A Linear Optimization Based Controller Method for Real-Time Load Shifting in Industrial and Commercial Buildings

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Abstract

Effective demand responsiveness (DR) is crucial to the stability of the electrical grid. With increasing penetration of renewable energy sources demands higher load variation adaptability. Therefore, consumer-side flexibility is required for responding to abrupt DR signals. Real-time pricing (RTP) offer a direct approach for continually communicating DR signals. RTP has shown effectiveness in residential applications, however, its implications are impaired in industrial buildings which are less price-elastic due to stresses imposed by just in time (JIT) manufacturing and market competition. In this paper, we propose an instantaneous demand control methodology for industrial and commercial buildings, where the DR action is continually updated as new DR signals are received. We utilize the hour-ahead RTP (RTP-HA) tariffs and the demand shifting concept. The instantaneous approach is independent of price prediction uncertainty and scheduling approaches. The controller algorithm is converted to a linear optimization problem which is solved optimally and saves computational time, making it practical for real-time use. The method is robust and verified using MATLAB/SIMULINK with actual, one week, data from eight industrial and commercial buildings in Florida. Results show modest reductions in consumers' electricity bills while maintaining required comfort standards. Results also address the load synchronization problem associated with RTP.

Keywords

Demand response (DR), load shifting, linear controller, load synchronization, MATLAB/SIMULINK, peak-to-average ratio (PAR), real-time pricing (RTP).

1. Introduction

The demand for electricity fluctuates widely throughout the day. This fluctuation in demand is difficult to predict, yet it must be matched with generation in real time, with tight tolerances. As a result, stresses on the electricity supply system increase considerably throughout the day. On their side, to handle load stresses, utility companies are continuously turning power production up and down by means of peaker plants running on fossil fuels which impact, among many other things, the environment and the future supply of energy. Buildings alone are accountable for 72% of the electricity demand impacts [1].

In the present time, governments are concerned with the shifting towards the smart-grid environment and increasing the reliance on renewable energy sources in lieu of fossil fuels. However, renewable energy supply is characterized by being of an unstable nature causing the power supply system to become even less adaptable to high load variations. In this environment, a large fluctuation in demand may lead to stability problems, power quality problems, and even an entire system collapse. Therefore, there is a significant need for investing in preeminent control systems to optimize scheduling and supply-demand matching in real-time [2-4].

In an effort to control the demand for the supply-demand scheduling process, some policymakers considered the use of the Real Time Pricing (RTP) tariffs. RTP tariffs are thought to impact demand variations, reduce peak demand, and meet utility-load obligations through increased consumer communication [5]. Under RTP, consumers are charged hourly-varying prices for electricity consumption, which reflect the contemporaneous marginal supply costs. Typically,

47 consumers are notified of the new hourly energy rates one day or less in advance. Relying on
48 available information about the hourly cost of energy in the short period, consumers can choose to
49 reduce, increase, or shift their energy consumption from a higher priced hour to a lower one.

50 While many residential consumers can respond to price variations by reducing heating,
51 ventilation and air conditioning (HVAC) loads or by scheduling the operations of household
52 appliances, it is difficult for industrial consumers to respond in a similar manner due to the stresses
53 imposed by just in time (JIT) manufacturing and market competition. Therefore, more research
54 found in literature about managing buildings' DR targeted residential consumers, like in [6-29],
55 compared to fewer research concerning commercial or industrial consumers [30-36]. Nevertheless,
56 HVAC systems in commercial buildings offer high potential for responding to DR events [37]. In
57 addition to responding to price variation in RTP markets, HVAC systems in commercial buildings
58 can provide frequency regulation services to the grid and fine-tune the balancing between supply
59 and demand in the grid [36, 38-46]. The analysis in [36] combines the objectives of optimizing
60 HVAC loads in response to day-ahead RTP, demand charges, and frequency regulation price
61 signals. The work in [42] show how the aggregation of large collection of on/off loads can provide
62 ancillary services to the grid and avoid load synchronization through a randomized control
63 strategy. The importance of automated, intelligent demand response control is highlighted in [40].

64 For utilizing RTP in DR, knowledge of the near future building energy needs is required
65 and automated smart meter-integrated controllers are preferred. The authors in [35, 47] covered
66 the energy estimation for large buildings topic. For the automatic controllers, their significance is
67 in the reduction of the dependency on consumers to consistently follow price changes, and react
68 in an energy-aware conduct, due to the lack of knowledge and diverse nature of human behavior
69 [5-7, 15, 29]. For example, some researchers introduced automated controllers to short-term

70 schedule the on/off cycles of residential HVAC units and the operation of other home appliances
71 based on information available about RTP rates in the upcoming short term period [10, 14, 15, 19,
72 23-25, 27-29, 48]. Fewer researchers considered a demand charge component of the electricity
73 rates in their methods [49, 50]. Other researchers, [7, 8, 12, 21, 35, 36, 51], introduced controllers
74 and strategies for adjusting HVAC temperature settings in accordance to rises or declines in hourly
75 electricity rates while considering the consumer's comfort-tolerance level. In [36, 52], the authors
76 considered demand shifting for utilizing the buildings' thermal storage in precooling. They noted
77 that precooling reduces the deviation from thermal comfort levels in DR periods. In [35], The
78 authors divided the day into four segments and assigned optimized discrete thermostat set points
79 to each segment relying on prediction of price and weather variables. While prices vary for each
80 hour, their approach is limited to assigning four set points to four time periods rather than assigning
81 set points for each hour and thus, increase the utilization of RTP. It is noted that all of the above
82 mentioned researchers assumed price knowledge for 24 hour periods or longer which is required
83 for the successful scheduling of residential loads. Mostly, they relied the day-ahead price (DAP)
84 availability, time of use (TOU) rates, or price prediction approaches.

