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HVAC energy cost minimization in smart grids: A cloud-based demand side management approach with game theory optimization and deep learning☆

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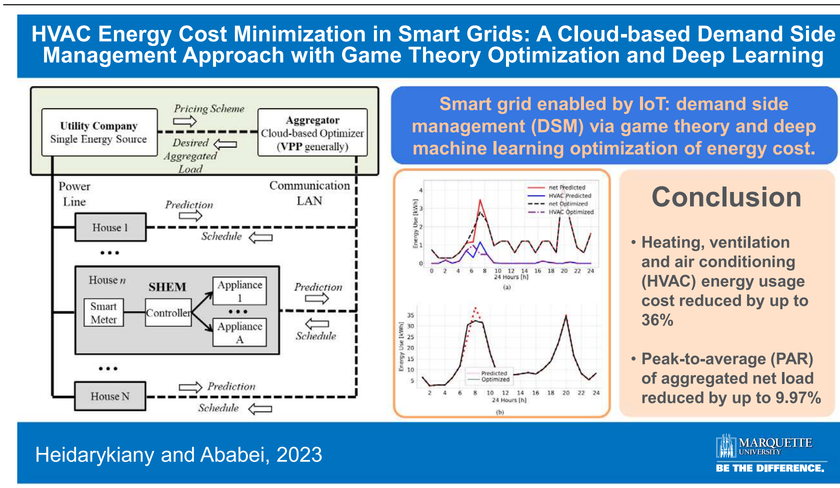
HIGHLIGHTS

- Novel cloud-based DSM approach for cost reduction of energy usage HVAC systems.
- Game theory algorithm to capture interaction between aggregator and customers.
- Solution provides peak shifting and reduction via rescheduling of HVAC energy usage.
- Simulations demonstrate HVAC energy cost can be reduced by up to 36%.

GRAPHICAL ABSTRACT



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ABSTRACT

In this paper, we present a novel cloud-based demand side management (DSM) optimization approach for the cost reduction of energy usage in heating, ventilation and air conditioning (HVAC) systems in residential homes at the district level. The proposed approach achieves optimization through scheduling of HVAC energy usage within permissible bounds set by house users. House smart home energy management (SHEM) devices are connected to the utility/aggregator via a dedicated communication network that is used to enable DSM. Each house SHEM can predict its own HVAC energy usage for the next 24 h using minimalistic deep learning (DL) prediction models. These predictions are communicated to the aggregator, which will then do day ahead optimizations using the proposed game theory (GT) algorithm. The GT model captures the interaction between aggregator and customers and identifies a solution to the GT problem that translates into HVAC energy peak shifting and peak reduction achieved by rescheduling HVAC energy usage. The found solution is communicated by the aggregator to houses SHEM devices in the form of offers via DSM signals. If customers' SHEM devices accept the offer, then energy cost reduction will be achieved. To validate the proposed algorithm, we conduct extensive simulations with a custom simulation tool based on GridLab-D tool, which is integrated with DL prediction models and optimization libraries. Results show that HVAC energy cost can be reduced by up to 36% while indirectly also reducing the peak-to-average (PAR) and the aggregated net load by up to 9.97%.

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1. Introduction

One of the components to transform the electric grid into a smart grid is demand side management (DSM), which encompasses methods implemented by the electric utilities to manage energy usage at the customer side. Actual practical implementations or deployments of such a concept may differ; however, they usually require smart meters, home energy management (HEM) systems [1], or energy management systems (EMS) [2], which can schedule household appliances and energy sources in a way that minimizes electricity cost for homes. In recent years, advances in internet of things (IoT) technologies and in machine learning (ML) have led to the development of smart home energy management (SHEM) systems [3] and cloud-based intelligent energy management services [4]. SHEM systems can communicate with the aggregator (which can be owned by the utility company itself) to transmit energy usage and schedule information and can also react to offers (i.e., suggestions) received from the aggregator by directly controlling certain appliances such as HVAC systems. It is important to mention that when there is a multitude of heterogeneous distributed energy resources (DER) in the grid subject to optimization, the communication is done to a virtual power plant (VPP) operated by the aggregator which is in charge with optimizations, including trading in electricity markets. Because in this paper we look at a distribution system with only one single power source (e.g., the substation or feeder), we will use the term *aggregator* and not VPP to refer to the entity that implements DSM activities and optimizations, sitting between utility and customers. Also, we adopt the terminology that uses energy *usage* and power *consumption*, even though previous literature used also the terminology of energy consumption.

