Applied Energy 183 (2016) 340–357

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Operation management of residential energy-supplying networks based on optimization approaches

Tetsuya Wakui [a,*], Hiroki Kawayoshi [a], Ryohei Yokoyama [a], Hirohisa Aki [b]

[a] Department of Mechanical Engineering, Osaka Prefecture University, 1-1 Gakuen-cho, Naka-ku, Sakai, Osaka 599-8531, Japan
[b] Research Institute of Science for Safety and Sustainability, National Institute of Advanced Industrial Science and Technology, 1-1-1 Umezono, Tsukuba, Ibaraki 305-8568, Japan

HIGHLIGHTS

- Operation management system for residential energy supply networks is developed.
- Energy demand prediction, operation planning, and operation control is integrated.
- Energy demands are predicted by using support vector regression.
- Energy demand prediction and MILP-based operation planning is updated in the day.
- Developed system saves energy consumption in residential energy supply network.

ARTICLE INFO

Article history:
Received 26 April 2016
Received in revised form 12 August 2016
Accepted 28 August 2016

Keywords:
Energy management
Microgrid
Cogeneration
Model predictive control
Support vector regression
Mixed-integer linear programming

ABSTRACT

An operation management system for residential energy-supplying networks using multiple cogeneration units was developed by hierarchically integrating energy demand prediction, operational planning, and operational control, using optimization approaches. The energy demand for multiple dwellings was predicted by support vector regression with information on occupant behavior as well as forecasted weather and energy demand history. Mixed-integer linear programming was employed for the operational planning of the cogeneration units to the predicted energy demand. The energy demand prediction and operational planning were updated using a variable frequency receding horizon approach. This was done to limit the unnecessary shutdown and start-up of the cogeneration units and to reduce the influences of prediction errors for energy demand. Regarding the operational control, the actual on–off schedule of the cogeneration units conformed to the operational planning result. Additionally, the power and heat outputs of the cogeneration units and the heat supply from the storage tanks were modulated in response to the actual energy demand, based on predefined rules. The developed operation management system was applied to annual operation simulation of a residential energy-supplying network consisting of four cogeneration units using fuel cells in a housing complex. For comparative analysis, history-based approaches for energy demand prediction and separate operation of each cogeneration unit were also considered. The results revealed the effectiveness of the developed operation management system as well as the high energy-saving performance of the residential energy-supplying network.

1. Introduction and objective

Energy-supplying devices, including cogeneration [1] and air-to-water heat pump units [2], are utilized worldwide for improving energy savings in residential sectors. In Japan, cogeneration units (CGUs) that use gas engines, polymer electrolyte fuel cells (PEFCs), and solid oxide fuel cells (SOFCs), as well as air-to-water heat pump units (HPUs) that use CO_2 as refrigerant are available [3]. The CGUs have varying heat-to-power supply ratios, and do not generally export surplus power [4]. For this reason, the CGU output is modulated to the power and heat demand for each dwelling and a storage tank is installed for intermittent heat supply [5]. The HPUs are mainly operated late at night by using economical night-time power; consequently, they require large-capacity storage tanks. However, there is considerable heat loss from the storage tanks [6]. These operational restrictions can prevent energy-supplying devices from achieving energy savings.

The present study therefore focuses on a residential energy-supplying network (R-ESN) using multiple energy-supplying

* Corresponding author.
E-mail address: wakui@ese.me.osakafu-u.ac.jp (T. Wakui).

http://dx.doi.org/10.1016/j.apenergy.2016.08.171
0306-2619/

Nomenclature

Operation management framework

H	horizon
j	index for sampling time in prediction and control horizon
t	sampling time
ΔT	sampling time interval, h

Energy demand prediction

b	bias, kW h/h
C	regularized parameter
f_{SVR}	support vector regression model, kW h/h
h	index for sampling time in prediction correction
i, I	index and number for train data set
L	number for divided groups of training data set
r	prediction error index
$\boldsymbol{u}$	input variable vector
v	prediction output, kW h/h
$\boldsymbol{w}$	weight coefficient vector
ε	insensitive error, kW h/h
ξ, ξ^*	slack variables
$\boldsymbol{\Phi}$	high-dimensional feature vector

Operational planning

a, c	performance characteristic parameters
E	power, kW h/h
G	gas consumption, m^3/h
J	objective function (primary energy consumption), MJ
k, K	index and number for piecewise linear equations
M	large positive number (parameter)
n, N	index and number for cogeneration units
Q	heat flow rate, kW h/h
S	amount of stored heat, kW h
δ	binary variable expressing on–off status
Λ	heat loss rate (parameter), 1/h
φ	conversion factor for primary energy (parameter), 1/h
$\hat{()}$	predicted value (parameter)
$\underline{()}$, $\overline{()}$	lower and upper limits (parameter)

Operational control

d	actual on-off status
l	index for sampling time in input horizon

Operating simulation

e	power, kW
f_{CGU}	performance characteristic model of cogeneration units
g	gas consumption, Nm^3/h
q	heat flow rate, kW
R	ramp rate, kW/h
s	amount of stored heat, kW h

Subscripts

CGU	cogeneration unit
D	demand
EH	electric water heater
GB	gas-fired boiler
GD	external grid
IN	input
M	measured value
P	prediction and control horizon
S	simulation
ST	storage tank

Superscripts

AC	air-cooled heat exchanger
C	consumption
DW	shutdown
E	power
F	full storage state
G	gas consumption
IN	inlet
OUT	outlet
Q	heat
SB	standby condition
STA	start-up
T	total value

Abbreviation

BL	baseline operation
CGU	cogeneration unit
HPU	air-to-water heat pump unit
LW	prediction using averaging energy demand at the same sampling time during the last week
PEFC	polymer electrolyte fuel cell
MILP	mixed-integer linear programming
MINLP	mixed-integer nonlinear programming
MPC	model predictive control
MV	prediction using deterministic energy demand
PD	prediction using energy demand at the same sampling time on the previous day
R-ESN	residential energy-supplying network
SE	separate operation of each cogeneration unit
SOFC	solid oxide fuel cell
SVR	support vector regression

devices [7] to enhance energy-saving performance. The power and heat produced by energy-supplying devices is interchanged to increase their operational flexibility. Our feasibility studies, based on mixed-integer linear programming (MILP) for gas engine-based CGUs [5,7], PEFC-CGUs [8], and SOFC-CGUs [9] demonstrated the effectiveness of R-ESNs for energy savings. However, the energy demand was regarded as deterministic in these feasibility studies. To actually achieve high energy-saving performance, an operation management system is required that manages operations of multiple energy-supplying devices, as well as power and heat interchanges in response to uncertain variations in energy demand.

Taking current practices into account, the present study develops an operation management system for R-ESNs using multiple CGUs by hierarchically integrating energy demand prediction, operational planning, and operational control, using optimization approaches. The energy demand for multiple dwellings is predicted by support vector regression (SVR) using quadratic programming [10]. An MILP approach is employed for the operational planning of multiple CGUs so as to meet the predicted energy demand. Consequently, the on–off and power allocation schedules of multiple CGUs are optimized. The energy demand prediction and operational planning are updated by using a novel variable frequency receding horizon approach. In this approach, the horizon for the energy demand prediction and operational planning recedes after a lapse of multiple sampling times, unlike a general receding horizon approach employed in a model predictive control (MPC) [11]. In the operational control to the actual energy demand, the