controller for a model power plant is coupled with a neural network time-series forecaster which prescribes power output for the grid. The goal of the system is to keep inadvertent flow of power across a control area's boundary as small as possible. If a difference exists between the power supplied and the power demanded in a control area, the load deficit or surplus would be either borrowed from or stored as the kinetic energy in rotating machines in the grid. The results presented show that the anticipatory approach may lead to substantial savings in maintenance and significant reliability gains.
**Keywords:** Anticipatory Systems, Neural Networks, Deregulation of Power Systems, Applied Intelligent Systems

## 1 Introduction

Differences between biological organisms and artificial systems are often the subject of debate in engineering and research circles. The ability to incorporate the levels of flexibility, adaptability, and goal-driven action of the biological world into manmade artifacts is highly desirable for advancing autonomous systems.

A crucial difference between life and artifact is the anticipatory nature of organisms. Anyone who has ever played "fetch" with a dog knows that after only a few trials the dog will learn to predict when you will throw the object. Even more astounding is that the dog will learn trends about where the object will land based purely on observation rather than on understanding laws of motion. And yet, as the eminent mathematical biologist Robert Rosen pointed out nearly two decades ago (Rosen, 1985), even though the notion of anticipation permeates our everyday life, nearly all engineering control systems act in a purely feedback mode. Predictions about the future states of the environment are just now being considered for incorporation into advanced control design. One of the barriers to their introduction is the difficulty of quantifying and operating on likely or unlikely events in the future control horizon.

More recent findings by Professor M. Dubois suggest that anticipation is present in non-biological systems as well including many of the systems and phenomena that traditionally have been under the purview of physics such as electromagnetism and relativity. Dubois has expanded Rosen's definition of an anticipatory system (a system which contains one or more models for prediction) by including in the category of anticipatory systems those systems that may use themselves for predicting their future. Thus, a useful distinction can be made between soft anticipation (that is, model-based) and strong anticipation (that is, system based). For a very interesting review of these important ideas the reader is referred to (Dubois, 2000), (Dubois, 2001).

Although anticipatory systems have been an integral part of life, the study of anticipatory systems is a relatively new area in engineering (Mikulecky, 1996), (Tsoukalas, 1998), (Tsoukalas, 1991). In recent years, phenomenal advances in both computational platforms and modeling tools (e.g., neural networks, fuzzy systems, statistical modeling) have made possible having a variety of models that can be used for prediction of a system's and/or environment's trajectory. Yet, many difficulties exist in implementing anticipatory control algorithms. They include, but are not limited to, prediction model selection, learning, having an appropriate time horizon, faster than real time computations, complexity control and controller reconfiguration. Most of these difficulties stem in one way or another from what we call the Golden Rule of Anticipation, which is that **in an anticipatory system, the capacity for prediction has to be in harmony with the ability to act.**

A question the present study seeks to answer is whether or not the notion of anticipation can be exploited to make an engineering system perform better or in a safer, more flexible, and generally more optimal manner. To address this question in a technically sound fashion, an iterative system for designing a combined predictive controller and environmental forecasting routine is utilized. The system is examined through application to the regulation of an electric power grid and comparison with conventional approaches.

In the present work an anticipatory system is assumed to be a system that utilizes predictions about the future states of itself and of its environment to direct present actions (Rosen, 1985). In a Dubois sense our systems is a soft anticipatory systems. In addition, as system environment we define the entity that the controller and plant are attempting to regulate.

The rest of the paper is organized as follows. Section 2 offers a brief description of the testbed or application context. Section 3 presents the prediction methodology which relies heavily on neural forecasting while Section 4 presents the anticipatory control methodology. Section 5 presents simulation results showing that the approach leads to significant reduction in control effort with concomitant gains in system reliability and overall performance. We conclude with a summary and discussion of future work found in Section 6.