2. Related work

2.1. Demand side management (DSM)

Several recent review papers highlighted previous approaches that studied load scheduling in DSM contexts [5–7]. Many of these previous studies developed optimization techniques that involved consumer classification, dynamic pricing, constraints, and appliance load profiles [8,9]. Electricity demand can be altered during specific periods through direct load control (DLC) and capacity market programs, but, they use different strategies to accomplish this. Through DLC, a utility/aggregator can directly control a home energy usage during specific periods, which may compromise preferences and possibly privacy. For example, the optimal control of a given SHEM can include heating and cooling setpoints based on user comfort, desired indoor temperature range, and offered energy scheduling. As a result of the SHEM optimal DR signals, load scheduling can be managed from an aggregator DSM perspective with maximum privacy [8,10]. An alternative approach is for the aggregator to provide offers with financial/market incentives to homes' SHEM systems to encourage reduction of their energy consumption during specific periods, with cost prioritization over comfort. Home users can be incentivized depending on their comfort preferences [8].

Recent DSM studies include [11–15]. For example, [12,16,17] formulated multi-objective optimization problems for load scheduling and proposed solutions based on heuristics/evolutionary algorithms. Other modern or hybrid heuristic approaches have been presented in [18–20]. Combined heuristics with machine learning to develop methods to reduce electricity costs were presented in [21]. We note that only a few previous studies addressed the challenging aspect of balancing utility and consumers interests in DSM [22–24], and most of them did not consider day-ahead optimization. The work in [25] presented a heuristic approach for day-ahead DSM that finds appliance scheduling solutions that balance utilities and consumers interests. In DSM approaches, a popular *optimization knob* is the type and number of appliances that are controlled. For example, the study in [26] assumed that 10–20 appliances can have *shiftable* operation; such appliances may include dishwasher, washer, dryer, and plug-in electric hybrid vehicles (PHEVs). The study in [27] focused on adjustable HVAC units for office buildings. Studies in [11,13] employed load shifting to achieve residential load management problem and to reduce peak load. In addition to peak reduction, one can focus on the objective of reduction of peak-to-average ratio (PAR) as in [14]. Optimization objectives like those were achieved by solving various optimization problems solved via a variety of approaches, including game theory (GT) [9,15,26,28,29].

We note that game theory particularly has been employed to address and balance the interaction between utility and consumers, in GT formulations solutions can be proven to be globally optimal as Nash equilibrium solutions. For example, using cooperative games theory, distributed energy demand management systems were developed to optimize energy demand costs in [30–32]. Many of these approaches appear to be suffering from ideal assumptions in framing the cooperative games, which in turn may result in poor results in practical settings [33]. The study in [26] presented a GT approach where home users represented players who can select their own daily appliance consumption schedules with the objective of maximizing their payoff, given a known pricing scheme and overall billing practiced by the utility. In [34,35], the Stackelberg GT model was used to explore the interaction between energy service providers and electricity consumers. Another interesting GT approach was presented in [36], where real-time wholesale prices in Sydney were used to minimize cost, PAR, and user discomfort, based on a community storage facility. A game-theoretic method that takes into account the perspectives of both users and power companies was presented in [37]. Using a two-stage game, the method aims at reducing peak-to-average power ratio and by employing a new pricing model, energy prices are adjusted based on total consumption. Simulation results reported that the power company could achieve efficient convergence, reduce energy costs, and improve predictability. Another game-theoretic method for reducing peak system load was presented in [38]. Users request energy from smart power providers, and providers adjust prices based on user load profiles. The objective is to minimize the peak-to-average ratio (PAR) by allowing users to charge their batteries during periods of low demand and discharge them during periods of high demand. Simulation results demonstrated a reduction in both PAR and total energy cost. Two game-theoretic methods (based on non-cooperative and Stackelberg games) were studied in [39]. These methods involved residential consumers with energy storage scheduling their energy use in an effort to minimize costs and utility provider setting prices to maximize profits while anticipating user reactions. Simulation results indicated that storage is capable of reducing costs and PAR as well.