85 An automated optimization-based residential load scheduler for the operation of household
86 appliance considering the trade-off between minimizing electricity cost under RTP tariffs and
87 minimizing waiting time was discussed in [14]. Similarly, in [9], an optimization model for
88 adapting the consumer's hourly load level in response to RTP tariffs was proposed with the
89 addition of ramping up/down model constraints.

90 All of the above cited researches fall in with targeting a specific schedulable load source;
91 mainly HVAC load for residential or office use. Their methods achieve the complete cycling
92 between the on and off phases of the targeted equipment. The exceptions are the research work in

[8, 9] which discusses ramping up and down of loads between limits. In [8], the research is focused on modifying the single speed residential HVAC compressor. In [9], the authors' method utilizes a building's Energy Management System (EMS) and a linear programming algorithm. However, they present a general formula assuming that a pre-known minimum daily building consumption must be met and that the daily load can be spread across the 24 hour period with fixed hourly ramp up and ramp down limits. While their assumptions are adequate for assessing the usefulness of smart metering and RTP, their method cannot be implemented realistically, specifically for large industrial buildings with inflexible load profiles. Moreover, limitations to their method include the uncertainty associated with an extended energy planning horizon of up to 24 hour period when hourly price knowledge is available for only 2 hours. Different than [8] and [9], the proposed method in this paper aggregates several industrial and commercial load types simultaneously which are designed for operation at variable load levels, the method's operation is in the real time mode with 2 hour or less planning horizon, eliminating assumptions for building load level or long term planning in the upcoming and foreseen periods.

It is important to mention that DR utilizing RTP does not necessarily reduce overall energy consumption. Buildings can use more energy over the year while paying less for it [15]. However, simultaneous shifting of loads to a cheaper time across all consumers would cause a new demand spike higher than any spike under the fixed price system; a problem that could be mitigated by using locational-based pricing [53] or inclining block rates [14, 54]. Moreover, the economic advantages of RTP were examined in [6, 18, 55, 56]. It was concluded that RTP is superior to other existing price models in producing significant gains in the long run. In the case of hybrid energy systems, RTP tariffs can be used for making decisions involving charging/discharging energy storage systems [57].

Different than most research, this study focuses on industrial and commercial buildings for several reasons; first, industrial and commercial buildings account for the majority of the total energy consumption in the United States. Second, industrial consumers have high demand and each consumer independently can have a sizeable effect on the overall system load shape whereas, in the case of residential consumers, demand must be aggregated among several individuals to produce a significant effect at the utility side. Third, as mentioned before, in contrast to residential-use equipment, larger equipment for industrial use operate in several load stages or can cycle at various frequencies through pulse-width modulation (PWM) controllers which facilitates load management approaches under RTP.

In this paper, we present a robust dynamic energy usage optimization controller algorithm. The controller is used for automatically adjusting equipment load in industrial and commercial facilities on an hourly basis according to price changes without impacting production levels. The optimization problem is then solved 24 times in a day. The method utilizes the use of the hour-ahead RTP (RTP-HA) in demand control where the consumer is notified of the price at least 60 minutes before becoming effective [5, 34, 58-61]. The controller is to work in link with existing energy management systems (EMS) at the facilities. EMS can be utilized in demand response events [9, 19, 22, 34, 62]. Currently, many EMS allows for auditing and controlling large adjustable loads found in manufacturing facilities like HVAC equipment, refrigeration equipment, compressed air systems, boilers, and even lighting. The proposed controller receives inputs from both the EMS and the utility then returns commands to the EMS for scheduling, ramping up, or ramping down the operation of the controlled equipment with minimal or no operator interference. The demand shifting concept is adopted where the buildings' thermal storage is utilized to maintain required comfort conditions in the case of HVAC loads. Communications between the controller,

EMS, and equipment are handled through a proposed regulator. The advantage of the proposed method and the RTP-HA use over longer term scheduling or the day-ahead tariff is in the reduction of the dependency forecasting methods and the associated errors.

For validation, we create a virtual load network and price-simulation model to mimic realistic prices in the real time environment. We demonstrate the proposed controller operation through simulation using real consumption data. The data were collected from energy assessments conducted by the industrial assessment center (IAC) program at the University of Miami (MIAC) for industrial and commercial facilities located in the state of Florida.

The contributions of this paper can be stated as the combination of the following: Developing a realistic price-simulation model useful for research purposes, formulating a practical linearized demand control algorithm to run frequently and instantaneously as new hourly price signals become available in contrast to other approaches of previous research, designing a framework for the conjunction between demand controllers at the equipment level, building EMS, utility and smart meters, and finally, demonstrating the proposed methodology using real and detailed data. To best of the authors' knowledge, this study is the first to utilize the hour-ahead RTP and an hourly-instantaneous demand control methodology for industrial buildings omitting reliance on price estimation or long period scheduling approaches unsuitable for the industrial buildings' dynamics.

The remainder of this paper is organized as follows: In section 2, the load data collection process for realistic load modeling part is explained. In section 3, the forecasted load modeling and the setting of RTP is explained. In section 4, the demand response methodology based on load shifting is presented and demonstrated for one building case. In section 5, the results are presented

and discussed. Finally, in section 6, the findings and conclusions obtained from this research are summarized.

2. Collecting building load data

During energy assessments, the MIIAC team implements a data-logging strategy to capture actual client's consumption to be used when making decisions and calculations in energy saving recommendations. Usually, the logging period extends from one week to a few months with data captured at 1 second, 15 seconds, or 1 minute intervals. Sometimes, the team gets involved with other projects which require logging for prolonged periods from several months to more than a year. From the MIIAC archive, eight companies from different industries were selected for this study. The companies were selected from assessments conducted in the hot season between the years 2010 to 2014. The companies, their location and their average demand are shown in Table 1.

