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# DEMONSTRATION OF A HYBRID INTELLIGENT CONTROL STRATEGY FOR CRITICAL BUILDING HVAC SYSTEMS


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# DEMONSTRATION OF A HYBRID INTELLIGENT CONTROL STRATEGY FOR CRITICAL BUILDING HVAC SYSTEMS

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**Abstract**

Many industrial facilities utilize pressure control gradients to prevent migration of hazardous species from containment areas to occupied zones, often using Proportional-Integral-Derivative (PID) control. Within these facilities, PID control is often inadequate to maintain desired performance due to changing operating conditions. As the goal of the Heating, Ventilation and Air-Conditioning (HVAC) control system is to optimize the pressure gradients and associated flows for the plant, Linear Quadratic Tracking (LQT) provides a time-based approach to guiding plant interactions. However, LQT methods are susceptible to modeling and measurement errors, and therefore a hybrid design using the integration of soft control methods with hard control methods is developed and demonstrated to account for these errors and nonlinearities.

**Key Words**

Optimal Tracking, Fuzzy Logic (FL), Neural Network (NN), Linear Quadratic Tracking (LQT), HVAC.

## 1. INTRODUCTION

The control of pressure gradients in industrial facilities, such as those found in the Heating, Ventilation and Air-Conditioning (HVAC) plant in the Department of Energy (DOE) complex, is key to preventing the migration of hazardous species from containment areas to normally occupied areas. When hatches or doors are opened to access these areas, in some cases for an extended period, the ventilation control system is expected to respond promptly to maintain the required pressure gradients.

When the disturbance is maintained for extended periods, operator involvement is often required to rebalance a large portion of the plant to achieve the desired condition. Since these control systems often use individual Proportional-Integral-Derivative (PID) or PI controllers, there is no consideration given to the obvious interactions that occur across the plant. To account for these interactions, a control method must provide an optimal solution to the model of an HVAC plant. The LQT method provides such a solution to optimally track a time-based reference, given that the reference is known and that the model is well known [1, 2]. As the ventilation profiles and pressure gradients through an industrial facility can be quite complex, the presence of modeling and measurement errors must be considered in the final control method.

Soft computing methods using Fuzzy logic (FL), Neural Networks (NN), Genetic Algorithms (GA) provide an avenue to incorporate variations in the model compared to plant operation and the ability to closely model nonlinear situations [3]-[6]. With the LQT method, simulation techniques are available that allow the simple incorporation of any plant model in state space form [7]. However, the implementation of a controller would normally involve the storing of data in the form of a function or lookup table. If multiple tracking references are desired for an individual controller, multiple functions or lookup tables would be required that are activated based on conditions. With a NN, the data for multiple tracking references can be captured through initial training. With the addition of an integral controller at the local control variable, steady-state offset can be achieved and corrected for variations between the model and plant operations. This design is beneficial in that the model for the LQT can remain simple while still providing an optimized path for the controller to follow.

Soft computing methods also provide for consideration of operator experience. When a ventilation system requires rebalance by an operator, the most experienced will provide the smoothest transition of the plant. As the condition of the plant that mandates the rebalance can change, i.e., doors or hatches that are maintained open in the building can vary, a rule base formed from operator experience is key to controller implementation. This experience can be captured in a FL predictor of the most effective tracking references to implement in desired areas of the plant, depending on desired set point.

In this paper, a linearized state-space model for an HVAC plant with three cells and a corridor is obtained using differential form of the idea gas law in terms of pressure and flow. A traditional PID controller is first used and found to be inadequate for changes in plant parameters. Therefore, a hybrid design using the integration (fusion) of soft control methods (such as using neural networks (NN), fuzzy logic (FL)) with hard control methods (such as PID, LQT) is proposed for demonstration to account for the errors and nonlinearities. The performance of the resulting hybrid control strategy is demonstrated through simulation and experimental testing as compared to a representative PID controller. The proposed hybrid control strategy resulted in the development of attractive and useful software for the analytical solution of matrix differential Riccati equation arising in LQT methodology that is not currently available in commercial software packages such as MATLAB[1]®.

## 2. Design of Hybrid Controller

### *2.1 HVAC Model*

Fig. 1 depicts a simplified flow diagram of a HVAC plant with three cells and a corridor, a Supervisory Controller (SC), and local controllers (LC). The development of an LQT controller for maintaining pressure gradients starts with the development of a model for the HVAC system. Consider the three cell ventilation situation depicted in Fig. 1. A simple state-space model for pressure and flow was developed using a differential form of the ideal gas law [7]-[9].

[1] MATLAB is registered trademarks of The MathWorks, Inc.