However, the potential of using deep learning was not discussed in these studies. Also, many of these studies consider retailers and not aggregators in DSM frameworks. Retailers are usually responsible only for selling energy directly to consumers, while aggregators focus on collecting and managing the demand response potential of a group of end-users and selling it to energy markets or utilities. Additionally, retailers usually have a direct contractual relationship with end-users, whereas aggregators typically have a contractual relationship with both end-users and energy markets or utilities.

2.1.1. Motivation for using a game theory based approach

Game theory provides a rigorous framework for exploring strategic interactions, particularly when heuristic methods fail to address the variety of players with different strategies [40–42]. Conflict and competition scenarios are particularly well addressed by this approach. In scenarios involving multiple parties, such as decisions related to reducing energy consumption, GT can be used to develop strategies that maximize utility or minimize conflict. A key strength of this approach is its formal, mathematical robustness for analyzing problems — under the assumption that agents in the game are rational, well-informed about their preferences, and consistently acting in a manner aligned with those preferences. As one of the most remarkable features, when it comes to conflict resolution, GT offers balanced solutions that are beneficial to all parties involved. In other words, Nash equilibrium solutions are identified where no player has any incentive to unilaterally deviate from their chosen strategy. This ensures stability and predictability between actors.

2.1.2. Why game theory is a good fit for demand side management

Because it effectively models the interactions among stakeholders (i.e., consumers and utilities), game theory is best suited to be used as a robust optimization framework for demand side management (DSM) in smart grids. Its strength lies in addressing the non-cooperative nature of participants behavior through non-cooperative game theory and Nash equilibrium analysis — which facilitates optimal resource allocation from the utility's point of view. By aligning demand with supply in a game theory based problem formulation, we can easily minimize energy usage and costs while at the same time enhancing electrical system flexibility and resilience, particularly through strategic demand response. Comparatively, game theory outperforms traditional DSM models by offering sophisticated tools for managing complex interactions and adapting to system dynamics. The excellent results we achieve in this paper, reported in the experimental results section — underscore the fact that game theory is one of the best approaches to DSM. Additional reported empirical applications of game theory in DSM, such as peak load management, further emphasizes that. Finally, game theory's potential for further research, especially in integrating machine learning for predictive analysis, highlights its ongoing relevance.

2.2. Deep learning techniques for energy management

Recent advancements in information technology and large data collection made for the role of the utility/aggregator in smart grids to become increasingly important and enabled them to engage more with deep learning techniques for optimizations. For example, the study in [43] presented a deep reinforcement learning-based pricing strategy for aggregators that outperforms conventional pricing algorithms when various complexity factors are taken into account. The approach was found to be more profitable and faster to learn than other strategies, especially when considering changes in the environment and the actions of competitors. The study in [44] presented an IoT-based deep learning method for controlling air conditioning (AC) in smart buildings. Using the YOLOv3 algorithm, the system detects the number of persons in a room and adjusts the AC operation accordingly. While deep learning can be very effective at managing energy in buildings, it suffers from being more susceptible to adversarial attacks, particularly when it comes to cases involving energy theft. On this topic, the study in [45] investigated generative adversarial networks (GANs) to disguise energy theft as regular energy consumption. The study showed that such attacks using fake data that mimic real data distributions can deceive AI systems, and underlined the need for more robust energy management systems.

The study in [46] focused on the optimal management of energy and the security of data for hybrid AC/D microgrids (MGs). The goal was to enhance data security by detecting data injection attacks using a deep learning-based intrusion detection based on long short-term memory (LSTM) models. Simulation results on the IEEE 33 bus test system showed the importance of strategically charging of hybrid vehicles and the superiority of the LSTM technique over traditional artificial neural networks for the protection of data. In another example, the study in [47] looked at how to enhance the energy management system (EMS) of a microgrid (which included wind turbines, energy storage systems, and different types of loads) with deep reinforcement learning (DRL). A deep deterministic policy gradients (DDPG) based approach was proposed in [48] for energy cost optimization in buildings. It was shown that DDPG has the ability to achieve optimization without prior knowledge of uncertainties in renewable energy outputs, outdoor temperatures, and varying power demands.