# 2 Anticipatory Test System

Two systems are needed to study the usefulness of anticipatory regulation applied to the electric grid. The first is the power consumption for a given control area, and the second is the mathematical simulation of the power-producing facility. These conform to the environment and the controlled machine respectively.

## 2.1 Data Test System

To assess the flexibility and power of the proposed model, data from an electric power grid will provide the testbed. Power consumption data obtained from a major power utility are used. Fig. 1 shows the power demand recorded for a specific residential feeder on the grid for July of 1999. The power data are sampled every 15 minutes. Two data sets are used to design the prediction system (July and August 1999), and three data sets are used to test the anticipatory control system (November and December 1999 and January 2000). The data sets from September and October of 1999 were of too low a quality to be implemented and tested.

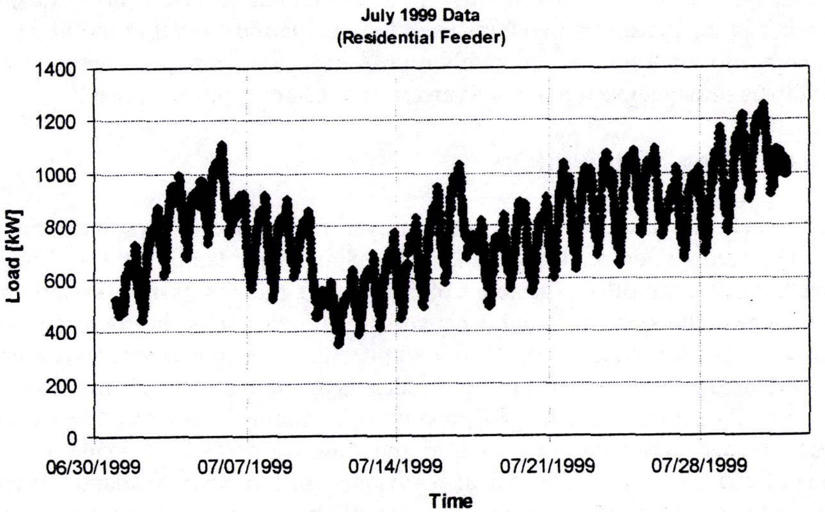


**Figure 1.** July demand.

## 2.2 Power Test System

The full-scale model used for final testing of the anticipatory control system is a direct implementation of the steam power plant model outlined by Ordys (1994) with minor changes. Fig. 2 shows a schematic of this model.

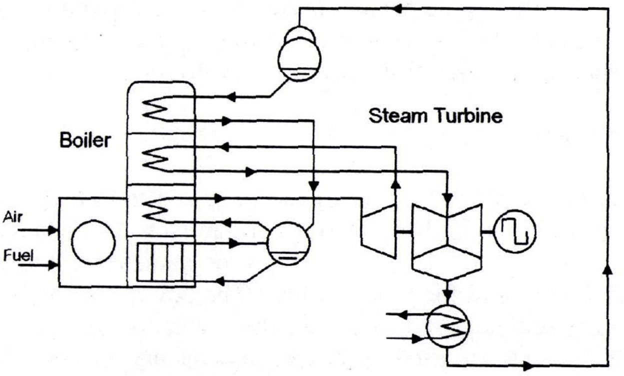


**Figure 2.** Power system model schematic.

This model was chosen because it was the most general representation (meaning the least number of empirical relationships used for calculation) found in the literature that gave enough information to be accurately reproduced. The work is a component-based, first-principles implementation of a pulverized coal steam generation unit.