1 week period of data logged on 1-minute intervals was extracted for each company. The data represents the three phase current amperage drawn by each company as measured from the main service entrances (MSEs). MSEs are the main building supply breakers used for metering and billing the consumption by the utility supplier. Knowing the voltage used at each company and assuming a fixed power factor of 0.9, the demand in kW was computed for each data point extracted, then the results were averaged over every 60 minutes data points as an approximation of the actual demand for the hour. It is costly in terms of capital and time expenses to use power meters for power factor calculations at all of the main service entrances and the individual equipment breakers. Because power factor is a controllable parameter by means of power factor correction capacitors, it is proper to assume a fixed power factor for the purpose of this research. The computed data were then used to simulate the load. Each consumer's simulated load is shown

in Fig. 1 and the aggregate system load is shown in Fig. 2. For the purpose of this study, it was assumed that all consumers are on the same distribution network.

It is clear from the data plotted that the total system demand from utility has an increasing behavior in the mid-day period and is generally lower during weekends than weekdays. 5 out of the 8 entities in the system follow the same trend in energy demand. The exceptions are MI0198, MI0246, and MI0265, where their energy demand is stable throughout the recorded period. This could be attributed to that some facilities work at full load for 24/7 period or to the necessity for keeping some types of loads, like cooling loads used for freezing processes. Cooling loads may be kept constantly on due to the products' storage requirement.

In addition to obtaining consumers' overall consumption data, data for some individual equipment with opportunities for demand reduction were obtained as well. For example, Fig. 3 shows five candidate HVAC components for demand response belonging to consumer MI0189. As it is shown, the consumption of these components account for roughly 30% of the building's peaking demand during a weekday. The equipment selected as candidate for demand shifting in this study are equipment of cyclic nature. These equipment are designed for continuous cycling between off and on operations as required in the industrial environment.

Table 1.

Companies used as entities in the simulation model

Company Reference	Industry	Location	Average Demand (kW)
MI0189	Aerospace products and parts manufacturing	Miami	153.9761
MI0197	Marinas	Miami	30.1444
MI0198	Aerospace products and parts manufacturing	Medley	225.6109
MI0234	Cosmetics and skin care products manufacturing	Hialeah	131.1498
MI0246	Chemical manufacturing	Miami	401.3903

MI0265	Flower wholesaler	Miami	404.0479
MI0267	Food wholesaler	Doral	534.1631
MI0268	Sign manufacturing	Hialeah	683.9466

Fig. 1. 1-Week demand profiles on 1-hour interval for each building.

Fig. 2. 1-Week aggregate system demand averaged on 1-hour intervals.

Fig. 3. Building MI0189 1-week demand profile with 5 candidate HVAC components for demand control on 1-hour intervals.

3. Modeling load forecast and RTP price setting

3.1. Demand Forecast

Hour-ahead prices are set based on the forecasted energy demand from the system in the upcoming hour. The forecasts are performed on a state-wide basis [63], meaning that the load data is aggregated over all entities in the system. Because demand forecast techniques are not within the focus of this research, we simulate forecasted data for a given period as using the actual data obtained and a forecast error value. A simulated forecast data point is computed as the inverse of the normal cumulative distribution function with the real data point as the mean, the error as the standard deviation, and at a corresponding random probability. The error in demand forecasting is selected from literature as 1.40% for the hour-ahead forecasts [64].

The hourly load data are used to simulate the forecasted data using the NORMINV function in MATLAB. Fig. 4 shows a plot of the forecasted demand along with the actual demand on the same axis

Fig. 4. Actual demand and simulated forecasted demand.

3.2. Real-Time Price Setting

The RTP tariff of interest in this study is the hour-ahead tariff (RTP-HA), where the tariff is adjusted and notified to the consumer one hour ahead of time [5, 34, 58-61]. The RTP tariff designs may incorporate either the bundled or unbundled rate structures. The former structure combines the commodity component costs and the transmission and distribution (T&D) costs under a single charge rate, while some of these components are charged separately in the latter structure [5]. Typically, a separate peak demand rate is charged to the consumer in the unbundled rate structure. Because the focus of this study is on the hourly price variations, the proposed method is based on the bundled rate structure. However, the peak demand impact is considered by introducing an alteration to the control design.

RTP tariffs reflect the marginal cost of energy production and therefore, these tariffs vary as the expected load varies. Fuel and variable operation cost derive the marginal cost of energy production. In [5], five approaches for estimating the marginal cost were explained. The most two commonly used approaches are the system lambda and the power pool approaches. In the system lambda approach, the marginal cost is calculated as the incremental cost of the generation unit operating above the base level. The incremental cost is obtained from the utility's dispatch model. In the power pool approach, the marginal cost is calculated as the spot market clearing price in the regional power pool.

Due to the limitation of the information available about generating units, the power pool approach was used. The spot market energy price from historical data available from Pennsylvania, Jersey, Maryland Power Pool (PJM) Interconnection LLC [65] were obtained. The real-time prices of energy in a typical summer 2-week period in the Mid-Atlantic region, starting July 14th 2014, along with load data were obtained. The obtained data were used to build a price estimation model using IBM SPSS software and SIMULINK. Using cross-validation, the model was used to simulate a realistic RTP scenario for the load network in this study.

