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Two-stage discrete-continuous multi-objective load optimization: An industrial consumer utility approach to demand response

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HIGHLIGHTS

- Two-stage model links discrete-optimization to real-time system dynamics operation.
- The solutions obtained are non-dominated Pareto optimal solutions.
- Computationally efficient GA solver through customized chromosome coding.
- Modest to considerable savings are achieved depending on the consumer's preference.

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ABSTRACT

In the wake of today's highly dynamic and competitive energy markets, optimal dispatching of energy sources requires effective demand responsiveness. Suppliers have adopted a dynamic pricing strategy in efforts to control the downstream demand. This method however requires consumer awareness, flexibility, and timely responsiveness. While residential activities are more flexible and schedulable, larger commercial consumers remain an obstacle due to the impacts on industrial performance. This paper combines methods from quadratic, stochastic, and evolutionary programming with multi-objective optimization and continuous simulation, to propose a two-stage discrete-continuous multi-objective load optimization (DiCoMoLoOp) autonomous approach for industrial consumer demand response (DR). Stage 1 defines discrete-event load shifting targets. Accordingly, controllable loads are continuously optimized in stage 2 while considering the consumer's utility. Utility functions, which measure the loads' time value to the consumer, are derived and weights are assigned through an analytical hierarchy process (AHP). The method is demonstrated for an industrial building model using real data. The proposed method integrates with building energy management system and solves in real-time with autonomous and instantaneous load shifting in the hour-ahead energy price (HAP) market. The simulation shows the occasional existence of multiple load management options on the Pareto frontier. Finally, the computed savings, based on the simulation analysis with real consumption, climate, and price data, ranged from modest to considerable amounts depending on the consumer's solution preference.

1. Introduction

The future electricity grid is characterized by high volatility in both the supply and demand sides. This is attributed to the shift towards the microgrid systems with distributed energy sources, the large-scale penetration of electrical vehicles (EVs) to the transportation sector, the increased reliance on intermittent renewable energy sources, the discouragement of fossil-fuel run generators due to their harmful effect on the environment, and the increased competition due to the expanding deregulation of electricity markets [1]. In response, market players must invest in preeminent demand management systems in order to optimize the supply and demand matching process [2–5].

1.1. Energy pricing for demand response

One direct approach adopted by suppliers in the deregulated market is the use of Real Time Pricing (RTP) [6]. RTP considers charging the consumer with the variable price of electricity reflecting the contemporaneous marginal supply costs. Therefore, consumers are charged higher rates during peak demand periods and lower rates during off-peak demand periods. This method is an example of demand response (DR) because it incentivizes consumers to become significant market

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Nomenclature

t	index for discrete time steps
m	index for HVAC loading stage
i	index for EV
H	simulation time horizon
M	controllable loads registered in the system for a given period
C	registered loads lumped capacity
S	HVAC system loading stages
N	number of commercial EVs
P^{EV}	EV charging/discharging power
T^s	preferred thermostat setpoint
T	indoor temperature
TOL^+, TOL^-	upper and lower tolerated deviations from T^s
τ	increment change in comfort for each additional loading stage m
λ^{FR}	consumer's threshold price
λ_t^{DR}	energy price for time t
a_i, b_i	EV i arrival and departure times
$SOC_{i,t}$	state of charge of EV i at time t
Q_i	battery capacity of EV i
$\mathscr{x}$	minimum allowed $SOC_{i,t}$
D_t	predicted base load for time t
$\acute{D}$	actual building base load
p^{D_t}	probability of D_t
$P_{p^{D_t}}^{t-1:t}$	state-transition probability from D_{t-1} to D_t
α, β, γ	quadratic function parameters
$U_m\{t,T\}$	time-utility functions for HVAC load m
$U_i\{t,SOC_{i,t}\}$, $U_i^{V2B}\{t,SOC_{i,t},\lambda_t^{DR}\}$	time-utility functions for EV i charging and discharging
$t_{f_i}\{t\}$	amount of time required by EV i to fully charge
$f_1(X)$, $f_2(X)$	individual objective functions of the multi-objective problem
V	set of M controllable loads
$L = \{l_1,...,l_M\}$	set of M load capacities
$W = \{w_1,...,w_M\}$	set of weights assigned to M loads
$X = \{x_1,...,x_M\}$	set of M binary decision variables for switching loads on or off
e	load shifting target