## 3 Forecasting Methodology

Neural networks have been repeatedly proven to be superior nonlinear time-series forecasting systems (Gentry, 1995; Park, 1994; Sun, 1997; James, 1997). In addition, adding adaptability or other variables of interest to the forecasting system requires simply retraining the system. Neural networks were chosen as the forecasting system for the study described here. The network architecture was chosen as a fully connected, feedforward neural net with a "tansig" hidden layer activation function and a linear output layer activation function. To prevent overtraining of the time-series data, the technique of early stopping was used in the training procedure. Due to seasonal variations of electric power data, it is also advantageous to have an adaptability system in place. To accomplish this, a concurrent neural network trained on more recent data than the primary network was implemented. When the second network consistently (for three days of data) predicted more accurately than the primary network, the weight matrices were switched and the process was repeated. The final network architecture used five historical electric load data points $L(t_i \cdots t_{i-4})$—giving five input layer neurons and four hidden layer neurons. The trained neural network then functions as a predictor of the next electric load data point $L(t_{i+1})$. Fig. 3 shows the network topology chosen based on parametric exploration.

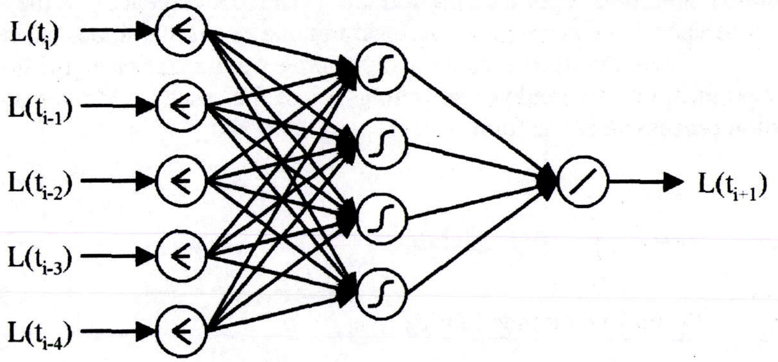


**Figure 3.** Environment prediction network.

Table 1 shows a portion of the sum square error results (in kilowatt-hours squared) for forecasting the November data set. Multiple trials were run to gauge the effect of random weight matrix initialization on the training process.

**Table 1.** Forecasting results.

| Trial no. | Nonadaptive NN error | Adaptive NN error | Error reduction |
|---|---|---|---|
| **1** | $1.12 \times 10^5$ | $1.01 \times 10^5$ | 10% |
| **2** | $1.16 \times 10^5$ | $1.09 \times 10^5$ | 5.7% |
| **3** | $1.40 \times 10^5$ | $1.15 \times 10^5$ | 17.6% |
| **4** | $1.16 \times 10^5$ | $1.02 \times 10^5$ | 11.6% |

## 4 Anticipatory Control Methodology

When the system model is nonlinear and the control actions are limited in rate and magnitude, an iterative approach to predictive control must be utilized. Note that when predictive control is coupled with forecasts of the system environment, anticipatory control is achieved.

The specific implementation of the predictive control system is similar to that described by Demircioglu (2000), with some exceptions. A constrained optimization procedure, minimizing the error between plant output $y(t)$ and target output $d(t)$ for set time window $\tau$, determines the anticipatory control response. The optimization system finds the piecewise linear control schedule $u(t)$ for a set number of points $n$ in the time window subject to rate and magnitude limits. The algorithm used for this research was a constrained nonlinear optimization routine. The convergence of the process is problem dependant. For systems where local minima or discontinuous functions cause optimizations to fail, a more computationally complex optimization algorithm—such as genetic optimization or random searching—must be used. Mathematically, the optimization process takes the form:

Minimize:

$$Error = \int_{t_0}^{t_0+\tau} |y(t) - d(t)| dt$$

Subject to:

Control Magnitude Limits $\quad u_{\min} \leq u \leq u_{\max}$

Control Rate Limits $\quad \left|\frac{du}{dt}\right| \leq \frac{du}{dt}_{\max}$

This optimization process is shown graphically in Figs. 4 and 5.

