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Optimal joint scheduling of electrical and thermal appliances in a smart home environment

Elham Shirazi, Alireza Zakariazadeh, Shahram Jadid *

Center of Excellence for Power System Automation and Operation, Dept. of Electrical Engineering, Iran University of Science and Technology, P.O. Box: 1684613114, Tehran, Iran

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ABSTRACT

With the development of home area network, residents have the opportunity to schedule their power usage in the home by themselves aiming at reducing electricity expenses. Moreover, as renewable energy sources are deployed in home, a home energy management system needs to consider both energy consumption and generation simultaneously to minimize the energy cost. In this paper, a smart home energy management model has been presented in which electrical and thermal appliances are jointly scheduled. The proposed method aims at minimizing the electricity cost of a residential customer by scheduling various type of appliances considering the residents consumption behavior, seasonal probability, social random factor, discomfort index and appliances starting probability functions. In this model, the home central controller receives the electricity price information, environmental factors data as well as the resident desired options in order to optimally schedule appliances including electrical and thermal. The scheduling approach is tested on a typical home including variety of home appliances, a small wind turbine, photovoltaic panel, combined heat and power unit, boiler and electrical and thermal storages over a 24-h period. The results show that the scheduling of different appliances can be reached simultaneously by using the proposed formulation. Moreover, simulation results evidenced that the proposed home energy management model exhibits a lower cost and, therefore, is more economical.

1. Introduction

In the past few decades, typically a power system is just dispatched generation sources since the vast majority of loads are not controllable. Moreover, flat rate of electricity price does not encourage the customers to schedule their energy usage. In a smart grid, the bidirectional data flow together with interoperability between houses and the grid have come up with possibility to optimize each customer's electricity usage and, simultaneously, improve entire system operation via peak reduction [1]. It is actually impractical to ask consumers to schedule their usage optimally since they are neither a system operator nor an economist. Hence, an autonomous load management technique is needed which requires little awareness of consumers for setting up and maintaining and then allow them to evaluate costs and benefits with various schedules.

A Home Energy Management System (HEMS) is definitely an integral part of the smart grid on the consumption side. The appliance commitment problem determines the best fit schedule for each device considering technical constraints and economic circumstances as well. In [2] a energy scheduling method aiming at minimizing the overall cost of electricity and natural gas for a building operation over a time horizon while satisfying the energy balance and operating constraints of individual energy supply equipment and devices has been presented. An Expert Energy Management System (EEMS) has been proposed in [3] in order to schedule a micro grid. It has been used artificial neural network (ANN) to predict wind turbine generation. A simple yet effective load management system, along with renewable and non-renewable sources, was proposed in [4], in order to reduce electricity bill together with carbon emissions. In [5], a model for predictive controller in buildings considering hierarchical building control concept has been proposed. The energy supply and consumption levels were joined only by the thermal load. In [6], Agent-based strategies have been employed in order to schedule smart appliances. In comparison to the appliance commitment strategy, this method has some restrictions such as agent intelligence upon an appliance and also appliance coordination. In [7], the Point Estimate Method (PEM) has been exploited for modeling the solar and wind power uncertainties. The operation problem was solved via Particle Swarm Optimization (PSO) algorithm considering technical constraints. An optimal energy management model of a hybrid power supply system including solar panel, diesel generators and battery for off-grid applications has been presented in [8]. The authors in

* Corresponding author. Tel.: +98 21 77491223; fax: +98 21 77491242.
E-mail addresses: elham_shirazi@elec.iust.ac.ir (E. Shirazi), zakaria@iust.ac.ir (A. Zakariazadeh), jadid@iust.ac.ir (S. Jadid).

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Nomenclature

Abbreviations, superscripts and subscripts

AC	air conditioning
AMI	Advanced Metering Infrastructure
ANN	artificial neural network
CHP	Combined Heat and Power
CN	Control Nodes
CPP	Critical Peak Pricing
CTA	Controllable Thermal Appliance
DER	Distributed Energy Resource
DG	Dispersed Generation
DI	Discomfort Index
EB	Energy Box
ECA	Electrically Controllable Appliances
ESS	Electrical Storage System
EEMS	Expert Energy Management System
EST	Earliest Starting Time
HAN	Home Area Network
HEMS	Home Energy Management System
HG	Home Gateway
HT	Heating Systems
IHD	In-Home Display
LB	Lower Bound
LFT	Latest Finishing Time
LOT	Length of Operation Time
CC	Central Controller
MILP	Mixed Integer Linear Programming
NG	Natural Gas
OCA	Optically Controllable Appliances
PDF	Probability Density Function
PHEV	Plug-in Hybrid Electric Vehicle
PEM	Point Estimate Method
PSO	Particle Swarm Optimization
RTP	Real Time Price
SM	Smart Meter
TCA	Thermally Controllable Appliances
TDM	Thermal Dynamic Modes
TOU	Time Of Use
TSS	Thermal Storage System
UB	Upper Bound
WSN	Wireless Sensor Network
WTR	Water

