Hardware-in-the-Loop Simulation of a Distribution System with Air Conditioners under Model Predictive Control

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***Abstract*—Many have proposed that responsive load provided by distributed energy resources (DERs) and demand response (DR) are an option to provide flexibility to the grid and especially to distribution feeders. However, because responsive load involves a complex interplay between tariffs and DER and DR technologies, it is challenging to test and evaluate options without negatively impacting customers. This paper describes a hardware-in-the-loop (HIL) simulation system that has been developed to reduce the cost and impacts of evaluating the effect of advanced controllers (e.g., model predictive controllers) and technologies (e.g., responsive appliances). The HIL simulation system combines large-scale software simulation with a small set of representative building equipment hardware. It is used to perform HIL simulation of a distribution feeder and the loads on it under various tariff structures. In the reported HIL simulation, loads include many simulated houses and air conditioners and one physical air conditioner. Independent model predictive controllers manage operations of all air conditioners under a time-of-use tariff. Results from this HIL simulation and a discussion of future development work of the system are presented.**

***Index Terms*— Demand response, hardware-in-the-loop (HIL) simulation, home energy management system (HEMS), power system simulation, smart grids.**

I. INTRODUCTION

FLEXIBILITY is required to effectively manage distribution feeders with high penetrations of distributed energy resources (DERs) that provide variable generation [1]. Many have proposed responsive loads that can participate in demand response (DR) programs and/or can be controlled by an energy management system to optimize the customer's comfort and expense as a viable option to provide flexibility to the grid [2]–[4]. Responsive loads are expected to have a significant impact on the operation of the distribution grid. However, while many simulation studies have been performed to estimate the impact of high penetration of rooftop photovoltaic (PV) systems on distribution systems [5], [6], the complex interplay between tariffs and DER and DR technologies makes it challenging to test and evaluate proposed responsive load implementations [1].

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This paper describes a hardware-in-the-loop (HIL) simulation system designed to evaluate the impact of emerging technologies on the electric power system. Technologies include DERs such as renewable generation and storage; advanced controllers such as model predictive controllers; and responsive appliances. HIL simulations have been used extensively in related fields, such as in evaluating smart inverter operations [7]. HIL simulation allows us to evaluate performance of actual hardware systems within the context of a specific distribution grid with high penetrations of new technologies without impacting customer service—which would happen with a pilot field deployment. We can simulate events and conditions that would be impossible or prohibitively expensive to set up in the field. We can also simulate various existing and proposed tariff structures and evaluate how financial incentives drive responses.

In this paper, we report on the use of this system for a HIL simulation of a distribution feeder with multiple buildings and their loads—including air conditioners whose operations are managed by model predictive controllers under a time-of-use (TOU) tariff—with the air conditioner for one house implemented in hardware. The capability to perform HIL simulations with an air-conditioning system and other building loads are likely to improve evaluation of the impact of building technologies distributed at scale in distribution systems. By combining large-scale software simulation with hardware evaluation of a small set of representative systems, the cost and time investment of an impact study can be reduced compared to separate simulation-only studies and pilot field deployments.

Past research using HIL for buildings have typically focused on single homes using simplified building thermal models. HIL simulation for validating building technologies was proposed in [8], where an HIL test bed based around an RT-LAB real-time simulator was used to assess the cost and thermal comfort performance of an energy management system. That analysis used a relatively simple second-order thermal model of the building's thermal properties and a resistive load to emulate the electric heater. A more sophisticated building model was used in [9], along with a custom configured cluster of personal computers to manage the real-time simulation, and a custom-developed power electronics converter to interface the real-time simulator and the heat-pump hardware under test.

The system described here advances the state of the art by extending the simulation scope to a HIL house interacting with a distribution system model that simulates a large number of homes. Therefore, one can evaluate the performance of hardware and an energy management system within a single home, but also, the grid-level impacts and interactions.

The rest of the paper is organized as follows: section II describes the HIL simulation system, section III presents results, and section IV draws conclusions and discusses future work.

II. Hardware-in-the-Loop Simulation System

A. Overview

A high-level block diagram of the HIL simulation system is shown in Figure 1. It consists of a large energy system simulation running on NREL's high-performance computer (HPC), Peregrine, which is interfaced to the hardware under test—a home air conditioner—through an internet-connected thermostat and lab data acquisition system.