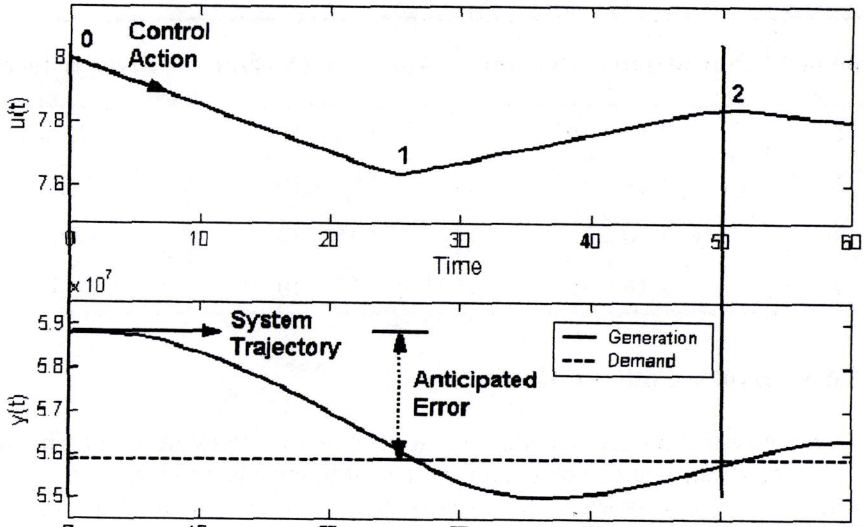


**Figure 4.** First iterative control optimization.

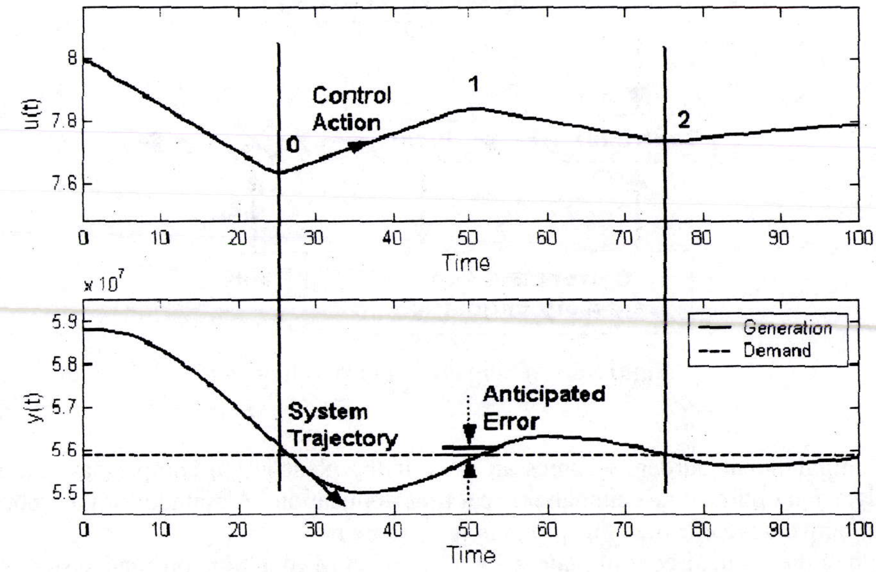


**Figure 5.** Second iterative control optimization.

The figures show the control actions $u(t)$ and the process output $y(t)$ for an arbitrary plant during specific time frames. For the pulverized coal power plant, $u(t)$ is the rate of change of fuel flow to the furnace and $y(t)$ is the mechanical power output. The desired output of the plant is the demand curve $d(t)$.

In Fig. 4, the system is repeatedly simulated from 0 to 50 sec. During these simulations control actions 1 and 2 occurring at times 25 and 50 sec are the variables to be optimized. Control action 0 is not a variable control parameter. Once the optimization procedure has converged (that is, the integral error for $y(t)$ has reached a minimum), the system is incremented to the next time window. This is the new state shown in Fig. 5. The simulation (or control optimization) window is now 25 to 75 sec; control action 1 is taken as the new control action 0, and control actions 1 and 2 at times 50 and 75 sec are the new variables to be optimized over the new horizon.