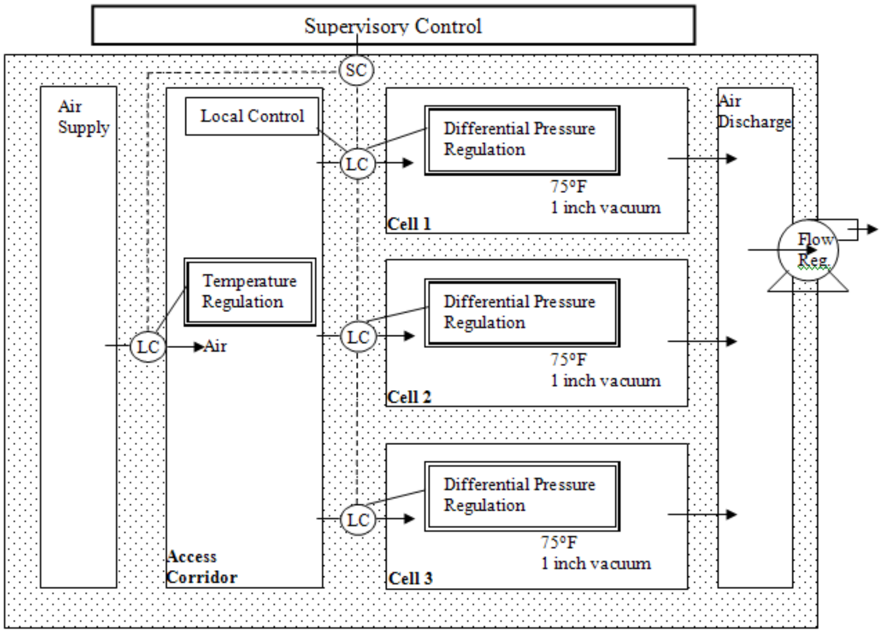


**Figure 1 A Simplified HVAC Plant**

Assuming little change in temperature, then linearizing for each cell:

$$\dot{x}_{(t)} = K_a x_{(t)} + K_b u_{(t)}, \qquad y_{(t)} = C x_{(t)}, \tag{1}$$

where:

*x(t)* - state vector, pressure,

*u(t)* - input vector, flow,

$K_a$, $K_b$ - constants, and

For the overall 3-cell system:

$$\dot{x}_{(t)} = K_{ta} x_{(t)} + K_{tb} u_{o(t)}, \qquad y_{(t)} = C x_{(t)}, \tag{2}$$

where:

$u_o$ - linear combination of cell inputs

$K_{ta}$, $K_{tb}$ - constants

Although only pressure has been mentioned as it is the primary state of concern in this paper, temperature must also be considered in the final hybrid controller. Wide swings in the temperature can cause discomfort and unacceptable working conditions for those that enter containment areas for work, especially considering the fact that those persons are often wearing personal protective equipment

(PPE). While many works have developed models for temperature control, the application of constrains for temperature in this work will be included in the FL tracking method [2, 10, 11].

The final state-space model for the ventilation system is obtained as follows:

$$\begin{bmatrix} \dot{x}1 \\ \dot{x}2 \\ \dot{x}3 \\ \dot{x}4 \end{bmatrix} = \begin{bmatrix} -19280 & 0 & 0 & 0 \\ 0 & -19280 & 0 & 0 \\ 0 & 0 & -19280 & 0 \\ 0 & 0 & 0 & -57840 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \\ x4 \end{bmatrix} + \begin{bmatrix} 5427 & 0 & 0 \\ 0 & 5427 & 0 \\ 0 & 0 & 5427 \\ 5427 & 5427 & 5427 \end{bmatrix} \begin{bmatrix} u1 \\ u2 \\ u3 \end{bmatrix}$$

$$\begin{bmatrix} y1 \\ y2 \\ y3 \\ y4 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \\ x4 \end{bmatrix} \tag{3}$$

*2.2 Linear Quadratic Tracking (LQT)*

The block diagram in Fig. 2 represents the hybrid controller scheme for controlling an HVAC system. The design involves the development of a global LQT controller, training of a NN with the LQT data, development of global FL tracking reference, and final combination with an integrator for local control.

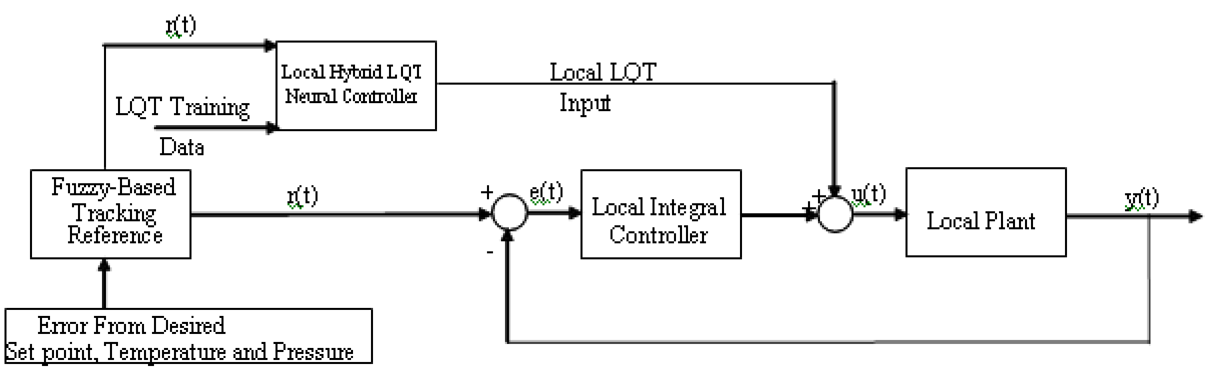


**Figure 2 Hybrid Controller Design Structure for HVAC Plant**

The resulting plant model is used to develop an LQT controller using recent results by the authors [7]. The normal state-space representation of a system is provided below

$$\begin{aligned} \dot{x}_{(t)} &= Ax_{(t)} + Bu_{(t)}, \\ y_{(t)} &= Cx_{(t)}, \end{aligned} \tag{4}$$

where $x$ is the n-dimensional state vector, $u$ is the r-dimensional input vector, and $y$ is the m-dimensional output vector, and $A$ *(nxn)*, $B$ *(nxr)* and $C$ *(mxn)* are matrices of appropriate dimensions and time invariant.