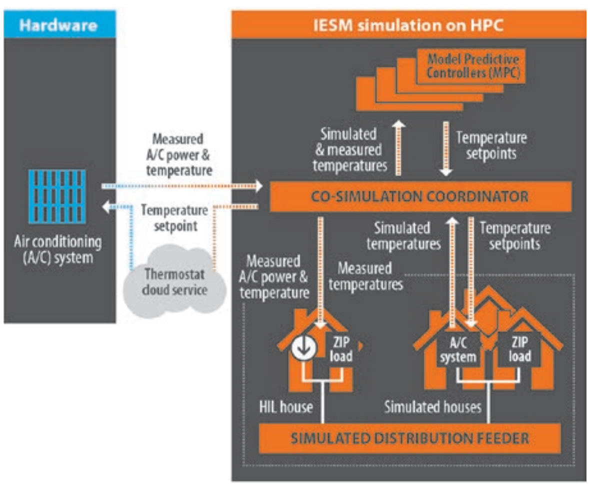

Figure 1. High-level block diagram of HIL simulation system

The Integrated Energy System Model (IESM) provides a co-simulation framework that integrates simulation of a distribution feeder, buildings (including thermal performance and building appliances), DERs (including PV and battery systems), and controllers such as a home energy management system (HEMS) [10], [11]. It is designed to run in an HPC system to allow the parallel execution of hundreds of instances of complex controllers—for example, HEMS algorithms based on a model predictive control (MPC) approach [12]. Smaller-scale simulations can be run on a single computer.

The co-simulation coordinator is implemented using the Discrete Event Systems (DEVS) formalism [13], which is built on the concept of abstract time. The co-simulation coordinator manages the timing of the execution of all the components with varying time steps and the exchange of data between them. It therefore interfaces with the distribution feeder simulation, building simulations of the simulated houses, the model predictive controllers, and the building simulation and physical air-conditioning system of the HIL house.

The HIL simulation system described here was developed as part of a research effort to investigate the impact of a high penetration of MPC-based HEMS on a distribution feeder, with an initial focus on control of air-conditioning systems under TOU tariffs [10], [14]. Air conditioning was chosen because it is one of the dominant residential load classes [15]. As part of our simulation-only studies [10], [14], we built a model of a distribution feeder with multiple residential buildings. The thermostat in each house can either be controlled by a predetermined setpoint profile that reflects the occupants' desired temperature profile, or by a setpoint received from the model predictive controller (MPC) for that specific house. For this paper, each house received temperature setpoints from its own model predictive controller.

The building simulations estimate the indoor temperatures and provide those values to the model predictive controllers as inputs for their next optimization. For one of the houses, referred to as the HIL house, the simulated air conditioner and thermostat were replaced with hardware and interfaced with the IESM simulation on the HPC through a network message bus.

For the HIL house, which has hardware and software components, the model predictive controller provides a setpoint through a cloud service application programming interface (API) to a real thermostat that controls the hardware air conditioner. The measured indoor temperature and air conditioner power consumption are returned to the model predictive controller and building simulation for the next iteration within a simulation scenario.

Each component is described in more detail in the following sections.

B. Distribution Feeder and Building Simulation

In its current implementation, GridLAB-D is used to simulate the electric power distribution feeder and the residential buildings. GridLAB-D is an open-source, agent-based, quasi-steady-state time-series (QSTS) power system simulation tool developed by the Pacific Northwest National Laboratory [16]. The house objects in GridLAB-D include explicit thermal models of the air-conditioning system, comprising a thermal model of the house, air conditioner (A/C), and thermostat; other building loads are modeled as an aggregated load using a ZIP load model [17].

The distribution system case-study used for the simulation is the IEEE 13-node feeder [18], populated with 20 identical houses, connected in groups of five through a single-phase center-tapped transformer (CTTF) at four nodes, shown in Figure 2.

Each house has its own desired cooling setpoint profile that includes a setup at night and at mid-day in accordance with Environmental Protection Agency guidelines [19].

