ABSTRACT
This paper proposes an intelligent Resilient Control Strategy (RCS) for Model-based building control to improve the Building Automation System (BAS)'s performance against unanticipated adverse conditions or incidents such as model mismatch, weather disturbances, and component failures/faults. The concept of resiliency of the BAS in terms of Quality of Control (QoC) is quantified and realized by the proposed RCS which make use of building operation data obtained from the BAS and the signals from the external sensors to provide an accurate analysis and intelligent control decisions under each operating condition. For building simulations, a co-simulation platform with run-time coupling of Matlab/Simulink and EnergyPlus is developed and used to verify the feasibility and effectiveness of the proposed control strategy.

INTRODUCTION
The current trend of BAS control research is focusing more and more on model-based approach. For example, Model Predictive Control (MPC) has been used as an advanced control technology for BAS to achieve optimal control and low energy consumption (Yu and Dexter 2009; Zhang and Hanby 2005). However model uncertainty and other unanticipated adverse conditions/incidents are not addressed adequately by current MPC technology for BAS. Traditional robust control or adaptive control strategies can tolerate certain uncertainties (Wen and Liu 2009), but not effectively enhance recovery of the control system from unanticipated adverse conditions as well as emergency situations.

Recently, the term “resiliency” has been introduced into the automation and control area (Wei and Ji 2010). Many literatures discuss the definition, properties, measurements, research areas and possible applications of resilient control systems. One definition of the resilient control system is proposed (Rieger et al. 2009) as “… one that maintains state awareness and an accepted level of operational normalcy in response to disturbances, including threats of an unexpected and malicious nature”. This paper introduces this resilient control concept into the building automation and control area for the first time and characterizes the disturbance and adverse conditions as incidents which impact control system’s resiliency. The approach we present is to quantify the concept of resiliency of the BAS in terms of Quality of Control (QoC), where QoC of a BAS is defined to evaluate the control performance on energy efficiency and occupants comfort, i.e. temperature, humidity, and luminance etc.

This paper is organized as follows: The first part presents a brief description of an existing advanced model-based optimization control strategy. The next part illustrates the main functionalities of the proposed RCS and its sub-components. Then the co-simulation platform coupling Matlab/Simulink and EnergyPlus is introduced to implement the resilient control and simulate the results of RCS based building control. The paper finishes by indicating our current plans for future work.

MODEL-BASED BUILDING CONTROL STRATEGY
Integrated Control and Optimization Strategy for Energy Management
An advanced and integrated optimization strategy is developed that integrates building control with day-ahead load forecasts. This model-based control strategy incorporates MPC technology with building automation system and takes into consideration of weather forecasting data, energy price and occupancy model to achieve energy saving. Figure 1 shows the high level control diagram of this Energy Management Control (EMC) strategy.

MPC technology is by far the most effective advanced control strategy in a wide variety of process industries (Joe and Badgwell 2003). In the building automation and control area, computer simulation has enabled more detailed modeling and analysis of building energy system which makes Model-based advanced control strategy applicable. The widely used building simulation packages such as EnergyPlus and TRNSYS provide the necessary building modeling tools for MPC applications. Once the simulation of the building is available, the MPC specific models can be obtained through system identification.

Co-Simulation Platform
In this research, EnergyPlus is used as a virtual building for system identification and control test. A co-simulation platform shown in Figure 2 connecting Matlab and EnergyPlus with MLE+ (Nghiem 2011) is used for the control development and validation. By using MLE+, the EnergyPlus model of the building becomes an S-function block in the Matlab/Simulink. The main advantage of this co-simulation setup is that it takes full advantage of the Matlab/Simulink environment of interactive simulation, debugging, and all available Matlab toolboxes.
The model-based EMC using MPC technology is implemented in Matlab language and communicates to EnergyPlus via MLE+. The detailed simulation architecture for the model-based optimization control strategy is shown in Figure 3. The operation data from EnergyPlus includes building comfort information as well as the energy consumption profile which is taken as the feedback information for the EMC. The outputs from the EMC are supervisory control signals including set-points of zone temperature, humidity, luminance and schedules of building control devices such as HVAC equipments, operable windows and blinds.

The Matlab/Simulink layout of the simulation is shown in Figure 4. The building EnergyPlus model is wrapped as a function block. The Energy Calculation and Display block calculates and displays the energy consumption and the simulated values of building environmental variables.

RESILIENT CONTROL STRATEGY

Based on the existing MPC framework described in the previous section and following a proactive control paradigm, a Resilient Control Strategy (RCS) is proposed in this paper. This RCS is synthesized as augmentation of existing robust and adaptive control strategies by maintaining state awareness of the building systems and altering its operational envelop in real time to deal with adverse conditions/incidents and emergency situations. The engineering-time and run-time architecture of this RCS is shown in Figure 5. The main tasks during the engineering-time include system identification for MPC algorithm development and operation data training for RCS strategy generation as indicated in Figure 5. Modeling can be done via various approaches such as physical modeling, black-box modeling with system identification, and other modeling methods. Data training for RCS is performed by introducing failure modes into the building model and using the same input and output data used for MPC modeling. The main task during the run-time for RCS is Fault/Failure Detection, Diagnosis, Prediction, and Mitigation (FDDPM). The detailed component function description and operation is described as follows.