The objective is to minimize the error ($e$) between a time-varying tracking reference ($z$) and the output ($y$) [1, 12, 13]. The error vector is therefore defined as

$$e_{(t)} = z_{(t)} - y_{(t)} = z_{(t)} - Cx_{(t)}. \tag{5}$$

To minimize the tracking error and the expenditure of control effort, a performance index is chosen as

$$J = \frac{1}{2} e'_{(tf)} F e_{(tf)} + \frac{1}{2} \int_{t0}^{tf} [e'_{(t)} Q e_{(t)} + u'_{(t)} R u_{(t)}] dt, \tag{6}$$

where $F$ *(nxn)* is the positive semidefinite terminal cost weighted matrix, and $Q$ *(nxn)* are the positive semidefinite error weighted matrices, and $R$ *(rxr)* is the positive definite control weighted matrix.

The Hamiltonian canonical representation takes the form

$$\begin{bmatrix} \dot{x}^*_{(t)} \\ \dot{\lambda}^*_{(t)} \end{bmatrix} = \begin{bmatrix} A & -BR^{-1}B' \\ -C'QC & -A' \end{bmatrix} \begin{bmatrix} x^*_{(t)} \\ \lambda^*_{(t)} \end{bmatrix} + \begin{bmatrix} 0 \\ C'Q \end{bmatrix} z_{(t)}, \tag{7}$$

where $\lambda$ is the n-dimensional costate vector, and the corresponding Riccati equation as

$$\dot{P}_{(t)} = -P_{(t)}A - A'P_{(t)} + P_{(t)}BR^{-1}B'P_{(t)} - C'QC\mathbb{F} \tag{8}$$

with boundary condition at final time $t_f$, $P_{(tf)} = C'_{(tf)} F C_{(tf)}$, and the LQT vector differential equation

$$\dot{g}_{(t)} = [P_{(t)}BR^{-1}B' - A']g_{(t)} - C'Qz_{(t)}, \tag{9}$$

with boundary condition at final time $t_f$ $g_{(tf)} = C'_{(tf)} F z_{(tf)}$.

Solutions of these equations for the Riccati coefficient ($P$) and vector ($g$) are dependent on design parameters $Q$, $R$ and $F$ defined in the performance index. The resulting optimal closed loop LQT controller (u) takes the form

$$u_{(t)} = -R^{-1}B'P_{(t)}x_{(t)} + R^{-1}B'g_{(t)}. \tag{10}$$

Using the analytical solution to the matrix differential Riccati Equation and extending it to the LQT problems provides a technique for providing the controller and outputs for a given time period [7].

A special feature of the proposed work in this paper is the development of attractive and useful software for the analytical solution of matrix differential Riccati equation arising in LQT methodology that is not currently available in commercial software packages such as MATLAB®.

*2.3 Neural Network Based LQT*

The output and controller data can be used as training data set for a predictive controller. The resulting controller provides a useful and flexible alternative to developing a lookup table for the LQT data, which can accept different reference inputs and provide an LQT output. However, it must be noted that delays in the NN implementation make the resulting controller suboptimal [14].

With the cause-effect relationship between the inputs and outputs allows them to be paired, the NN will be implemented as local controllers [7, 15]. The NN technique used is based on the receding horizon technique. The NN model provides a control output over a specified time horizon, and is built into the MATLAB® control toolbox. The predictions are used by a numerical optimization program to determine the control signal that minimizes a given performance criterion shown below:

$$\sum_{j=N_1}^{N_2}(y_r(t+j)-y_m(t+j))^2+\rho\sum_{j=1}^{N_u}(u'(t+j-1)-u'(t+j-2)), \tag{11}$$

where $N_1$, $N_2$, and $N_u$ define the horizons over which the tracking error and the control increments are evaluated. The $u'$ variable is the tentative control signal, $y_r$ is the desired response and $y_m$ is the network model response. The $\rho$ value determines the contribution that the sum of the squares of the control increments has on the performance index.

The proposed NN is composed of three delayed inputs, three delayed outputs and three hidden layer neurons. Figures 3 and 4 depict the input and output data of the LQT and LQT-trained NN without disturbances, respectively. Note that the plant outputs are smooth at the beginning and endpoints, resulting from the NN optimization scheme smoothing LQT controller response. This is a positive result from the use of a NN for modeling of the LQT data, as compared to a lookup table, providing a better transition on startup and removing an undesired transition at the end. This is of more importance when considering limitations on the scale of instruments and movement of field devices with an experimental system, not to mention excessive wear of field devices.