The optimization of control actions can be thought of as looking at the projected error of the system based on forecasting and any load schedules that are known a priori, looking at the direction the system output is moving, and finding open-loop control actions to correct for the projected error. Instead of comparing process output to target output, estimating the direction the plant is moving closes the feedback loop in the anticipatory control system. A schematic of this process is shown in Fig. 6.

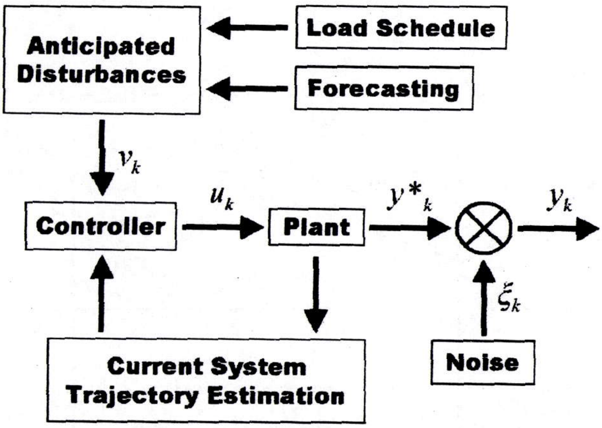


**Figure 6.** Anticipatory control schematic.

Computational burden becomes an issue if the plant is too complex to iteratively simulate and optimize fast enough for real time application. A method for incorporating neural networks to alleviate this problem is presented.

When the optimal control pattern for a given set of time horizons and system states is found, the results are logged in a control action table. Figs. 4 and 5 show the variables that are logged for two optimized control iterations. The predicted error for the system at the first control action $e\left(t_{i+t(u1)}\right)$ is stored, along with the error direction of the plant output at the initial time $\frac{de}{dt}(t_i)$. This provides a control log that lists the optimal change in fuel mass flow $\frac{d\dot{m}_f}{dt}$ to issue for a given set of error circumstances. If a log file will be used instead of iterative simulation to estimate the corrective action necessary for an error input, it must have a sufficient number of control examples. To this end, the log file was built spanning the range of minimum to maximum power error signal and power change rate. The log file for this research prescribes a two-dimensional matrix of control actions. After the file has been obtained, iteration and optimization for error correction is no longer needed and computational requirements are significantly reduced.

Once the log has been created, the relationship between the control actions and the error and system states can be learned. A neural network is trained to accomplish this task. There are certainly other ways to do this, but neural networks are able to model nonlinear functions very well and are computationally efficient after training (Tsoukalas, 1997). Fig. 7 shows the neural net design used for this portion of the work. It has four hidden nodes, two inputs, and the same activation functions as the forecasting neural network.

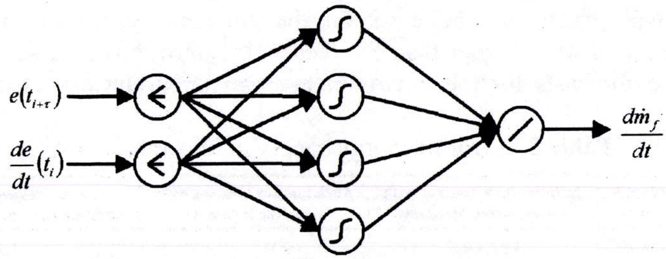


**Figure 7.** Neural network controller.

## 5 Simulation Results

The boiler model was first iterated to find suitable anticipatory control actions for a large set of known preview errors, and then a neural network was trained to learn the anticipatory control relationship. Fig. 8 shows the general response of the full-scale model to known load changes. The controller is clearly well tuned for this system because all of the generation lines intersect near the centers of the set-point step changes—the minimum error point for symmetrical system lags. The full-scale anticipatory control model was tested with forecasts from the neural network for November 1999, December 1999, and January 2000.