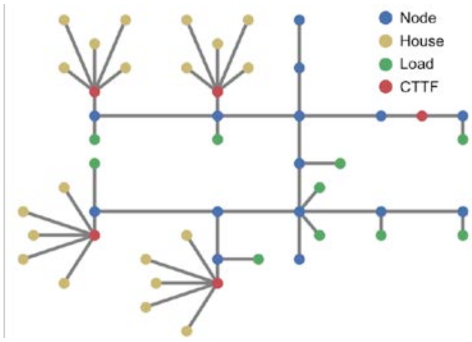

Figure 2. Diagram of IEEE 13-node feeder populated with 20 houses

C. Air-Conditioning System

The single air-conditioning system's hardware implementation involved a separate form of HIL, shown in Figure 3, to ensure that the air conditioner operated realistically without being in a physical house. An EnergyPlus [20] building model was run with one-minute time steps for a house that mirrors the single home specifications in GridLAB-D. The EnergyPlus model calculated changes to the indoor temperature as the air conditioner turned on and off using the building's modeled characteristics and internal loads and, the weather data used the GridLAB-D model.

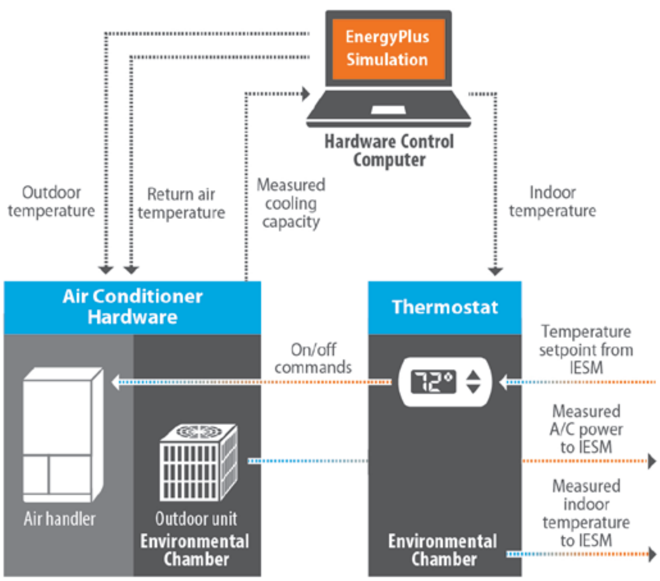

Figure 3. Air-conditioning system

A SEER 21, two-stage, 2-ton air conditioner was used. The outdoor unit was located inside an environmental chamber whose temperature was controlled to match the outdoor temperature in the weather file. The air-handler portion of the air conditioner was installed in a duct loop with heaters to ensure that the return air temperature matched that predicted by the EnergyPlus simulation. The air flow supplied by the air handler along with return and supply air temperature measurements were used to calculate air conditioner cooling capacity, which was used by the EnergyPlus simulation instead of that of a simulated air conditioner.

A Nest thermostat, located in a small environmental chamber, controlled the air conditioner. The air temperature inside the small environmental chamber was controlled to match the indoor temperature from the EnergyPlus simulation.

The thermostat's setpoint was determined by the house's model predictive controller and communicated to the Nest thermostat via the Nest cloud [21]. A data acquisition system collected the measured indoor temperature from the small environmental chamber and measured air conditioner power consumption, and that information is communicated to the IESM co-simulation running on the HPC.

D. Model Predictive Controllers

The model predictive controllers that determine the optimal temperature setpoints are based on HEMS algorithms previously developed by our team [12]. The HEMS algorithms implement a stochastic, multi-objective optimization model within a MPC framework, which determines the optimal operational schedules of residential appliances including heating, ventilation and air-conditioning systems, electric water heaters, refrigerators, residential batteries, electric vehicles, standalone micro combined heat and power generators, dishwashers, washer dryers, and pool pumps.

The algorithms take into account consumer preferences, electricity price, weather forecasts, and forecasted power generation from rooftop PV systems. The optimization is solved using a mixed-integer linear programming (MILP) approach. For this HIL simulation, only the cooling setpoints were optimized and the objective function was set to minimize the weighted sum of occupant discomfort and energy cost. The desired cooling setpoint is provided as an input to the model predictive controllers, along with a minimum and maximum allowable setpoint to keep the house comfortable as the controllers vary the setpoint.

The model predictive controllers are implemented in the General Algebraic Modeling System (GAMS), which calls on a Gurobi solver. The model predictive controllers run every 15 minutes, so an optimized setpoint for each house is updated every 15 minutes.