Figure 3 Simulation Platform
Prognostic Engine

The core of the proposed RCS is a component called Prognostic Engine as shown in Figure 5. The Prognostic Engine serves the purpose of capturing anticipated and unknown abnormal system behavior in both system level and subsystem level. It includes Detection Agent, Diagnostics Agent, and Prediction Agent, and implements prognostic algorithms. Detection Agent quantitatively measures system performance degradation and detects sudden system malfunction. It also localizes contributing source(s) of a certain failure or anomaly. Diagnostics Agent identifies the type of faults by interpreting the characteristic of the input-output patterns. Prediction Agent predicts the future behavior of the system, e.g., the possibility of cascading failures. The results from the
Diagnostics Agent and Prediction Agent triggers appropriate measures called resilient policy in the controller to mitigate the effects caused by the system malfunction and enhance system recovery. The building model required for MPC design is used to generate the training data for the prognostic algorithms used by the Prognostic Engine as well. The data training is done at the engineering time by using the PE engineering tool as shown in Figure 6. The RCS algorithm is implemented on top of an existing model based optimization control framework as described in previous section which has the simulation platform shown in Figure 3. The MPC modeling and controller design is not the focus of this paper and is not addressed in this paper.

**PE Model Training**
Data-driven models are adopted as the aforementioned agents of the prognostic engine. All model training, which can be time consuming, is done in the PE engineering tool. The trained models are used for run-time operation.

- Detection Agent is an unsupervised model trained using the data collected in normal operating conditions as the baseline. Newly collected data is compared with the baseline statistically and a distance measure is given to indicate the current system behavior. Larger distance indicates higher degree of the system degradation. Detect agent detects any abnormal behavior whether this anomaly is previously experienced or not. An unsupervised self-organizing map (Kohonen 1990) algorithm is adopted as the detection agent.

- Diagnostics Agent is a supervised model trained using both the data collected in normal operating condition and data collected close to catastrophic failures happen. The diagnostics agent detects the previously experience failures by giving a probability to each type of failure. The type of failure which has the highest probability is identified as the current failure type. A supervise self-organizing map is trained and a Gaussian mixture model (Liao and Lee 2009) is used to calculate the probability of each failure type.

- Prediction Agent is a statistic model which interprets the future system behavior by trending the related time series of features/variables that are monitored. A failure probability is calculated based the overlap of the predicted feature space and the normal feature space. The autoregressive moving average (Pandit and Wu 1993) model is used to predict the trend of the related features and a Gaussian mixture model is used to calculate the aforementioned overlap and the failure probability.

**Failure Modes**
In this paper, we mainly focus on component failure in the building control systems. Two component failure modes are considered in this paper.

1. Component degradation: The status of the component in between of the normal state and the failure state. The component can still function, but it is not at its best performance.
Component failure: The component has degraded into a state that its performance is not acceptable. The failure can be caused by a certain type of fault or a combination of several fault types.

Resilient Policy
The purpose of the resilient policy is to mitigate the adverse impact caused by the component failure. It consists of the following resilient strategies (Venkatasubramanian et al. 2010) which will be triggered by different PE run-time agents based on the failure modes:

1. Controller tuning
   This strategy adjusts existing control loops in a parametric way to compensate for the performance degradation caused by the component failure. This strategy is triggered when degraded component performance is detected by the Detection Agent and identified by the Diagnostic Agent.

2. Reconfiguration
   This strategy is applied when component failure is detected by the Detection Agent and identified by the Diagnostic Agent. This strategy will use alternative or redundancy, etc.

3. Fall back Procedure
   When specific component failure identified by Diagnostics Agent or predicted by prediction agent, the fall back procedure will select a predefined control procedure such as switching off the component or parts of the process, etc. This may help to isolate a problem and prevent further propagation of disastrous effects and help to guarantee a certain minimum level of performance.

Simulation Results

Simulation Setup
The proposed RCS enabled MPC Framework is implemented on the co-simulation platform described in a previous section. The simulation setup is shown in Figure 7. The small office building example (SmOffPSZ.idf) provided by the EnergyPlus is used as the virtual building test bed. This building example has 4 zones with independent HVAC systems: ZSF1 (Zone 1), ZNF1 (Zone 2), ZSF2 (Zone 3), and ZNF2 (Zone 4). In this paper, we consider each HVAC system has components with possibility of degraded performance and even failure. In the simulation, we simulate the following HVAC component failures: Air Supply Fan, Outside Air (OA) Damper, and Heating Coil. So the Monitored equipments in this example include 4 Air Supply Fans, 4 OA dampers, and 4 Heating Coils. The detection agent will detect abnormal data and the Diagnostic Agent will identify which component has problem and in which zone.