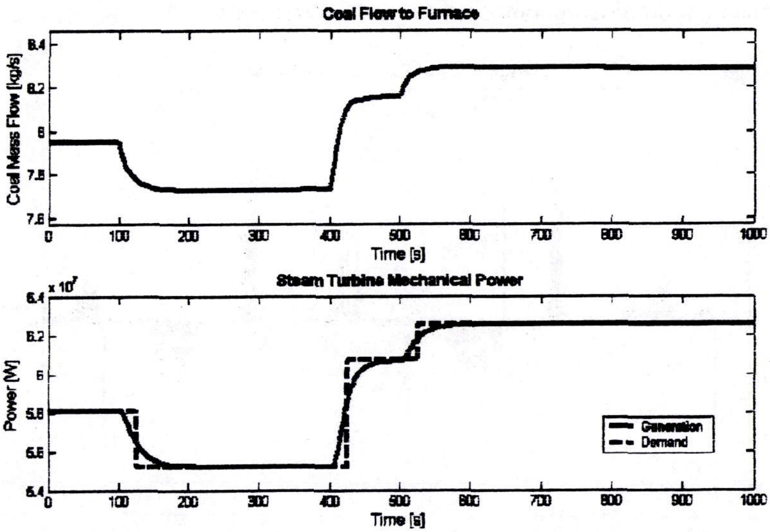


**Figure 8.** Simulated anticipatory control response.

Table 2 shows the kilowatt-hour difference between electric demand and generation for the anticipatory and feedback (model predictive with and without environment forecasts) control strategies. The error for the anticipatory control system without adaptability in forecasts is higher than the feedback control error. This shows that the accuracy of the forecasts for the environment is an important aspect of anticipatory control.

**Table 2.** Error in energy supply in kilowatt-hours.

| Data set | Feedback control | Anticipatory control with nonadaptive forecasts | Anticipatory control with adaptive forecasts | Energy savings for adaptive anticipatory vs. feedback control |
|---|---|---|---|---|
| **November** | $4.56 \times 10^4$ | $4.62 \times 10^4$ | $4.34 \times 10^4$ | 4.80% |
| **December** | $5.00 \times 10^4$ | $5.14 \times 10^4$ | $4.21 \times 10^4$ | 15.66% |
| **January** | $4.68 \times 10^4$ | $4.72 \times 10^4$ | $4.51 \times 10^4$ | 3.61% |

One of the theoretical advantages of anticipatory control is smoother control actions than with feedback control. This makes sense when considering the control system because the controlled variable is the change in fuel flow rate to the boiler in kilograms per squared second. This value is integrated over time to find the mass flow rate into the boiler system. If a larger time is allowed for the rate adjustment, the value need not be as high to generate the same integrated signal.

Figs. 9 and 10 illustrate simulation results for changes in fuel flow rate. These figures show that the anticipatory control effort is about 4% of the feedback control actions. The anticipatory controller gives better energy efficiency for less control effort. This reduction in control effort has the additional benefits of reducing the wear on the control system and reducing temperature gradient stresses.