Using curve estimations in SPSS and after several regression tests, with price as the dependent variable (DV) and all of the time of the day, day of the week, and the peak-to-average ratio (PAR) as independent variables (IVs), we found that the relationship between the DV and both of the time of the day and day of the week is cubic and its relationship with the load is exponential. From regression and mediation tests, we concluded that both the hour of the day and the day of the week have an indirect effect component on the price that is mediated through the load. Therefore, the model can be depicted by the path diagram shown in Fig. 5. The following regression equation can be used to estimate the real-time market price of fuel

$$C_{Fuel}^t = e + f.H^t + g.(H^t)^2 + h.(H^t)^3 + i.D^t + j.(D^t)^2 + k.(D^t)^3 + l.e^{m.PAR_{total}^t} \quad (1)$$

Where C_{Fuel}^t is the real-time market price of fuel expressed in \$/MWh at time t , e, f, g, h, i, j, k, l , and m are the constant and coefficients obtained from the regression analysis, H^t and D^t are the hour of the day and the day of the week of a simulation time instant t , and PAR_{total}^t is the peak to average ratio calculated as

$$PAR_{total}^t = \frac{L_{total}^t}{\bar{L}_{total}^t} \quad (2)$$

Where L_{total}^t is the lumped system load at time t . For parameters estimation in (1) and (3), we used a combination of the global optimization toolbox in SIMULINK and nonlinear regression analysis in SPSS. We identified the pattern search method as the best to find acceptable coefficients then we refined the solution using the Levenberg-Marquardt algorithm in SPSS.

This model, like many time-varying parameter regression models, helps in predicting the systematic and periodic portion of variability in the spot electricity price, however, a large share of variability is still missing and cannot be consistently forecasted using any price prediction model formulated in previous researches [66]. The high volatility in the actual price obtained from the PJM data is missing in the predicted price. Therefore, a sinusoidal component was added to artificially simulate the actual spot price volatility. The sinusoidal component is

$$n.e^{(PAR_{total}^t)^o}.sin(p.H^t + q.PAR_{total}^t{}^r) \quad (3)$$

The overall model has a high coefficient of determination of 0.6. The optimized model coefficients are presented in Table 2. The resemblance between the price volatility of the actual PJM price and the estimated price is demonstrated by Fig. 6. It should be noted that the purpose of this pricing model is to simulate the realistic volatility of the RTP tariffs for the load network

assumed in this study, as opposed to price prediction models where future price prediction is the goal.

Fig. 5. Path diagram for price prediction model.

Table 2.
Optimized coefficient of the spot market fuel price formulation model.

Coefficient	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>	<i>i</i>	<i>j</i>	<i>k</i>	<i>l</i>	<i>m</i>	<i>n</i>	<i>o</i>	<i>p</i>	<i>q</i>	<i>r</i>
Value	2.78	-	0.19	-	-	1.62	-	15.67	1.03	0.73	2.91	64.27	76.13	0.05
		1.39		0.01	9.92		0.05

Fig. 6. Load and spot market price (Mid-Atlantic region data for two weeks starting 7/14/2014).

4. Demand control methodology

4.1. Demand control strategy

In previous researches concerning residential buildings, achieving demand control using RTP tariffs was easily modeled using functions of tradeoffs between a consumer's comfort level, price elasticity, and tolerance to waiting in the cases of scheduling home appliance operations. However, the same methods cannot be realistically applied to industrial and commercial consumers due to the throughput and time constraints imposed by JIT systems and market competition. Therefore, industrial consumers are inflexible to rescheduling production lines operations or other machinery simply in response to changes in energy tariffs. Nevertheless, from the results of energy audits conducted by the MIIAC in Florida, it was observed that industrial and commercial consumers waste energy through controllable means like: setting low thermostat temperature, increasing compressed air pressure, and continuously running AC motors at full capacity. From energy audits experience, it was perceived that such behavior is attributed to a combination of negligence, preference for high comfort and security levels. For example, an industrial consumer may use higher than required compressed air pressure because they prefer having a surplus in compressed air to facing shortages if a new air leak was to occur. Therefore, due to the conflicting goals of being energy efficient and having a high comfort or security level, a trade off would be temporarily trimming such energy wastes using automatic, RTP triggered control systems.

Many EMS available in industrial and commercial buildings allow for more than just monitoring the energy consumption of various equipment. For example, intelligent EMS allow users to set the operation capacity of equipment, schedule the on and off cycles of HVAC systems or other equipment, control the speed of motors attached to variable speed drives (VSD), control compressed air storage tanks, and setting lighting levels. Moreover, the data collected from EMS

can be used in intelligent prediction models like artificial neural networks (ANN) or can be used in model predictive controls (MPC) to estimate the future state of equipment.

The main contribution in this paper is in designing a control system to work in integration with available EMS in the industrial market and in developing the control algorithm. The controller objective is to automatically adjust the operation set points of controllable equipment in large industrial and commercial buildings as triggered by real time price variations instantaneously as the price is updated. The user defines minimum, maximum, and preferred equipment operation set points in the EMS and defines a reference price of energy in the proposed controller. The controller then receives projected load data from EMS and sends back the required operation load level to the EMS. This process is managed through a regulator to manage the information flow between EMS, proposed controller, and ultimately operation signals to the controlled equipment. For example, In the case of a thermostat load, the output of the controller is a real number representing the optimal amount of energy needed to be shifted. The regulator then processes the controller's output and matches it to a temperature thermostat set-point which is selected from a table of assigned set-points to different energy ranges using the schema presented in Fig. 9. Simultaneously, the EMS monitors the energy level and makes necessary adjustments as well through controller input. In contrast to demand shaving, the demand shifting approach insures minimal impact to the preferred comfort conditions by increasing the buildings' thermal inertia prior to the temporarily reduction in HVAC loads.