Simulation Result
The assumptions that are made for the simulation are described as follows:

- **Heating and cooling cases**: heating and cooling are two different use cases for the HVAC control system. Only heating case is chosen to run the simulation for clarity and simplicity.
- **Zone selection**: there are four zones in the building model. Zone 1 and Zone 2 are on a different floor from the floor where Zone 3 and Zone 4 are located. Hence, Zone 1 and Zone 2 can be assumed to be independent from Zone 3 and Zone 4. Different failure modes are simulated in both Zone 1 and Zone 2.

Weather condition and data selection: PE model training uses data simulated under weather condition from 01-02-2010 to 01-12-2010 of Pittsburgh, PA. The EnergyPlus model variables used for training are described in the following section. After training, the models are used for runtime prediction. Testing data that is linked to the trained PE models should be collected under similar weather condition patterns and similar set points. In the simulation, both nominal condition and failure conditions are simulated under the same weather condition and set points. In real cases, a pattern classification algorithm can be used to classify weather condition and set points into clusters. PE models should be trained separately within each cluster. Testing data should be classified by weather condition and set points and then linked to the right trained models for prediction.

- **Failure modes**: besides nominal condition, the failure modes that are simulated are:
  - Failure 1: Zone 1 Heating coil 1 efficiency degradation
  - Failure 2: Zone 1 OA damper 1 stuck 50%
  - Failure 3: Zone 1 Supply fan 1 degradation
  - Failure 4: Zone 2 Heating coil 2 efficiency degradation
  - Failure 5: Zone 2 OA damper 2 stuck 30%
  - Failure 6: Zone 2 supply fan 2 degradation

1) Data training for RCS
Anomaly detection model for detection agent is trained using the data collected in the nominal condition for both Zone 1 and Zone 2, which means the system is running with no fault. Diagnosis model for diagnosis agent is trained using data which includes nominal condition and different types of failure conditions and appropriate labeling of the data. The variables related to Zone 1 and Zone 2 are used for training and these variables provided by EnergyPlus are listed as follows:
The above variables are chosen based on the knowledge and experience of what impacts can be expected from those defined failures.

2) Runtime anomaly detection

After model training, the detection agent can be used to output run-time anomaly indicator, which is shown in Figure 8, when new data comes in. Lower anomaly indicator values indicate normal condition since the performance is close to the nominal baseline that is used to train the detection agent. High anomaly indicator values indicate possible degradation/failure may happen since the performance looks statistically significantly deviating from the baseline.
3) Runtime Diagnosis
As shown in the Figure 8, Failure 2 and 3 show similar level in terms of anomaly indicator values. Diagnosis function is triggered to differentiate failure types by given a probability of how likely a certain type of failure may happen. As proof of the successful diagnosis, the following Figures 9, 10, 11 and 12 show the differences of the input data in both nominal condition and failure condition, when diagnosis agent gives the highest probability to indicate a certain type of failure may happen. The following figures show the variables that are only associated with Zone 1. When failure happens in Zone 2, it shows similar patterns in the variables which are not shown here.

4) Runtime Prediction
If a certain type of failure is a gradual degradation process (e.g. OA damper stuck increases gradually), a prognostics model can be built to predict the degradation trend or remaining useful life if at least a set of run-to-failure dataset becomes available. However, the degradation process is usually very dynamic and it is not a trivial task to make a simulation close to real situation. Authors prefer not to simulate the entire degradation process, but to continue this research in the future work.

5) RCS Policy Simulation Results
If a certain type of failure is detected and diagnosed, appropriate resilient strategy can be triggered to maintain operational normalcy, e.g. the following strategies can be used when aforementioned Failures 1, 2 and 3 occurred:
Controller Tuning: Adjust zone temperature set-point or supply air temperature to compensate for the supply fan degradation (Failure 3). The result of zone temperature with and without this mitigation strategy is shown in Figure 13. It is clear that this RCS strategy maintains the system operational normalcy in terms of zone thermal comfort in the presence of Failure 3.

Reconfiguration: If implemented, reroute the outside air through a redundant air loop to compensate for the OA damper stuck fault (Failure 2) and schedule maintenance.

Fallback Procedure: For Failure 1, heating coil efficiency loss will cause significant energy loss and even break down of the total gas heating system, so this failed component should be switched off and then schedule maintenance before sudden total system break down happens.

Figure 13 Zone Temp. with Failure 3 Mitigation

CONCLUSION AND FUTURE WORK

A model prediction and prognostic engine based resilient control strategy for building automation and control system is proposed in this paper. Run-time component failure detection, diagnosis, prediction, and mitigation fit the concept of the resilient control with the aim to maintain an accepted level of operational normalcy in response to adverse conditions such as component failure. Co-simulation platform with MATLAB/SIMULINK and Energy+ are used to implement both the engineering-time configuration phase and the real-time operation phase of the BAS simulation and verify the feasibility and effectiveness of the proposed resilient control methodology.

The future work includes further investigating how to incorporate the model mismatch and emergency situations into the RCS framework. The consideration of resiliency of the control system to handle system model uncertainties will be useful to release the burden of accurate modeling of building processes and online tuning of controllers. More run-time simulations will be performed with this co-simulation platform to explore and verify more resilient strategies incorporating real-time weather data disturbances.

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