The model predictive controller uses a thermal model of the house to estimate the impacts of air-conditioning system operations. Specifically, the thermal model predicts the house's indoor air temperature and the air-conditioning system's electrical power consumption. Based on prior work [22], [23], a first-order difference equation is used as the thermal model:

$$T_{room}[k+1]-T_{room}[k]=\alpha_1\left(T_{out}[k]-T_{room}[k]\right)+\alpha_2 P_{a/c}[k] \quad (1)$$

where T_{out} is the outside air temperature, T_{room} is the indoor air temperature, and $P_{a/c}$ is the air conditioner's electrical power consumption. The coefficients for the model were determined by performing a linear regression on training data from a 2-week portion of simulated data generated by GridLAB-D for the fully simulated houses. A similar approach was used to extract the parameters for the HIL house from data generated with EnergyPlus [20] using the same house model as in the air-conditioning system.

To assess its accuracy, the model was used to predict room temperature and power consumption of the air conditioner over twenty successive 24-hour intervals starting from the end of the training data period. The root-mean-square-error (RMSE) between the predicted values and the simulated values were computed every 15 minutes, over each 24-hour interval (i.e., 96 increments per interval). The mean air conditioner power consumption RMSE was ±0.20 kW and the mean indoor air temperature RMSE was 1.1°F. These precisions substantiate the use of the first-order model.

E. Co-Simulation Coordinator

The IESM employs a distributed real-time discrete event modeling and simulation paradigm. To adhere to Systems Theory and ensure the direct connectivity between various components, we employ DEVS formalism [13], as described in more detail in [11]. Per the simulation protocol, in each iteration: 1) The DEVS coordinator requests the time of the next event (t_n) from each of the components; 2) The DEVS coordinator determines a future time that all the components should advance to (t_{adv}) by selecting the minimum time of the next event, and broadcasts it to all the components; 3) Each of the components then advances to t_{adv}, updates their internal clocks (through the DEVS model wrappers described in [11]) and executes any code or input events; and 4) Each component shares output messages. The structural relationships between the components of the system, including the physical components of the experimental setup—the HPC, air conditioner, and thermostat—are illustrated through a UML component architecture diagram available in [11].

Before attempting the actual HIL integration, a software-only simulation was executed in virtual time on the HPC [11]. Then the HIL simulation system was implemented by developing APIs to interface with hardware components, e.g., the Nest thermostat; developing a network messaging platform using ZeroMQ to exchange messages between the HPC, the air-conditioning system, and the Nest cloud; and developing read-write policies (e.g., polling frequencies, pushing data from hardware into databases) for various components as they exchange messages in real time.

As described in section II.D, the IESM simulation is run on the HPC, and one house's modeled air conditioner and thermostat are replaced with a physical air conditioner and thermostat. A data acquisition system collects data from the air-conditioning system at 5 Hz. An asynchronous message bus (implemented using ZeroMQ's publish-subscribe formalism) is used to exchange data between the hardware system and the simulation system through the co-simulation coordinator. The message bus subscribes to data from the data acquisition system at 5 Hz and publishes to the simulation system at 1 Hz. An in-memory database in the HPC also subscribes to the published data at 1 Hz for post-simulation analysis and verification.

The measured air conditioner power data are averaged over 1-minute intervals and are used instead of the simulated air conditioner power, thereby integrating the physical air conditioner with the simulated house. A new setpoint is then calculated by the model predictive controller and relayed through the Nest cloud service to the Nest thermostat.

III. Hardware-in-the-Loop Simulation Results

Several HIL simulations lasting from several hours to several days were performed and results are presented here.

A. Simulation Parameters

For the simulation case study presented here, we used outdoor air temperature and solar irradiation for a typical meteorological year for Charlotte, North Carolina [24]. These data are used by both the GridLAB-D and EnergyPlus building simulations. For the HIL house, we selected a desired cooling setpoint profile with a daytime temperature of 74°F that is set at 6:45 a.m. It is set up by 3°F to 77°F at 8:15 a.m., returning to 74°F at 5:45 p.m. It is set up by 6°F to 80°F at 10 p.m., where it remains through the night to 6:45 a.m. Simulated houses have similar setpoint profiles but they vary in desired temperatures and time when modes are shifted.

We used the weekday retail residential TOU electricity tariff available in North Carolina in 2015. The electricity price varies over the day with an off-peak rate of \$0.06936/kWh, a shoulder rate before the peak of \$0.11961/kWh, a peak rate of \$0.2368/kWh, and a shoulder rate after the peak of \$0.1523/kWh. The peak hours are from 1:00 p.m. to 6:00 p.m. and shoulder rates are in effect during the two hours before and after the peak hours [25]. Vertical shaded areas in Figure 4 indicate peak and shoulder pricing time periods.