The controller algorithm achieves the shifting of planned demand from an upcoming high price hour to a current low price hour, or from a current high price hour to an upcoming low price hour. The first process is named backward demand shifting (BDS) and the latter is named forward

demand shifting (FDS). The simplified flow chart in Fig. 7 demonstrates the proposed demand shifting controller strategy.

Fig. 7. Flow chart of demand shifting controller in a RTP scheme where price information are available for the current hour and the following hour only.

4.2. Mathematical formulation of the demand control algorithms

The proposed BDS and FDS algorithms aim to minimize the sum of squared deviation of the cost of energy consumed in two consecutive hours under dynamic pricing tariffs from a virtual cost incurred with a reference flat rate (FR) determined by the user. For the BDS, the model is formulated below

$$\underset{x_{loss}^{t+1}=x_{gain}^t+\varepsilon}{\operatorname{argmin}} \left\{ [\lambda_{FR} \cdot L^t - \lambda_{DR}^t \cdot (L^t + x_{gain}^t)]^2 + [\lambda_{FR} \cdot L^{t+1} - \lambda_{DR}^{t+1} \cdot (L^{t+1} - x_{loss}^{t+1})]^2 \right\} \quad (4)$$

Subject to:

$$x_{loss}^{t+1} \leq x_{max}^{t+1} \quad (5)$$

$$x_{gain}^t \leq c_{max}^t \quad (6)$$

$$x_{loss}^{t+1}, x_{gain}^t \geq 0 \quad (7)$$

$$x_{loss}^{t+1} = x_{gain}^t + \varepsilon \quad (8)$$

Where L^t is the consumer's expected load at current time t . x_{loss}^{t+1} is the amount of load to shift away from the upcoming hour period $t + 1$ by to become x_{gain}^t in the current hour period t and thus constraint (8) is applied. ε is an arbitrary value set by the user to identify whether to enforce a complete load shifting or to allow for partial load shifting. In this study, we assume complete load shifting and thus ε is set to 0. λ_{FR} and λ_{DR}^t are the flat and dynamic rates of energy at time t . x_{max}^{t+1} is the maximum amount of energy allowed for reduction during the upcoming hour period $t + 1$. c_{max}^t is the maximum available capacity at time t for load increase. L^t and L^{t+1} are determined by the smart meter and EMS using intelligent forecast methods and information about building state from EMS. x_{max}^{t+1} and c_{max}^t are determined from EMS using the user's set tolerance

limits and information about the building state. λ_{FR} is a constant set by the user. λ_{DR}^t and λ_{DR}^{t+1} are communicated to the controller from the utility provider.

Because the objective function (4) in this model is nonlinear, a linearization of the model is achieved by substituting the quadratic components of (4); $(L^t + x_{gain}^t)^2$ and $(L^{t+1} - x_{loss}^{t+1})^2$, with two new variables; y and z correspondingly. Because of constraint (8) elimination of the nonlinear components; x_{gain}^t and x_{loss}^{t+1} , is possible by subtracting y and z together and adding constraints (13), (14), and (16) to the linearized model. The first two constraints eliminate the minimization bias by insuring that the x_{loss}^{t+1} chosen will not reduce the values of y and z to zeroes. The new model becomes

$$\begin{aligned} \text{Minimize } \{ & -2\lambda_{FR} \cdot \lambda_{DR}^t \cdot L^t \cdot x_{gain}^t + 2\lambda_{FR} \cdot \lambda_{DR}^{t+1} \cdot L^{t+1} \cdot x_{loss}^{t+1} + \lambda_{DR}^t \cdot y + \lambda_{DR}^{t+1} \cdot z \\ & - 2\lambda_{FR} (\lambda_{DR}^t \cdot L^{t^2} + \lambda_{DR}^{t+1} \cdot L^{t+1^2}) + \lambda_{FR}^2 (L^{t^2} + L^{t+1^2}) \} \end{aligned} \quad (9)$$

Subject to

$$x_{loss}^{t+1} \leq x_{max}^{t+1} \quad (10)$$

$$x_{gain}^t \leq c_{max}^t \quad (11)$$

$$x_{loss}^{t+1}, x_{gain}^t, y, z \geq 0 \quad (12)$$

$$y \geq L^{t^2} + 2L^t \cdot x_{gain}^t \quad (13)$$

$$z \geq L^{t+1^2} - 2L^{t+1} \cdot x_{loss}^{t+1} \quad (14)$$

$$x_{loss}^{t+1} = x_{gain}^t \quad (15)$$

370

$$y - z = L^{t^2} - L^{t+1^2} + 2x_{loss}^{t+1}(L^t + L^{t+1}) \quad (16)$$

371 This model is now linear and can be solved using linear programming solvers. Similarly, the

372 FDS model formulation is

$$\begin{aligned} \text{Minimize } \{ & 2\lambda_{FR} \cdot \lambda_{DR}^t \cdot L^t \cdot x_{loss}^t - 2\lambda_{FR} \cdot \lambda_{DR}^{t+1} \cdot L^{t+1} \cdot x_{gain}^{t+1} + \lambda_{DR}^{t^2} \cdot y + \lambda_{DR}^{t+1^2} \cdot z \\ & - 2\lambda_{FR} (\lambda_{DR}^t \cdot L^{t^2} + \lambda_{DR}^{t+1} \cdot L^{t+1^2}) + \lambda_{FR}^2 (L^{t^2} + L^{t+1^2}) \} \end{aligned} \quad (17)$$