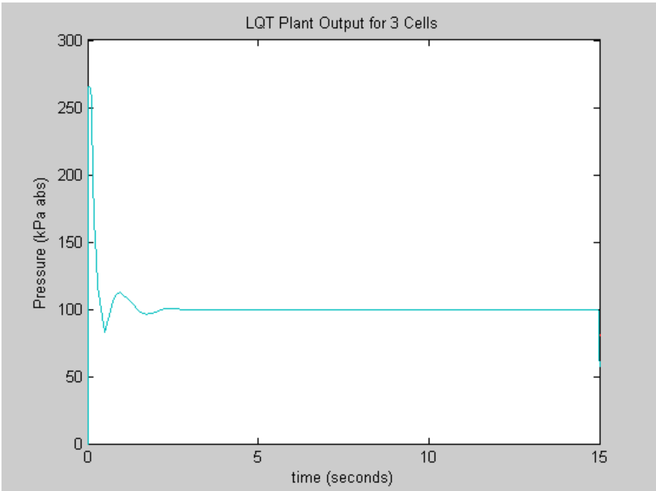


**Figure 3 Three Cell Plant Outputs with LQT Controller**

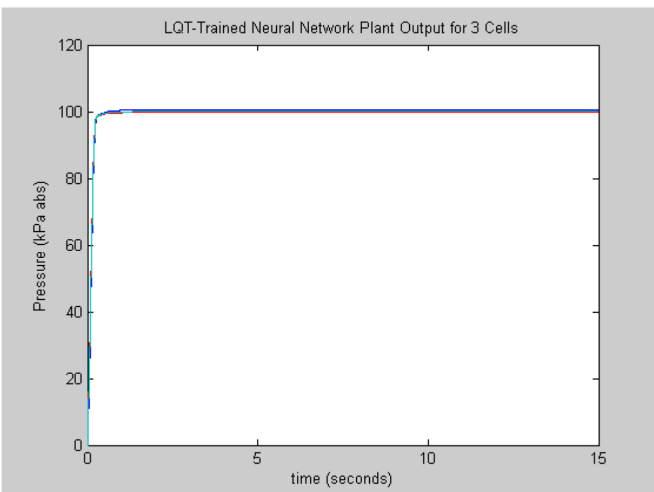


**Figure 4 Three Cell Plant Outputs with NN Controller**

For experimental implementation of the NN, a user developed add-on to Labview® is used, which is called aNETka and developed at Cardiff University [16]. The multilayer perceptron is fundamental NN that is applicable to modeling or mapping inputs to outputs, in similar vane to the simulation implementation, while providing a nonlinear activation function that is intended to replicate firing within the brain [17].

*2.4 Fuzzy Logic Based Tracking Reference*

Normally the reference trajectories that will be implemented for each control variable would be dependent solely on the layout of the HVAC flow balance. This method requires a significant modeling effort to account for plant nonlinearities that occur during many potential disturbance conditions. A much easier approach is to embed plant operations knowledge into a FL controller, which will also ensure that temperature control is factored in to the overall control scheme. This is crucial when plants have an upstream air-handling unit (AHU), which provides a single set point for the discharge temperature that feeds all the cells. For ease of implementation in MATLAB®, a Mamdani scheme is chosen.

The Mamdani FL scheme used has three outputs and six inputs, which includes for each cell, the error between the pressure and the desired set point and the same for temperature [18]. Triangular membership functions (MF) were used, with three MF on each of the three pressure error inputs, three MF on each of the three derivatives of pressure error inputs, five MF on the temperature error inputs and five MF on the three outputs. This arrangement allows for creating a rule base that grades the relative importance of pressure over temperature control, as any shift in pressure requires correction but small changes in temperature do not.

The rule base is designed to place higher priority on pressure error. In the case of simulations, the FL controller allows for multiple outputs and hence cell-to-cell interactions could also be tested. Therefore, an additional rule base was established to place priority on cell 1 pressure gradients over that of the other cells. In this way the control response to disturbances that affect each cell, such as the incoming pressure, would affect cells 2 and 3 more than cell 1. Tables 1 and 2 provide a listing of the 21 rules used.

**Table 1 Fuzzy Rule Base, Each Cell**

| Cell Pressure Error | Cell Pressure Derivative Error | Cell Temperature Error | Out |
|---|---|---|---|
| Low | Low | Ok | Low |
| Low | High | Ok | Ok |
| Ok | Low | Ok | ~Low |
| Ok | Ok | Ok | Ok |
| Ok | High | Ok | ~High |

| | | | |
|---|---|---|---|
| High | Low | Ok | Ok |
| High | High | Ok | High |
| Low | Ok | Low | High |
| Ok | Ok | Low | ~High |
| Low | Ok | High | ~High |
| Low | Ok | Ok | ~High |
| Ok | N/A | ~Low | Ok |
| Ok | N/A | ~High | Ok |
| High | Ok | Low | ~Low |
| High | Ok | Ok | ~Low |
| Ok | Ok | High | ~Low |
| High | Ok | High | Low |

**Table 2 Fuzzy Rule Base, Cell-to-cell Interactions**

| Cell 1 Pres. Error | Cell 2 Pres. Error | Cell 3 Pres. Error | Cell 1 Temp. Error | Cell 2 Temp. Error | Cell 3 Temp. Error | Out1 | Out2 | Out3 |
|---|---|---|---|---|---|---|---|---|
| Low | Low | Ok | N/A | N/A | N/A | High | ~High | Ok |
| Low | Ok | Low | N/A | N/A | N/A | High | Ok | ~High |
| High | High | Ok | N/A | N/A | N/A | Low | ~Low | Ok |
| High | Ok | High | N/A | N/A | N/A | Low | Ok | ~Low |

~High = Somewhat High
~Low= Somewhat Low

*2.5 Integral Controller*

An integral controller is placed on each cell to provide a zero steady-state offset. The contribution of this controller and the local NN controller is the input to the HVAC plant. The integral constant used is the same or smaller than that used with a PI implementation in a reference DOE plant, providing less integral “action.” Note that these same PI implementations provide the baseline for comparison to the hybrid design.

## 3. Simulation Results and Discussion

The results that follow are provided by a MATLAB® representation and simulation of the hybrid controller depicted in Fig. 2 [19]. LQT controller data and training of the NN occurred before the simulation of the hybrid controller. Step disturbances are injected into the system, which include two pressure step disturbances in cell 1, and two temperature step disturbances, also in cell 1. The set point for control is 100 kPa absolute (abs). The pressure disturbances are 50% of the normal gauge pressure and the temperature disturbances are 25% of normal. These were selected based on the type of disturbances expected in a reference DOE plant, albeit the pressure disturbances correlate better to a step than the temperature, which would more often be expected to be a ramp when a heat-generating process goes into operation. However, a step response provides a more effective tool at determining the performance of the controller. For this simulation it is assumed that the supply air is hotter than the cell air, such as in winter conditions.

Fig. 5 depicts the fuzzy tracker output based on the startup differential and disturbances. Due to the size of the error, the pressure gradient on the initial startup and the temperature disturbances cause a transition in the tracking output of the fuzzy tracker. The initial transition affects all cells, but the latter affects only cell 1 in line with the disturbance.