2.3. Prediction with deep machine learning

In smart homes, deep learning (DL) models can be used to predict energy usage. IoT sensors and smart home devices generate large amounts of complex data, which naturally invites the study and use of DL models and algorithms towards even better DSM approaches. Such models are particularly effective at identifying patterns and trends in the data that may not be immediately apparent to humans. SHEM systems can exploit such findings to optimize energy usage, improve security, and provide better user experiences. For example, the study in [49] proposed an energy management system based on IoT and machine learning (ML) techniques to predict the energy generated by photovoltaic panels. However, the study did not consider the challenge of balancing the interests of utility and consumers. Combining game theory and deep learning is what we advocate for in this paper because one can leverage the strengths of these techniques to develop dynamic hours or day-ahead energy management. Deep learning techniques can be used to analyze large amounts of data to develop accurate energy demand predictions. This can help aggregators better manage their future demand. On the other hand, game theory can be used to model the interactions between aggregator and end-users or players. By understanding the incentives and motivations of these players, GT can help design mechanisms to encourage players to change their energy usage behavior — towards more efficient and sustainable use of energy resources. An example of a previous study in this arena is the work in [50] where supervised machine learning models were used to predict building energy usage for the purpose of demand-side control.

2.4. Reducing energy costs for HVAC systems

In this paper, our main focus is on reducing the cost of energy usage by HVAC systems. Therefore, we briefly review here relevant recent studies that also focused on reduction of costs. The study in [50] presented a closed-loop moving-horizon scheduling for HVAC central plant operations based on a general mixed-integer linear programming approach. The main advantage of this approach is its robustness against inaccurate forecasts and minimal economic impact from shortened prediction horizons when feedback mechanisms are utilized. Dynamic programming and genetic algorithms are employed to balance electricity demand and production against economic and comfort considerations in the study in [51]. The study reported that the genetic algorithm achieved closer approximation to optimal values, leveraging more photovoltaic system electricity for HVAC operation. However, dynamic programming outperformed the genetic algorithm when both are paired with a simplified thermal model (STM), albeit its effectiveness is constrained by the limitations of STM, particularly its disregard for thermal inertia. The study in [52] introduced a novel methodology for the holistic optimization of both air- and water-side components of HVAC systems in commercial districts, a departure from existing literature which typically focuses on either component in isolation. This integrated optimization outperformed previous strategies limited to waterside demand, underscoring the efficacy of considering both air- and water-side components for energy savings in commercial HVAC systems. Model predictive control (MPC) was used to reduce energy costs by integrating a micro-scale concentrated solar power (MicroCSP) system with the HVAC system of an office building in the study from [53]. They reported significant reductions of HVAC energy costs compared to a standard HVAC system managed by an MPC without MicroCSP integration. A so called brute-force method was used to conduct a parametric evaluation of courtyard design variants in residential buildings across different climates, focusing on indoor thermal comfort and utility costs in the study from [54]. The study assessed the impact of design variables like courtyard geometry, window-to-wall ratio, envelope materials, and set-point dead-bands on energy load and occupant comfort. Note that while the above previous studies focused on studying solutions to reducing energy costs for HVAC systems, none of them focused on the HVAC cost minimization problem in the context of *smart grids* of residential homes based on a demand side management (DSM) approach. In this paper, we present a novel game theory optimization solution that integrates deep learning models for prediction as well, and this has not been done before.

