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Foresee: A user-centric home energy management system for energy efficiency and demand response

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HIGHLIGHTS

- A user-preference-driven home energy management system called **foresee** is proposed.
- **Foresee** learns the preferences and needs of the occupants and acts on their behalf.
- **Foresee** predicts future comfort needs, energy costs and grid service availability.
- **Foresee** optimizes how a home operates to concurrently meet the occupants' needs.
- **Foresee** is built upon lightweight algorithms for deployment on embedded platforms.

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ABSTRACT

This paper presents foresee™, a user-centric home energy management system that can help optimize how a home operates to concurrently meet users' needs, achieve energy efficiency and commensurate utility cost savings, and reliably deliver grid services based on utility signals. **Foresee** is built on a multiobjective model predictive control framework, wherein the objectives consist of energy cost, thermal comfort, user convenience, and carbon emission. **Foresee** learns user preferences on different objectives and acts on their behalf to operate building equipment, such as home appliances, photovoltaic systems, and battery storage. In this work, machine-learning algorithms were used to derive data-driven appliance models and usage patterns to predict the home's future energy consumption. This approach enables highly accurate predictions of comfort needs, energy costs, environmental impacts, and grid service availability. Simulation studies were performed on field data from a residential building stock data set collected in the Pacific Northwest. Results indicated that **foresee** generated up to 7.6% whole-home energy savings without requiring substantial behavioral changes. When responding to demand response events, **foresee** was able to provide load forecasts upon receipt of event notifications and delivered the committed demand response services with 10% or fewer errors. **Foresee** fully utilized the potential of the battery storage and controllable building loads and delivered up to 7.0-kW load reduction and 13.5-kW load increase. These benefits are provided while maintaining the occupants' thermal comfort or convenience in using their appliances.

1. Introduction

The evolving electrical grid is facing increasing challenges. High penetrations of intermittent renewable energy, fast-growing and variable demand, and new pricing and market structures are all changing the way the grid has traditionally operated. Although developing solutions from the generation and grid perspective can alleviate some of these challenges, analyzing the contribution and control of the demand side can also provide a powerful perspective to address these grid-level issues. Residential buildings in particular account for a higher electricity consumption in the United States than any other sector, including commercial buildings, industrial buildings, and transportation [1]. Within the residential buildings sector, space heating and cooling, water heating, and wet cleaning are among the top end-use types and account for about half of the sector's total electricity consumption. These loads can be coordinated and scheduled to improve building energy efficiency (EE) or provide grid services such as demand response (DR) at the request of the utilities.

Home energy management systems (HEMS) enable the coordination and scheduling of building equipment according to certain performance

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Nomenclature

Acronym

DR	demand response
EE	energy efficiency
MPC	model predictive control
HEMS	home energy management system
HVAC	heating, ventilation, and air conditioning
PV	photovoltaic
SOC	state of charge
RBSA	residential building stock assessment
MIP	mixed-integer programming
TCL	thermostatically controlled load
DER	distributed energy resource

Parameters

α	coefficient of the battery cycling fading
γ	coefficient of the house model
β	weighting factor of user preferences
UA	surface heat loss coefficient (W/K)
η	efficiency
C	heat capacity or thermal capacitance (J/K)
H	prediction horizon in model predictive control
c_e	utility rate of electricity ($/kWh)

Variables

J	total objective function
T	temperature (°C or °F)
P	power consumption $(+)$ or generation $(-)$ (W)
Δm	flow rate of water draws (kg/s)
SOC	battery state of charge (%)
E_e	solar irradiance (W/m^2)
U	control variable of building equipment
Φ	objective function for a single objective
I	binary indicator for a scheduled cycle
ET	elasped time from the scheduled start of a cycle
RT	average runtime (prediction steps) of an appliance
t	time step in model predictive control

Subscripts and superscripts

dhw	domestic hot water
wh	water heater
dw	dishwasher
out	outdoor condition
unctrl	uncontrollable electrical loads
cd	clothes dryer
grid	net power from the electrical grid
low	lower node of a water heater
up	upper node of a water heater
bat	battery
in	indoor condition
c	cooling mode of HVAC
h	heating mode of HVAC
min	minimum allowable value
max	maximum allowable value
dis	battery discharging
ch	battery charging
nom	nominal value
app	home appliances
conv	user convenience
cmft	thermal comfort
dgrd	equipment degradation
cost	energy cost
carbon	carbon dioxide emission
load	building loads
Ah	ampere-hour throughput of a battery

criteria. These systems can improve the efficiency, economics, and reliability of residential buildings with regards to their occupants and the grid. Because of these benefits, HEMS have been a target of considerable recent research. A comprehensive review of the various types and categories of HEMS can be found in [2].

Rule-based methods such as "if-then" rules [3,4] are widely used in current HEMS because of their simplicity and low computation load. However, these control strategies may be oversimplified and lack look-ahead capabilities for predictive controls. Advanced HEMS usually involve optimization techniques, such as mixed-integer programming (MIP) [5–12], dynamic programming [13], or genetic algorithms [14]. Although these methods are able to solve more sophisticated scheduling problems, many of them have practicality issues and may not be feasible for implementation on resource-constrained computing platforms that would typically be deployed in an actual household. For example, MIP techniques include binary variables in the optimization process to represent the on/off characteristics that can be found in most home appliances, but the inclusion of mixed-integer variables renders the resulting optimization problem nonconvex, and may require the use of an expensive or computationally intensive commercial optimization solver.

Many HEMS are able to communicate and coordinate with the electrical grid, usually in the form of demand response or incentive signals [2,4,5,8–11,15]. DR programs engage users by reducing or shifting the electricity usage during peak periods to balance the demand and supply in the grid. Pilot DR programs include time-based pricing and direct-load control. In direct-load control programs, utility companies or aggregators cycle home appliances, such as air conditioners and water heaters, on and off during peak demand periods in exchange for a financial incentive and lower electric bills for the consumer. A review of existing residential DR techniques with a specific view on pricing signals and optimization solvers was provided in [16] and the performance of these techniques was compared using multiple criteria. In [17], the residential appliances were categorized into different types based on their distinct spatial and temporal operation characteristics, and optimization methods were explored to decide the optimal scheduling of residential appliances for DR using MIP.

In contrast to many building loads, battery storage systems have unique characteristics such as high flexibility and quick response, and are becoming attractive DR assets because of the rapidly decreasing battery cost [18]. Home battery systems help unlock the DR potential of many building loads that would otherwise not be able to provide DR services as a result of thermal comfort constraints. With home battery systems, building loads could be easily shifted to avoid the peak demand as well as improve the self-consumption of photovoltaic (PV) generation. In turn, building loads and PV help reduce the battery size while meeting the needs of end users and utilities. Because of the higher availability and reliability of the DR resources enabled by a home battery system, utilities are likely to provide greater incentives to offset the initial capital cost of the battery. Prior residential DR research has used either building loads [16,17], battery storage in the form of stationary storage or electric vehicles [5,19], or both [8,12,20,21]. However, if not properly controlled, home battery systems can increase the overall energy consumption and electricity system emissions resulting