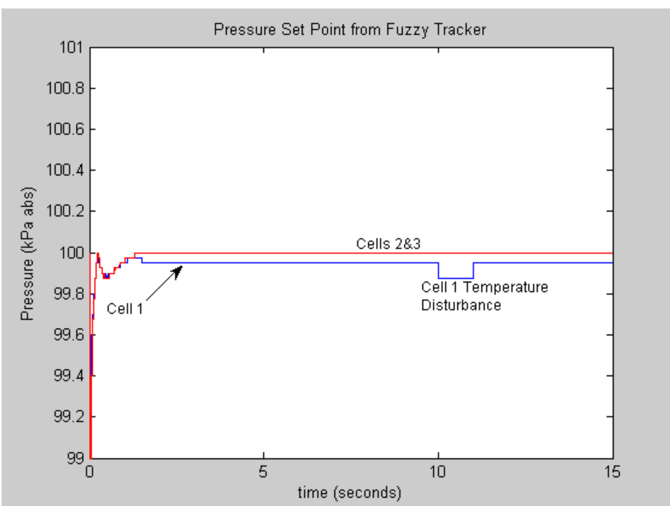


**Figure 5 Three Cell Fuzzy Tracker Output**

As the fuzzy tracker is essentially providing a supervisory or master controller design, the set points provided to the NN is important to guiding the actions of the plant. Between 2 and 10 seconds the fuzzy tracker does not give a response, which is desirable and prevents the NN controller from tracking unnecessary changes and minimizes control energy. Also note that the response for cell 1 is reduced from the other cells as a result of the prioritization relative to cells 2 and 3 to keep the pressure lower.

For comparison with the hybrid design, the same plant was simulated with PI controllers configured the same as a reference DOE plant. As the simple PI controller system is designed to look at pressure only on a local level, and therefore this scheme lacks the capability of the hybrid controller to consider temperature. Performance indicators for the response given by the PI and hybrid controller are provided in Table 3. These standard error measures include both the Integral of the Squared Error (ISE) and Integral of the offset Time multiplied by the Absolute Error (ITAE). The hybrid controller provided notable improvements over simple PI control, leveling off quicker on startup and quicker leveling for pressure variations. In response to the FL rule base, minor disturbances do not impact the tracking reference. This is also an appropriate application of the integral controller in the hybrid design, which ensures a zero steady state offset with minimal control energy. Similar offsets would be expected for modeling and measurement errors, and the primary reason for its inclusion in the hybrid controller design.

**Table 3 Simulation Controller Performance Indicators**

| Controller | Location | ISE | ITAE |
|---|---|---|---|
| PI Controller (Startup) | Cell 1 | 12400 | 11300 |
| | Cells 2&3 | 12400 | 10900 |
| PI Controller (Disturbances) | Cell 1 | .05 | 83 |
| | Cells 2&3 | 0 | 0 |
| Hybrid Controller (Startup) | Cell 1 | 4500 | 28 |
| | Cells 2&3 | 5300 | 16 |
| Hybrid Controller (Disturbances) | Cell 1 | 1.1 | 13 |
| | Cells 2&3 | 0 | 0 |

Figures 6-8 depict the pressure data for the three cell plant. As the fuzzy tracker rule base favors cell 1 pressure and therefore has a more aggressive response to out-of- specification conditions, it is noted that the initial response peak for cell 1 is somewhat reduced compared to the peaks for the other two cells. The pressure disturbances into cell 1, caused by an increase then decrease in flow, create an expected increase in pressure, then decrease. Temperature disturbances in cell 1 causes a direct response from the fuzzy tracker, as mentioned earlier, causing an immediate decrease in flow of hot air to the room resulting in cooling and a synonymous reduction in pressure. As the temperature disturbance goes away, the flow increases and the pressure immediately increases before stabilizing.