373 Subject to

$$x_{loss}^t \leq x_{max}^t \quad (18)$$

374

$$x_{gain}^{t+1} \leq c_{max}^{t+1} \quad (19)$$

375

$$x_{loss}^t, x_{gain}^{t+1}, y, z \geq 0 \quad (20)$$

376

$$y \geq L^{t^2} - 2L^t \cdot x_{loss}^t \quad (21)$$

377

$$z \geq L^{t+1^2} + 2L^{t+1} \cdot x_{gain}^{t+1} \quad (22)$$

378

$$x_{loss}^t = x_{gain}^{t+1} \quad (23)$$

379

$$y - z = L^{t^2} - L^{t+1^2} - 2x_{loss}^t(L^t + L^{t+1}) \quad (24)$$

The BDS and FDS models can then be solved optimally using linear programming solvers. The linearity of the algorithm makes it practical for controller application to permit timely response in real time settings. x_{max}^t is computed from:

$$x_{max}^t = \sum x_{i,max}^t \quad (25)$$

Where $x_{i,max}^t$ is the maximum amount of energy that can be reduced for equipment i at time t . $x_{i,max}^t$ and c_{max}^t are calculated from EMS data using the user's tolerance levels and other parameters in the system depending on the type of load. For example, for cooling loads, as demonstrated by the diagram in Fig. 9, $x_{i,max}^t$ may be expressed as

$$x_{i,max}^t = f(R_T, T_{out}^t, T_{in}^t, e_i^t) \quad (26)$$

Where $x_{i,max}^t$ is a function of the maximum temperature given by the consumer's tolerance level (R_T), the outside temperature (T_{out}^t), the indoor temperature (T_{in}^t), and the measured energy demand for equipment i at full load (e_i^t).

4.3. Modifications to the demand control algorithms considering peak demand charges

The dynamic price (λ_{DR}) considered in 4.2 represents the bundled electricity tariff. In the case of the unbundled tariff, where a high peak demand penalty rate is charged in addition to the energy rate, a modification to the algorithm is desired to oblige the peak demand level from increasing through load shifting. Although this study mainly considers the bundled RTP-HA tariff, the following two modifications are introduced for impeding a peak demand increase: in the first approach, the upper bounds in (11) and (19) are replaced with (27) and (28) respectively, where L_{peak} is the maximum desired peak level as contracted with the utility company or from historical data and ψ^{t-1} is the delayed controller feedback signal from time $t - 1$. The second approach is

to add the new term $(\alpha \cdot s)$ to the objective functions (9) and (17), where α is a penalty cost and s is an unbounded load change limiting decision variable defined by constraint equation (29).

$$x_{gain}^t \leq \min \left\{ c_{max}^t, \begin{cases} v = L_{peak} - (L^t + \psi^{t-1}), & v > 0 \\ 0, & otherwise \end{cases} \right\} \quad (27)$$

$$x_{gain}^{t+1} \leq \min \left\{ c_{max}^{t+1}, \begin{cases} v = L_{peak} - L^{t+1}, & v > 0 \\ 0, & otherwise \end{cases} \right\} \quad (28)$$

$$s = \begin{cases} L_{peak} - (L^t + x_{gain}^t + \psi^{t-1}), & BDS \\ L_{peak} - (L^{t+1} + x_{gain}^{t+1}), & FDS \end{cases} \quad (28)$$

4.4. Demonstration of the demand control operation

The following is a demonstration of how load shifting can be achieved for one of the buildings in this study: From the energy audit for consumer MI0189, Five components in the HVAC system were identified as candidates for load controlling; air duct fans, direct expansion (DX) compressors, DX air handlers, exhauster fans, and the Roof Top Units (RTUs). EMS can be used to control fan motors' and RTUs' consumptions through VSD and automatic control of thermostat settings. The audit recorded that the thermostat settings were set to between 68°F to 72°F during production hours while the recommended range is from 68°F to 76° according to the OSHA standards [67]. Also, the exhauster, air handler and duct fans were running at full or close to full capacity when turned on. The weekly consumption of these components compared to the overall consumer's demand is shown in Fig. 3. This data shows that the five candidate components summed account for roughly 30% of the peaking demand during workdays. We demonstrate the operation scheme of the controller on the in line duct cooling/ventilation systems since they account for significantly large amount of energy consumption in the building. The

418 MATLAB/SIMULINK framework for the proposed controller for this example is shown in Fig. 8.

419 Real data were used to simulate the actual building and EMS. The data were collected during the

420 energy audit for 1 week using programmable data loggers, current transducers, indoor and outdoor

421 temperature sensors, and air flow meters. Using the parameter estimation toolbox in SIMULINK,

422 a realistic thermal model for the building was created. The estimated parameters for the thermal

423 model represent both the heat gains as a linear function of the ambient temperature due to the

424 building's thermal resistivity, and the periodic nonlinear heat gains due to solar loading, machine

425 operation, and human traffic. The validation step proved that the simulation model produces

426 energy and temperature outputs matching the actual measured data. In this example, it is assumed

427 that the one-time user input to the controller sets his reference price to \$0.1/kWh and his lower

428 and upper limits for temperature to 70°F and 78°F respectively. The controller then solves the

429 optimization functions for BDS and FDS for each time step and outputs the proposed amount of

430 energy to trim/add for the current and forthcoming time steps. The regulator translates the

431 controller's output to thermostat set points and to on/off signals which manage the cycling between

432 the parallel systems. The regulators' operation schemas are provided in Fig. 9 and Fig. 10. Fig. 11

433 shows the duct system's demand profile before and after the implementation of the proposed

434 algorithm in the RTP environment. The results show savings of 17.9% in HVAC energy cost from

435 the duct system alone and 10.2% savings in HVAC energy although energy reduction is not the

436 main target of this controller. The main controller success is in shifting 50% and 100% of the duct

437 system's demand away from the peak periods. Fig. 12 shows that the impact to the consumer's

438 thermal comfort level is insignificant due to the cooling energy shifting which increased the

439 building's thermal inertia prior to demand reduction intervals.