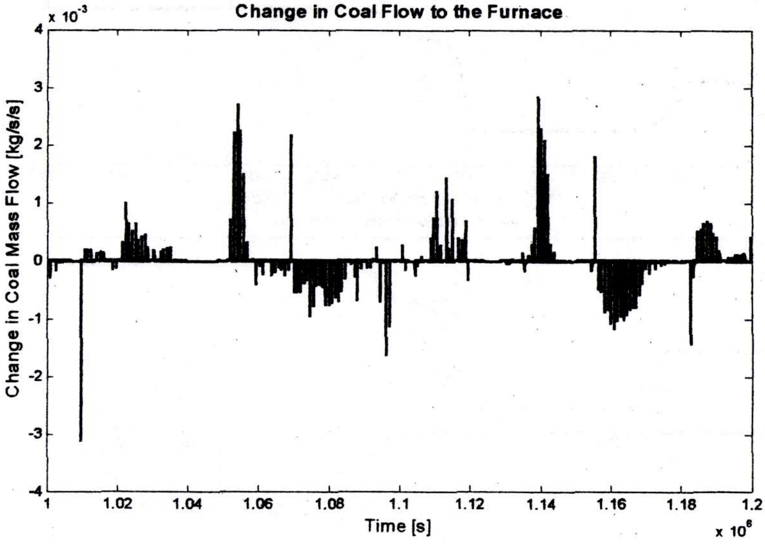


**Figure 9.** Feedback control effort.

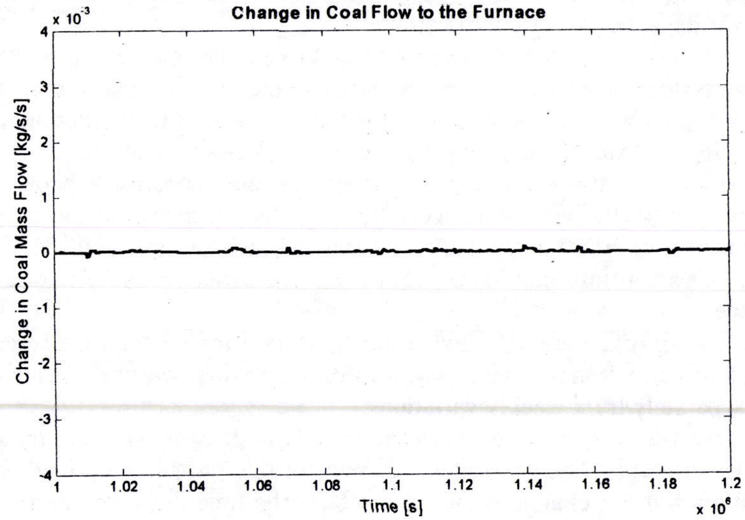


**Figure 10.** Anticipatory control effort.

## 6 Conclusions and Future Work

Anticipatory control attempts to improve system performance by using knowledge about future events. As an anticipatory system predicts future states of the environment, it can adjust control actions earlier in time to lessen sudden changes in control. This approach is especially advantageous for systems with dead times and limited control actions. However, very little previous research exists that ties together predictive control and time-series forecasting in a unified system.

The system developed in this research is a general control approach that uses very little system information and few parameters in the design process. Nearly the entire design was given to the computer to determine. The drawback to limiting the amount of information used in the controller design process is that the computational burden increases dramatically and convergence is not guaranteed. Nevertheless, modern computer workstations are well equipped to handle the burden. All of the simulation and testing reported in this article was performed on 500-MHz Pentium III computers using the MATLAB programming environment. The simulations all ran faster than real time for control schedule calculation, despite the slow performance of MATLAB. If the system is required to run faster, the approach can be coded in FORTRAN or C.

Note that the results listed are biased toward feedback control in two ways in a deliberate attempt to analyze the effect of pure anticipatory control versus pure feedback control. The first bias is that no dead time between control signal and action was incorporated into the model. It is clear that anticipatory control would eliminate an error due to dead time in the fuel delivery system. The second bias is that the limits on the control actions were never achieved for either control system. If the rate limit for the feedback controller were a limiting factor, the results would likely have been even more favorable for the anticipatory control strategy.

The anticipatory control approach developed in this article is in an early stage of testing. For the system developed in this research, there are two main areas where improvements are possible. The first of these areas is in the prediction of the environment or electric load of the grid. The literature shows that the use of weather data in electric load forecasting can make the predictions more accurate (Cheok, 1995). This makes sense physically because on very hot days the electric load on the power system under consideration is higher due to increased usage of air conditioners. We recommend that weather information be tested for inclusion in the environmental prediction scheme.

Another way to improve the prediction system is to decompose the time series into long-term and short-term trends. This would allow capturing seasonal variations in power demand separately from weekly variations.

The second area where improvements in the model are possible is in the predictive control of the power plant. The controller designed for this project is optimal for this specific application, but if a change occurs that affects the time dynamics of the plant, the performance of the tuned controller will suffer. An adaptable tuning mechanism for changes in the plant dynamics using a system identification approach would allow the plant controller to be adaptive—not just the environment forecasting system.