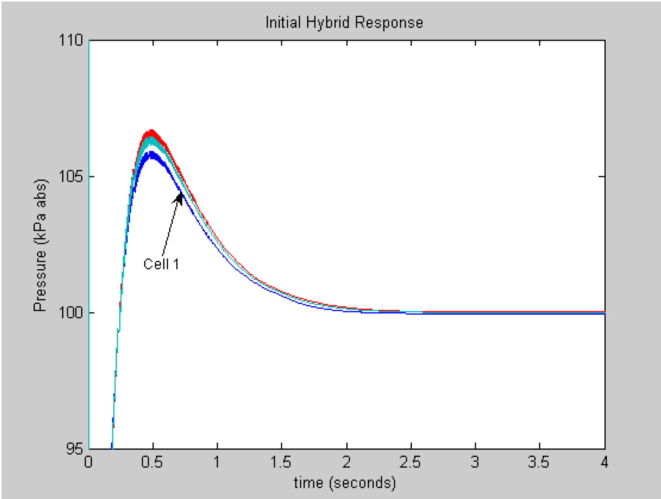


**Figure 6 Initial Hybrid Controller Response**

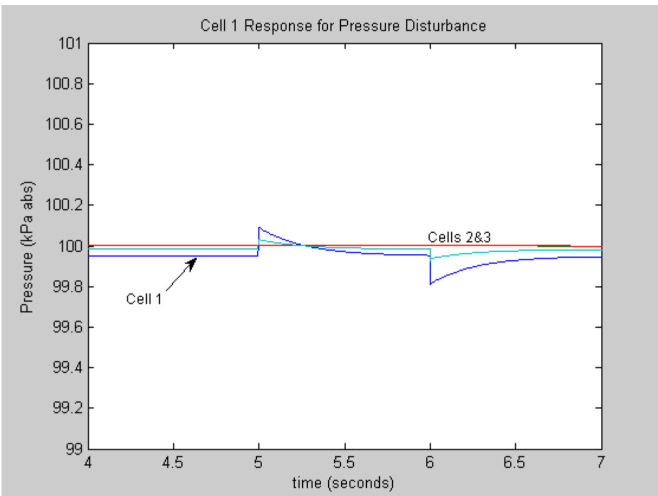


**Figure 7 Hybrid Controller Response for Pressure Disturbances**

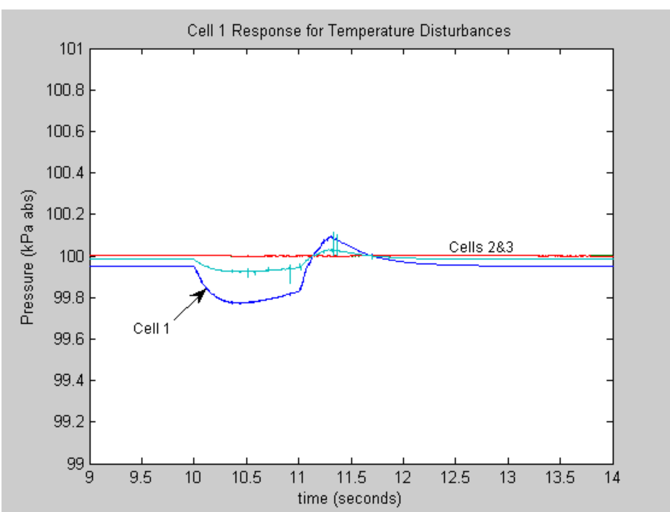


**Figure 8 Hybrid Controller Response for Temperature Disturbances**

## 4. Experimental Results and Discussion

An experimental system designed and instrumented after Fig. 1 was constructed to test performance of the hybrid controller, and is shown in Fig. 9. The set point for the three cells is 0.08 kPa vacuum (vac). The disturbances in these experiments are generated on cell 2, and comparable in size to the simulation. Typical experimental responses from the hybrid controller are provided in Figures 10-12. They indicate a quick transition for the startup and correction from the disturbances. Referring to Table 4, this result is confirmed, and the performance indicators suggest a large reduction in settling time from the PI controller for both the startup and pressure disturbances. The initial benefit of the startup gain from the NN LQT is minimized during the disturbance, as a larger portion of the control output response is provided by integral action.

The response from the temperature disturbances is subtle compared to the simulation, and the controller response necessary is minimal and stable. Therefore as long as the error in the pressure differential is maintained within the range of importance, adjustments can be made in the temperature of the cell through variation of airflow. The pressure affect of the FL rule change is small, but the actual change in the damper position can be 10% or greater. If greater regulation of air temperature from one AHU is quite limiting, a finer control would be achieved through a separate AHU for the areas of interest. As an option, higher airflow rates can be used in general to increase the heat transfer in the cell, and then the adjustments necessary for maintaining the desired occupancy temperature could be achieved with the FL design shown.