Parameters

V	wind speed (m/s)
k	shape factor of Weibull distribution for wind speed
C	scale factor of Weibull distribution for wind speed
EP_t^{WT}	wind turbine power output
EP_t^{PV}	solar cell power output
η^{PV}	the conversion efficiency of solar cell array (%)
A^{PV}	solar cell array area (m^2)
I_t	the sun irradiation at time t (kW/m^2)
T_t^{OUT}	the outside air temperature (°C)
β_1	scale factor of Weibull distribution for sun irradiation
β_2	scale factor of Weibull distribution for sun irradiation
α_1	shape factor of Weibull distribution for sun irradiation
α_2	shape factor of Weibull distribution for sun irradiation
η^{chp}	the CHP efficiency
$\mu^{chp,htp}$	heat-to-power ratio of CHP
$EP_{\min}^{CHP}$	the minimum electrical output of CHP
$EP_{\max}^{CHP}$	the minimum electrical output of CHP
$\Delta EP_{\max}^{CHP}$	the CHP electrical output maximum ramp rate
U_{ini}^{chp}	the CHP initial status
η^{Boi}	conversion efficiency of boiler
$TP_{\min}^{Boi}$	the minimum output of boiler
$TP_{\max}^{Boi}$	the maximum output of boiler
$EP^{ESS,sdc}$	self-discharging rate of ESS
η^{ESS}	ESS efficiency
EE_{ini}^{ESS}	the initial value of ESS
EP_{UB}^{CH}	upper bound of ESS charge rate
EP_{UB}^{DCH}	upper bound of ESS discharge rate
EE_{UB}^{ESS}	upper bound of ESS energy
$TP^{TSS,sdc}$	self-discharging rate of TSS
TE_{ini}^{TSS}	the initial value of TSS
TP_{UB}^{CH}	upper bound of TSS charge rate
TP_{UB}^{DCH}	upper bound of TSS discharge rate
TE_{UB}^{ESS}	upper bound of TSS energy
A	an appliance which belongs to ECA
h	the hour of the day
d	the day of the week
w	the week of the year
δ_{step}	the computational time step (s or min)
σ_{flat}	the standard deviation for social random factor
P_{social}	the social random factor
P_{season}	the seasonal changes
P_{hour}	the hourly probability factor
P_{step}	the step size scaling factor
TW^{fr}	the fridge time window
β^{fr}	the activity probability effect on the fridge temperature
α^{fr}	the model the effect of the on and off states on the fridge temperature
γ^{fr}	the models the thermal leakage due to the difference between the fridge and room temperature
TW^{ac}	the AC time window over which the AC can operate
TW^{ht}	the HT time window over which the HT can operate
β^{ac}	the activity probability effect on the indoor temperature (cooling system)
β^{ht}	the activity probability effect on the indoor temperature (heating system)
ρ^{ac}	the effect of outdoor and indoor temperature differences on indoor temperature (cooling system)
ρ^{ht}	the effect of outdoor and indoor temperature differences on indoor temperature (heating system)
$V_t^{CLD,WTR}$	the volume of the cold water which replaces the hot water in water tank at time t
$T^{CLD,WTR}$	the temperature of cold water which replaces the hot water in water tank at time t
C^{WTR}	the specific heat of water
V_{ST}^{WTR}	the volume of water storage
K_t	the "price elasticity" of the lighting load
L_t^{OUT}	outdoor illumination at time t
$L_t^{z,\min}$	the minimum required illumination level of zone z at time t
T_{des}^{fr}	desired fridge temperature
T_{des}^{frz}	desired freezer temperature
T_{des}^{WTR}	desired water temperature
T_{des}^{IN}	desired indoor temperature
$T_{\min}^{fr}$	minimum fridge temperature
$T_{\min}^{frz}$	minimum freezer temperature
$T_{\min}^{WTR}$	minimum water temperature
$T_{\min}^{IN}$	minimum indoor temperature
$T_{\max}^{fr}$	maximum fridge temperature
$T_{\max}^{frz}$	maximum freezer temperature