## Acknowledgments

This work was supported in part by *EPRI DOD Complex Interactive Networks* under contract No. EPRI-W08333-02; by the *National Science Foundation* under grant No. 500-1290-3597, and by the *Purdue Research Foundation* under grant No. 690-1290-3043. This project would not have been possible without the data and support from many members of the *Consortium for the Intelligent Management of the Electric Grid Group (CIMEG)*. The help provided by Dr. David Schooley of Exelon is especially appreciated. Special thanks are due to Professor D. M. Dubois for his invaluable comments and constructive criticism of the manuscript.

## References

Cheok, K., K. Kottathra, T. Pryor, and G. Cole, "Load Forecasting for Remote Area Power Supply Systems," in *Proc. 11th Conf. on Artificial Intelligence for Applications*, pp. 231-237, Los Angeles, CA, 1995.

Demircioglu, H., and E. Karau, "Generalized Predictive Control," in *IEEE Control Systems Magazine*, pp. 36-47, October 2000.

Dubois, D.M., "Review of Incursive, Hyperincursive and Anticipatory Systems – Foundation of Anticipation in Electromagnetism," *Proceedings of the Third International Conference Computing Anticipatory Systems: CASYS'99*, Vol. 517, pp. 3-30, American Institute of Physics Conference Proceedings 517, 2000.

Dubois, D.M., "Theory of Incursive Synchronization and Application to the Anticipation of Chaotic Epidemic," *International Journal of Computing Anticipatory Systems,* Vol. 10, pp. 3-18, ASBL CHAOS, Belgium, 2001.

Gentry, T.W., "A Comparison of Traditional Forecasting Techniques and Neural Networks," in *Proc. 1995 Artificial Neural Networks in Engineering*, pp. 765-770, St. Louis, MO, 1995.

James, B.E., "Analyzing Time Series Data: A Comparison of Backpropagation and Classical Winters' Methods," in *Proc. 1994 Artificial Neural Networks in Engineering*, pp. 213-218, St. Louis, MO, 1994.

Mikulecky, D.C., "Robert Rosen: Why are Organisms Different from Machines?" in *Proc. 1996 Artificial Neural Networks in Engineering*, pp. 193-198, St. Louis, MO, 1996.

Ordys, A.W., A.W. Pike, M.A. Johnson, R.M. Katebi, and M.J. Grimble, *Modeling and Simulation of Power Generation Plants*, New York, NY: Springer-Verlag, 1994.

Park, D.C., M.A. El-Sharkawi, R.J. Marks, L.E. Atlas, and M.J. Damborg, "Electric Load Forecasting Using an Artificial Neural Network," *IEEE Trans. on Power Systems*, vol. 6, no. 2, pp. 442-449, 1991.

Rosen, R., *Anticipatory Systems Philosophical, Mathematical & Methodological Foundations*, New York, NY: Pergamon Press, 1985.

Sun, X., Q. Wang, and D. Zhu, "Function Approximation and Prediction: A Comparative Study with Neural Networks and Regression Models," in *Proc. 1997 Artificial Neural Networks in Engineering*, pp. 79-84, St. Louis, MO, 1997.

Tsoukalas, L. H. "Neurofuzzy Approaches to Anticipation: A New Paradigm for Intelligent Systems," *IEEE Transactions on Systems, Man, and Cybernetics* – Part B, v 28, n 4, p 573-582, Aug. 1998.

Tsoukalas, L.H., and R. Uhrig, *Fuzzy and Neural Approaches in Engineering*, John Wiley & Sons, New York, 1997.

Tsoukalas, L.H., Bargiotas, D. and Berkan, R.C., "Knowledge-Based Modeling of Power Plant Systems within the Anticipatory Paradigm," *Proc. of the International Conference on the Analysis of Thermal and Energy Systems (ATHENS '91),* American Society of Mechanical Engineers (ASME), 845-855, Athens, Greece, 1991.