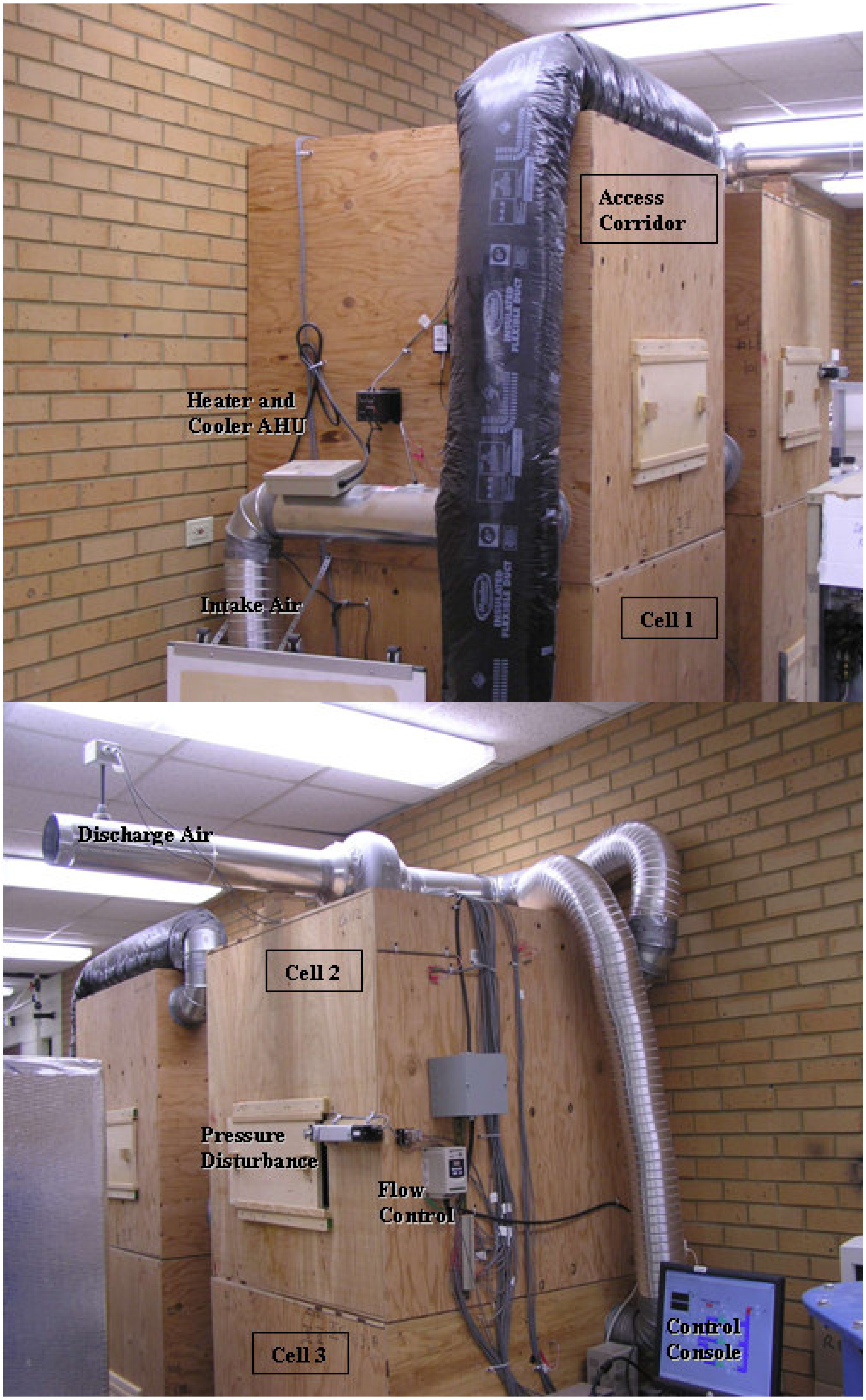


**Figure 9 Experimental HVAC System**

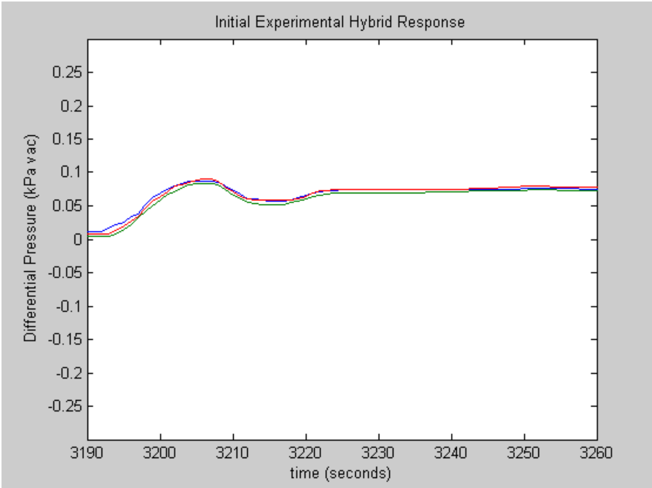


**Figure 10 Initial Hybrid Controller Response**

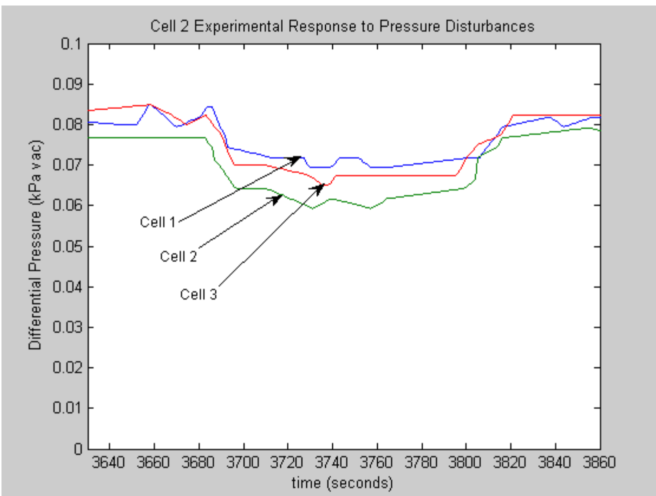


**Figure 11 Hybrid Controller Response for Pressure Disturbances**

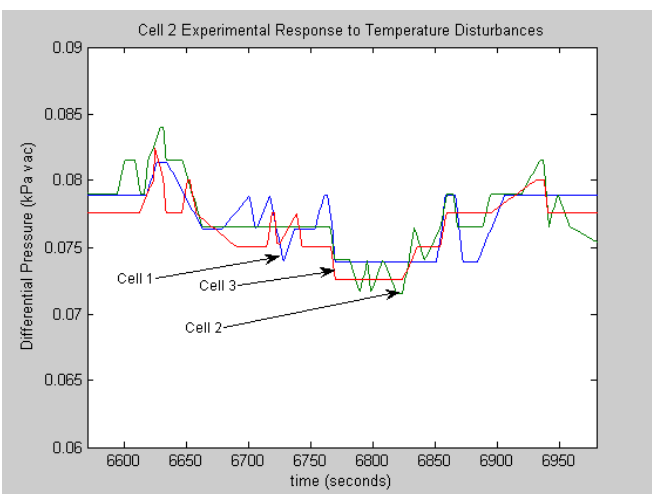


**Figure 12 Hybrid Controller Response for Temperature Disturbances**

**Table 4 Experimental Controller Performance Indicators**

| Measure | Cell | Mean ISE | Mean ITAE |
|---|---|---|---|
| PID Controller | | | |
| Startup | 1 | 2 | 4650 |
| Startup | 2 | 1.41 | 1786 |
| Startup | 3 | 1.44 | 2226 |
| P Disturbance | 1 | .083 | 668 |
| P Disturbance | 2 | .24 | 1170 |
| P Disturbance | 3 | .13 | 1110 |
| Hybrid Controller | | | |
| Startup | 1 | .59 | 62 |
| Startup | 2 | .71 | 90 |
| Startup | 3 | .73 | 78 |
| P Disturbance | 1 | .083 | 331 |
| P Disturbance | 2 | .26 | 608 |
| P Disturbance | 3 | .14 | 479 |
| T Disturbance | 1 | .024 | 159 |
| T Disturbance | 2 | .029 | 216 |
| T Disturbance | 3 | .025 | 202 |