Fig. 10. Regulator schema for cycling between parallel HVAC units based on input value from controller (x).

Fig. 11. Demand profile of a building's duct system before implementing the proposed controller (top) and after (bottom).

Fig. 12. Comparison of the indoor climate conditions before and after controller implementation

5. Results

5.1. Consumer Impact

In order to confidently validate the functionality of the proposed load shifting controller method, we assumed conservative conditions when running the simulation; we assumed that there will be no reduction in energy allowed in contrast to the case results discussed in section 4. We forced only complete shifting of load from one period to another even if the buildings' state monitoring system does not show a necessity for accepting significant demand increase as a result of load shifting. This can be regarded as the worst case scenario or the case of storing energy for use during the more expensive time periods. Simulations were run using SIMULINK. The obtained results indeed indicated reductions in HVAC and compressed air systems costs for all eight consumers in the system under RTP-HA tariffs, assuming the worst case scenario. The equipment energy costs savings are provided in Table 3. Additionally, the unbundled tariff structure was considered using the two approaches suggested in 4.3. The results for both approaches are provided

in Table 4 and Table 5. In the bundled tariff mode, the T&D component was added to the simulated rates as \$0.0673/kWh while in the unbundled mode, an additional charge of \$10/kW was assumed for the highest peak demand. As indicated in the tables, the second approach yields better savings than the first, therefore, discussions on the first approach results are omitted from the remainder of this paper

Comparison of the demand profiles for each of the eight building between when the load shifting controller is turned on or off is shown in Fig. 13. Fig. 14 shows the change in each building's equipment energy demand when the load shifting controller is applied. The drops and spikes in Fig. 13 and Fig. 14 indicate the magnitude of load being successfully shifted in response to price signals from the utility. This results in energy cost savings for the consumers. For example, a reduction of HVAC energy costs for consumer MI0189 by 3.06% was achieved. Which is equivalent to annual dollar savings of \$1029.6. The savings are obtained from controlling the cycles and operation of the duct fans, DX compressor, DX air handler, and the air conditioning RTUs. Building MI0268 showed the highest savings of 4.52%, which is equivalent to \$22,100 savings in annual energy bills for that building. Building MI0268 savings are achieved from controlling the building's air compressors and air conditioning RTUs. The equipment utilized in each buildings for the building's energy demand shifting are listed in Table 6. It is concluded that the dissimilarity in the savings achieved among buildings is attributed to, among other factors, the building's load shape. For instance, buildings with higher volatility in the demand profile, like MI0268, achieve higher savings from the reduction of peaks during expensive hours, than buildings with less volatile demand profiles, like MI0246. It is also important to note that the price volatility in real time is a significant factor which affects the utilization of the proposed method.

In the case of the unbundled tariff with a separate demand charge, the resulted new building and equipment load profiles are shown in Fig. 15 and Fig. 16. The savings in the unbundled tariff scenario are modest compared to the savings occurred from load shifting in the bundled tariff system, without any peak mitigation.

The savings from applying the proposed control method would be much higher in the cases of residential consumers due to their higher flexibility compared to commercial and industrial consumers where goals like productivity, throughput, and the requirements of JIT manufacturing limit the flexibility in scheduling energy demanding operations. Thus, many researchers target the residential sector as a good candidate for demand shifting or shaving. The industrial consumer's inflexibility was accommodated for by assuming that only a small portion of the demanded energy, such as that consumed by HVAC systems or compressed air systems, can be shifted only between two consecutive hours, either by increasing the utilization at one hour on the expense of the following or preceding hour, or through storage systems use.

The focus of this study is on load shifting, although, realistically, demand shaving can be achieved by impacting the comfort level at the peak hours. The results indicate that costs can be reduced by HVAC's demand shifting methods driven by the real-time tariffs. However, as shown in Fig. 13 and Fig. 14, the dynamic tariffs exercised do not always result in reducing the highest peak in demand, instead, peak demand is shifted to a cheaper hour and may even become higher during that hour if new peaks are not penalized. It should be noted that load shifting and peak load shaving are two contrasting objectives, however, both objectives can be merged. The main focus of the proposed method is on the former objective.

It is vital to mention that the continuous on/off cycles due to demand shifting may increase maintenance costs for some machinery and equipment. Therefore, there is a limitation for the

proposed demand control method when applied to some equipment types or for residential equipment use. This limitation is insignificant in this study due to the design considerations of the selected equipment. The equipment selected were designed for continuous on/off cycles like large industrial air compressors and DX compressors, or equipment with the ability to operate at various stages with ramping up/down of loads like VSD fans and multi-stage chiller systems. EMS and VSDs should be utilized to allow for the soft-start of equipment and thus reduce load and torque on equipment when shifting between operation phases.

Table 3

Selected equipment energy cost savings from applying the demand shifting controller method

Consumer	MI0189	MI0197	MI0246	MI0265	MI0198	MI0267	MI0234	MI0268
Savings (%)	3.06%	1.08%	0.41%	2.41%	0.30%	0.48%	2.69%	4.52%
Equivalent annual savings (\$)	\$1,039.6	\$327.6	\$572	\$7,436	\$260	\$988	\$535.6	\$22,100

Table 4

Equipment energy cost savings in the unbundled tariff scenario using the first approach

Consumer	MI0189	MI0197	MI0246	MI0265	MI0198	MI0267	MI0234	MI0268
Savings (%)	0.48%	0.35%	0.13%	0.50%	0.17%	0.45%	1.57%	0.55%
Equivalent annual savings (\$)	\$62.4	\$36.4	\$62.4	\$520	\$52	\$312	\$119.6	\$936

Table 5

Equipment energy cost savings in the unbundled tariff scenario using the second approach