2.5. Motivation for a centralized approach

A centralized approach employing digital twins to solving the problem of HVAC energy usage cost minimization and energy reduction – as proposed in this paper – offers several advantages that make it better suited for several aspects of DSM optimization: (i) unified data management: centralized systems provide a singular point for data collection, analysis, and decision-making. Using digital twins (virtual replicas of physical systems) allows for a comprehensive and one-time overview of the demand-side landscape, improving decision accuracy. (ii) advanced analytics and optimization: centralized systems can leverage powerful computational resources to run complex optimizations with higher dimension. This can lead to more effective DSM strategies that are difficult to achieve with distributed systems due to computational constraints. (iii) standardization and control: a centralized approach ensures uniformity in data handling, analysis methodologies, and control strategies. This can be particularly advantageous for large-scale operations that require consistent performance across different locations and systems. (iv) enhanced security: centralizing DSM optimization can offer better security measures; that is because it is easier to implement and monitor cyber security protocols across a single, unified system rather than multiple distributed ones. (v) cost efficiency: while distributed systems have their benefits in scalability and fault tolerance, centralized systems can be more cost-effective in terms of infrastructure and maintenance. With centralized DSM optimization, it is easier to manage costs associated with data processing, software updates, and system maintenance.

To the best of our knowledge, we are not aware of any previous approach that focuses on HVAC energy cost reduction in a DSM context that combined game theory and deep learning. We propose such an approach in this paper to demonstrate its ability to reduce both energy costs and peak to average ratio (PAR) in smart grids. The game theory problem is formulated and solved in a centralized fashion in the cloud by the aggregator, which finds day-ahead optimized schedules for HVAC systems based on HVAC load predictions obtained with minimalistic long short term memory (LSTM) models.

3. Contributions

We are not aware of any previous work on DSM optimization focusing on day ahead scheduling based on predictions of energy usage — as collaboration between DL models in houses' SHEMs and GT optimization techniques at the utility/aggregator DSM side. This paper attempts to fill in this research gap. We present a different and more sophisticated game theory based solution to the problem of energy cost minimization in a district with residential homes supplied with energy by a single source such as a sub-station. Adopting the theoretical framework from [26], we make novel contributions as follows:

- *Three Distinct Problem Scenarios:* We examine three unique scenarios for HVAC energy management: (1) rescheduling of energy usage, (2) rescheduling of energy usage combined with potential reductions with up-to a certain percentage for each household, and (3) rescheduling of energy usage and uniform reduction with a fixed percentage for each household. Note that the first problem scenario is the one addressed in [26].
- *Specific Focus on HVAC Systems:* Our problem formulation has the ability due its centralized approach to incorporate into the game utility objectives such as line capacity control and loss reduction through the addition of new constraints; as opposed to for example the asynchronous and distributed approach from [26]. We focus on energy cost minimization at district level via offers for HVAC energy usage scheduling and reduction because HVAC accounts for the majority of household energy usage.
- *Deep Learning Based Predictions:* To predict HVAC energy usage for all households in the district, we utilize minimalistic long short term memory (LSTM) models that we discussed in our recent work [55]. Using these models each household SHEM generates predictions for 24 h ahead and transmits this information to the aggregator. The aggregator in turn uses that information to conduct its own optimization and it returns to each household optimized offers of schedules for the next day. Consequently, the aggregator's role is elevated above merely dictating prices (as in [26]) as it now actively engages in the game, facilitating interactions between the utility and consumers.
- *Game Theory Based Framework:* It is the aggregator that plays a pivotal role by centrally executing a game theory algorithm that iteratively seeks to reduce the overall energy cost within the district. Using this approach, each household behaves as a virtual game player with the primary objective of reducing their energy costs. Although the game is centrally managed, the unique perspectives of individual players are preserved, simulating an asynchronous and distributed approach similar to that described in [26]. The structure facilitates the representation of household interactions in a realistic manner.
- *Validation Through Advanced Simulations:* We validate the proposed energy cost minimization approach through simulations with a custom simulation tool based on GridLab-D tool – integrated with deep learning prediction models and optimization libraries – with the capability of simulating an instrumented testcase for an arbitrary number of days. We present results for a modified IEEE 13 node testcase that has attached 15 houses to its 7 buses.