For the purposes of achieving better control for traditional HVAC systems, several combinations of advanced control theory have resulted in a form of hybrid controller [2, 20]. By hybrid, combinations of soft computing and hard computing are used to achieve better comfort or efficiency, or in some cases the desire to regulate two process variables [21]. The hard computing methods include optimal control methods that attempt multi-input multi-output robust control designs that have been extended from simulation to experimental designs [22, 23]. Considering the traditional HVAC system from a reference DOE plant, the desire to capture what can be perceived as a better method of controlling these systems is clear, as are the limitations of PID control. While the benefits of each control technique in the form of a hybrid controller have been described in this paper, testing of the individual techniques was also performed. The results and comparisons of this testing is provided in Table 5, which provide a summary of startup and disturbance performance results for simulation and experimental testing of PID, fuzzy logic with and without derivative action, neural network and hybrid control methodologies. Reviewing the performance for the fuzzy, neural, and hybrid controller designs, it is clear that all provide advantages over the PID tuned as in the DOE facility. While it is possible that better tuning of an individual controller may improve performance of the individual cell, the cell-to-cell dynamics are a primary reason this is often avoided in these designs. Only with the consideration of the plant as a whole in a supervisory capacity can individual changes at the local level be considered and implemented, accommodating individual improvement without compromising the stability of the overall HVAC system [21, 23].

**Table 5 Experimental Testing Results of Intermediate and Final Hybrid Controller Design**

| Controller | Location | ISE | ITAE |
|---|---|---|---|
| PID Controller (Startup & Disturbances) | Cell 1 | 12400 | 11400 |
| | Cells 2&3 | 12400 | 10900 |
| PID Controller (Disturbances) | Cell 1 | 0.05 | 83 |
| | Cells 2&3 | 0 | 0 |
| Fuzzy Controller w/o derivative (Startup & Disturbances) | Cell 1 | 28 | 138 |
| | Cells 2&3 | 31 | 151 |
| Fuzzy Controller w/o derivative (Disturbances) | Cell 1 | 14.8 | 62 |
| | Cells 2&3 | 17.7 | 67 |
| Fuzzy Controller with derivative (Startup & Disturbances) | Cell 1 | 28 | 138 |
| | Cells 2&3 | 31 | 151 |
| Fuzzy Controller with derivative (Disturbances) | Cell 1 | 15.2 | 62 |
| | Cells 2&3 | 18 | 67 |
| Neural Controller (Startup & Disturbances) | Cell 1 | 4878 | 14.4 |
| | Cells 2&3 | 4878 | 12.6 |
| Neural Controller (Disturbances) | Cell 1 | 0.085 | 0.23 |
| | Cells 2&3 | 0 | 0 |
| Hybrid Controller (Startup & Disturbances) | Cell 1 | 4544 | 40.5 |
| | Cells 2&3 | 5326 | 15.5 |
| Hybrid Controller (Disturbances) | Cell 1 | 1.06 | 12.8 |
| | Cells 2&3 | 0 | 0 |

The neural controller design implemented provides a unique method for implementing an LQT design. The performance improvement achieved on startup is most noticeable. The benefit of this design is to consider HVAC system interactions within the model design. If greater interactions are recognized, the framework for implementing the resulting LQT controller is provided. The primary cost in developing a neural design is in the development of the plant model that is the basis for the LQT, and not the normal training required for plant dynamics for a traditional neural implementation

[20]. However, the traditional neural implementation does not result in an optimal controller, only a characterization of the current nonlinearities for the system.

The results confirm the benefits of a fuzzy logic design that can consider temperature and human comfort where differential pressure is the primary control characteristic. Like all plant designs, whether HVAC or another operation, the initial design of the plant equipment and associated parameters is important. If the air flow and heating/cooling capacity of the ventilation through a cell have been considered for the heat load of the equipment in the cell, such use of a fuzzy logic design could be beneficial. When available within an industrial controller design, fuzzy logic controllers that provide for multiple outputs to individual local controllers can be used to consider many cell-to-cell interactions and to prioritize the interactions. As the fuzzy logic is the supervisor in the hybrid controller, its ability to characterize operator knowledge is most appropriate. With existing HVAC plants and diverse unconnected PID controllers, an operator's knowledge is the only way to assure smooth transitions for major disruptions in HVAC changes, such as a hatch pull.

The hybrid design implemented in this research considers not only the benefit of these designs, but the practicality of implementation. The hybrid controller implemented in this research has two significant differences in that the NN controller is effectively an optimal design and the FL controller is implemented as a method of supervisory control. The implementation of the hybrid controller is performed using Labview®, which although is used for small control systems is used on full scale plants.

## 5. Conclusions

While energy efficiency is key to many advanced control designs in the area of HVAC, industrial facilities such as those in the DOE complex focus on pressure controls to prevent migration of hazardous substances. However, temperature controls must also be considered in the design, as personnel with PPE must enter these areas to perform maintenance tasks. Simple PID or PI designs do not consider the performance of the plant as a whole, or provide a global control. However, LQT controls can provide outstanding control for an entire plant. Implementation using a NN and FL inference system providing a tracking reference, the data provided have demonstrated that a hybrid controller can be implemented which focuses on the need to optimize global pressure control while still providing consideration of temperature effects [24]. Proper application of a rule base can ensure that the fuzzy tracker prioritizes the control responses to key control variables, while minimizing control energy. Inclusion of an integral controller can offset small disturbances and modeling errors in the LQT design, reducing the overall effort required by the hybrid controller.

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