Consumer	MI0189	MI0197	MI0246	MI0265	MI0198	MI0267	MI0234	MI0268
Savings (%)	1.68%	2.28%	0.33%	1.16%	0.62%	0.67%	2.39%	0.79%
Equivalent annual savings (\$)	\$218.4	\$239.2	\$156	\$1,196	\$192.4	\$468	\$182	\$1,352

Table 6

Equipment utilized per building as candidates for demand shifting

Building	Equipment types for demand shifting
MI0189	Duct fans, DX compressors, DX air handlers, RTUs
MI0197	Air compressors, DX compressors, DX air handlers
MI0198	Air compressors, chiller systems, RTUs
MI0234	Air compressors, DX compressors, DX air handlers
MI0246	Air compressors, chiller systems, DX air handlers, RTUs
MI0265	Air compressors, chiller systems, production water chillers, cooling tower fans
MI0267	Chiller systems, RTUs, water coolers
MI0268	Air compressors, RTUs

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527 Fig. 13. The eight buildings demand Profiles prior and Post to demand shifting in the bundled RTP tariff system.

Fig. 14. The eight buildings' lumped equipment load profiles prior and Post to load shifting in the bundled RTP tariff system.

Fig. 15. The eight buildings demand Profiles prior and Post to demand shifting in the unbundled RTP tariff system.

Fig. 16. The eight buildings' lumped equipment load profiles prior and Post to load shifting in the unbundled RTP tariff system.

5.2. Utility Impact

When all buildings in the system follow the proposed demand shifting method guided by the RTP tariff system, the new aggregated load impacts the utility by creating new load spikes away from the expected peak hours as shown in Fig. 17. The load synchronization occurs where all buildings shift a portion of the load to the cheapest hours resulting in new and higher spikes. The new aggregated peak in the one week simulation data becomes 3999 kW instead of 3737 kW before implementing demand response. This corresponds to a 7% increase in the PAR which in result, would threaten the stability of the system and invalidate the purpose of demand controlling through imposing dynamic tariffs. This problem can be fixed or reduced by offsetting the controller triggers either at the building level or the equipment level to start at different time instances from each other. Moreover, a finer RTP system can aid in this issue where new prices are generated every 15 minutes instead of every hour. Fig. 18 shows a reduction in the load synchronization when the controllers start times are randomly offset in each building.

Utility cost analysis was performed using the simulation results. We calculated a drop in utility cost of generation by 0.3% as a result of large load reductions during peak hours. The drop would be higher when load synchronization is avoided. The utility revenue using RTP becomes 3.4% higher than when using the conventional flat rate tariff. Therefore, we conclude that all parties benefit from switching to RTP system guiding an effective load shifting method like the one discussed in this paper. This 3.4% expresses the maximum amount of reduction in the RTP tariff which the utility can apply as a form of incentive without affecting their initial revenue achieved when using the FR tariff.

The pricing system could be improved more in future work. It is evident that a less aggregated or a consumer-customized method for determining dynamic tariffs is required to overcome the impact of the load synchronization effect. The other problem witnessed in the results is the co-dependency between price and demand which is not accounted for when generating new prices each hour. These problems lead to future research opportunities with the goal of developing new, adaptive algorithms for generating near-optimal prices with the purpose of reducing the PAR accounting for the consumer's response.

Crucial to the observed outcome of this study, was the collection and use of a one week set of real data from different building types. If only one building of the residential type or one day of data was relied on, the outcome may become misleading and the load synchronization effect may not be observed. Which would lead to the invalid conclusion that dynamic tariffs alone help reduce the PAR.

Fig. 17. New load synchronization peaks when buildings use demand shifting controllers at the exact same time instances.

Fig. 18. Reduction in load synchronization peaks when buildings use demand shifting controllers at randomly offset time instances.

6. Conclusion and discussions

In this paper, an algorithm for instantaneous load shifting was proposed. The algorithm is to be used in controller systems reading price signals set an hour in advance by the RTP-HA tariff system. The algorithm is transformed to a linear problem, which does not require computational time, making it practical for use in a fast-paced real time environment.

Realistically volatile prices were generated using a proposed price simulation model. However, the price model is limited to mimicking prices following the historical patterns in the PJM market. The model should not be relied on to forecast future prices and it does not consider the state of the generation mix.

Real data were used to test the proposed system through simulation. The data were measured from eight industrial and commercial buildings in Florida during the summer period. The results demonstrate that instantaneous demand response can indeed be achieved without the requirement for longer planning horizons considered in previous research, the demand shifting concept resulted in minimal impact to the consumers' comfort standards, and the RTP-HA varying price signals can be utilized in lowering consumption costs for consumers. Moreover, the method can be used to address problems with existing pricing systems, including the load synchronization effect. An improvement to the selected system would be if the RTP was more dynamic, where price tariffs update every 15 or 30 minutes.

Although the RTP-HA is fairly mature, it should be noted that some utility companies offer this tariff type for commercial and industrial companies. The Georgia Power Company [59] and the Alabama Power Company [60] are examples of utility providers offering the RTP-HA option for commercial and industrial buildings. One of the goals of this research is to extend the future utilization of this type of tariffs. RTP-HA driven controllers offer more flexibility over

conventional dynamic tariffs because it allows the utility to produce instantaneous DR in emergency or unforeseen abrupt events.

The research focus in the future should be on developing adaptive and consumer specific tariffs to eliminate the load synchronization effect. Moreover, further research is required for the experimental evaluation of RTP-HA in automated demand control. Another contribution of this study was in the usage of a whole week set of real data collected from several buildings of different types (commercial and industrial), where most studies found in literature target one building type (mostly residential or offices) and heavily rely on simulation data.

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