B. Simulation Results

The compiled results from two separate experiments are shown in Figure 4 for a simulation time period from 9:00 a.m. on July 15 through 9:00 a.m. on July 19—thus, a total of 4 days. The vertical line at midnight between July 16 and 17 indicates the end of the data from the first simulation and the start of the data from the second simulation. More detailed results for July 17 are also shown.

We can see that the measured indoor temperature drops below the desired cooling setpoint to the minimum allowable setpoint prior to an increase in price (from off-peak to shoulder pricing and from shoulder to peak pricing) because the air-conditioning unit turns on. After the price increase takes effect, the indoor air temperature increases because the air conditioner turns off. The indoor air temperature also increases prior to a price reduction (from peak to shoulder pricing and from shoulder to off-peak pricing), and drops after the price reduction.

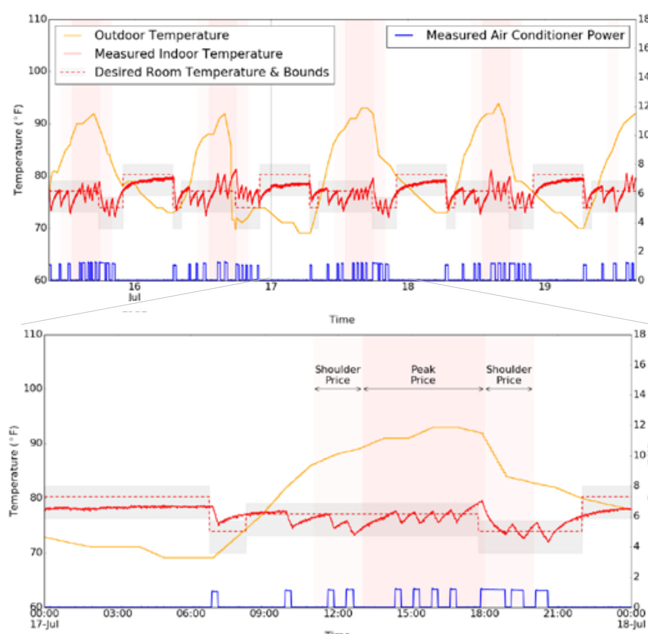

Figure 4. HIL simulation result with the different lines described in the legend. Vertical shaded areas represent shoulder and peak pricing.

This behavior is a result of the MPC-based optimization performed by the HEMS. It anticipates the price increase and precools the house—to the extent allowed by the constraints placed on the thermostat set points—prior to the price increase. As a result, the air conditioner power consumption increased at the end of the lower-price periods and decreased at the start of the higher-price periods, and this leads to lower energy cost while maintaining customer comfort. Similarly, the HEMS allows the indoor air temperature to rise—to the extent allowed—prior to the price reduction and this decreases air conditioner power consumption at the end of the higher-price periods. Then the air conditioner is turned on at the start of the lower-price period to drive the indoor air temperature closer to the desired cooling setpoint. The behaviors of the simulated houses were similar.

The control of the air conditioner depends on the weights assigned to the HEMS objective components. A higher weight for discomfort would cause a smaller deviation in indoor air temperature from the desired temperature profile during peak price periods, but the cost savings would be lower.

IV. Conclusions and Future Work

In this paper, we presented a hardware-in-the-loop (HIL) simulation system designed to evaluate the impact of emerging technologies on the electric power system—with a focus on responsive load because the complex interplay between tariffs and demand response technologies makes it challenging to test and evaluate proposed responsive load implementations. We presented results from an experimental setup that connects a real air conditioner and thermostat to the Integrated Energy System Model (IESM) co-simulation framework running on the high-performance computer at the National Renewable Energy Laboratory. This work represents the initial steps toward full smart home HIL capability that will include responsive and conventional appliances, distributed energy resources, and a home energy management system.

The experimental results presented show that all the components of the HIL simulation system work together seamlessly and the overall system behavior is as expected. Next steps are to add more appliances and to connect the appliances (including the air conditioner) to a controllable power source, which regulates their input voltage to that of the point of common coupling, where the house is connected in the simulated distribution system. We will also extend the IESM co-simulation platform to allow control of additional simulated and hardware appliances from the model predictive controllers.

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