players by adjusting their demand in response to the price signals. In RTP, energy rates are typically cleared one day prior to their execution as in the day-ahead pricing (DAP), where both the generators and retail suppliers submit their hourly price and demand bids in the wholesale market before the operating day. The winning bids constitute a supply and purchase commitment. However, during the course of the operating day, the committed supply often falls short of the actual demand in real time. This forces suppliers to refer to the highly volatile real-time energy market in order to balance the difference in demand. The tariff communicated to the consumer should cover the administrative costs of scheduling, bidding, and flow of power among other costs, but the costs of real-time volatility are burdened mostly by the supplier, specifically as the competition level increases. Alternative to the DAP, rates can be cleared an hour ahead of their execution as in the hour-ahead pricing (HAP) system which is offered by fewer suppliers [6–8]. HAP is less common due to the difficulty in consumer adaptation and load scheduling with short notice, although it is advantageous to the supplier who can mitigate the costs of long term forecast errors and inefficient bidding in the wholesale energy market. Current technologies are hindering the prevalence of the HAP system. Such system requires intelligent, instantaneous, and autonomous DR controllers as the one suggested by this research.

1.2. Residential DR

RTP potentials for the residential consumer have been addressed in research from work discussing thermostatic loads control [9–14], to scheduling household appliance operations [15–24], to managing photovoltaic (PV) panels, and energy storage units including thermal and battery storage or electrical vehicles (EVs) [15,16,18,20,23].

The most promising opportunities for effective DR are in the control of thermostatic loads like in the heat, ventilation, and air-conditioning (HVAC) systems [25]. A price-responsive intelligent thermostat was presented in [9]. The author's approach to DR is through modifying the operation speed of a residential HVAC compressor so that loads are ramped up or down in response to price signals. In [11,13] the authors assigned thermostat operational set-points in response to varying price signals. The authors in [10] had a similar approach with the inclusion of model predictive control (MPC) in controlling the environment conditions for consumers. Similarly, a momentary control algorithm was presented in [12] which determines set-points for heating and thermal storage tanks according to energy prices in real time. The study in [14] evaluated HVAC control strategies and noted that profits from set-point-based control methods are highly dependent on the climate conditions associated with the geographical location. However, their study was limited to the time-of-use (TOU) tariff which is not as economically successful for driving DR as DAP or HAP [26–28].

For non-thermostatic load controls, DR can be achieved by scheduling the operation of residential appliances, control EV charging, and managing storage systems. In [16,21], the authors presented a scheduling algorithm for residential appliance and EV while considering the waiting time as a factor in the objective function. Their method relies on price prediction and utilizes simple linear programming techniques. A similar work is presented in [15] with the addition of PV panels and energy storage units as part of the decision variables. Their objective function however is a mixed-integer nonlinear programming (MINLP) type but they used linear approximation methods for find the solution using simple linear programming methods. In [17], the authors considered inclining block rates (IBR) on top of the RTP predictions in the appliance scheduling problem. Rather than solving the scheduling problem ahead of time, the authors in [18] presented an event-triggered controller which is suitable for both DAP and HAP. The controller algorithm is based on mixed integer linear programming (MILP) methods. Similarly, the authors in [22] assumed duration-based DR event triggers irrespective of the energy pricing system used. For the less dynamic pricing systems, the residential appliance scheduling under DAP system was discussed in [19]. In [20], the authors compared DAP with TOU and the flat rate system. They included EV charging and storage systems in the MINLP scheduling problem. Appliances and battery storage scheduling using MINLP in TOU only is addressed in [23]. Uniquely, the authors in [24] suggested a linear appliance scheduling and a novel pricing approach where energy rates are cleared after consumption had occurred. The argument for their approach is in favor of avoiding undesired scenarios in the aggregate system resulting from unbalanced responses among consumers. As a result, suppliers can charge the full realized cost of bulk energy to the consumers.

1.3. Industrial DR

While the residential sector receives higher attention in DR research due to consumer flexibility and load schedulability, the sizeable impact of larger commercial or industrial consumers on the electricity grid makes them a better candidate for DR. The DR product of one industrial consumer outweighs the aggregated DR from hundreds or thousands of