3.1. Importance of the three scenarios

The output of the proposed DSM optimization approach consists of new optimized HVAC schedules that are identified by the aggregator and communicated to house users. These schedules represent effectively demand response signals in the smart grid (e.g., temperature changes for HVAC systems in smart homes). To maximize the flexibility of these demand response signals and to give as many options as possible to homeowners, we consider three different levels of energy usage offers. Each of these three levels introduces specific disturbance levels for homeowners and specific lost chances of selling energy for energy provider: (1) Level-1: rescheduling of energy usage. In this scenario, the energy provider is not disturbed in terms of the amount the energy sold (it is only that the energy usage is moved at different times). On the homeowners side, disturbance is minimal (e.g., it is in terms of acceptable temperature differences). In this scenario, we test our model for participants who prefer minimum risks and Nash equilibrium. (2) Level-2: rescheduling of energy usage combined with potential reductions with up-to a certain percentage for each household. In this scenario, the energy provider is minimally disturbed (i.e., energy provider sells less energy). Smart homes can experience a variety of disturbance levels. In this scenario, we test our model for participants who do not bother occasionally larger changes (i.e., in indoor temperature), but, still looking for Nash equilibrium. (3) Level-3: rescheduling of energy usage and uniform reduction with a fixed percentage for each household (this fixed percentage is maximum allowable percentage). In this scenario, the energy provider is losing the most in terms of energy not sold. Smart homes are also maximally disturbed. In this scenario, we test our model for participants who look for maximal rewards in terms of energy cost reduction, with being bothered by largest changes (i.e., temperature differences compared to the desired temperature setpoints). In summary, our proposed approach can provide different options for both participants in DSM (utility and smart homes) based on their preference and accepted level of risk. Such different options can be very valuable in practice (real world) as they can contribute to stronger and trusted connections between DSM participants.

3.2. Significance of minimalistic LSTM models

Minimalistic LSTM models excel in predicting energy usage within smart homes due to their ability to process time-series data effectively. Their efficiency does not compromise their predictive accuracy or their ability to adapt over time, crucial for responding to changing energy usage patterns and environmental conditions. Comparatively, minimalistic LSTMs outperform traditional deep learning models by delivering higher prediction accuracy. This is due to technical innovations that enable them to manage long-term data dependencies efficiently. The improved accuracy of energy usage predictions directly impacts energy management, allowing for more precise demand forecasting, optimized energy consumption. The lightweight nature of minimalistic LSTM models makes them ideal for deployment on resource-constrained devices common in smart homes. In other words, these models are particularly suited for edge computing devices (such as thermostat controllers), where data processing occurs near the data source, enhancing efficiency and security. By operating locally, these models minimize latency, reduce bandwidth usage, and maintain privacy, which is crucial in today's interconnected world. Essentially, minimalistic LSTM models combine the benefits of advanced predictive analytics with the practicalities of edge computing, offering a scalable, efficient, and privacy-conscious approach that aligns with the evolving needs of modern energy systems.

4. Models

In this section, we describe the system model that we use in this paper.

4.1. Load model

We adopt and modify the theoretical modeling framework from [37–39], and use primarily the notations from [26], whose notations are preserved here for consistency. The simplified block diagram of the power system modeled in this work is shown in Fig. 1. It is a simple distribution network where we have a single power source, which is the utility company. All houses form what we call a district and are equipped with smart meters and SHEMs that allow to optimize individually a selected number of appliances; while these appliances can be all those whose load is *shiftable*, in this work we focus only on HVAC, as the only and major consumer in a house [56]. In addition, we assume that the smart grid infrastructure includes a local area communication network (LAN) that allows information exchange between aggregator and house users. Note that because we model only a single power source, the role of the general VPP optimizer is played by the aggregator/utility's own cloud-based optimizer. Nevertheless, this distinction between aggregator/utility optimizer and VPP does not change at all the overall smart grid operation.

In the system from Fig. 1, we denote with $\mathcal{N}$ the set of all houses in the district. The magnitude of this set is the total number of houses $N \triangleq |\mathcal{N}|$. We also denote by $l_n \triangleq \{l_n^1, \ldots, l_n^H\}$ the daily energy load vector for a given house user $n \in \mathcal{N}$, where l_n^h represents the total load of house n at hour $h \in \mathcal{H} \triangleq \{1, \ldots, H\}$. Because we work with time granularity of one hour, we have $H = 24$. With these notations, we can write the expression for the load across all houses at any hour $h \in \mathcal{H}$ as:

$$L_h \triangleq \sum_{n \in \mathcal{N}} l_n^h \tag{1}$$

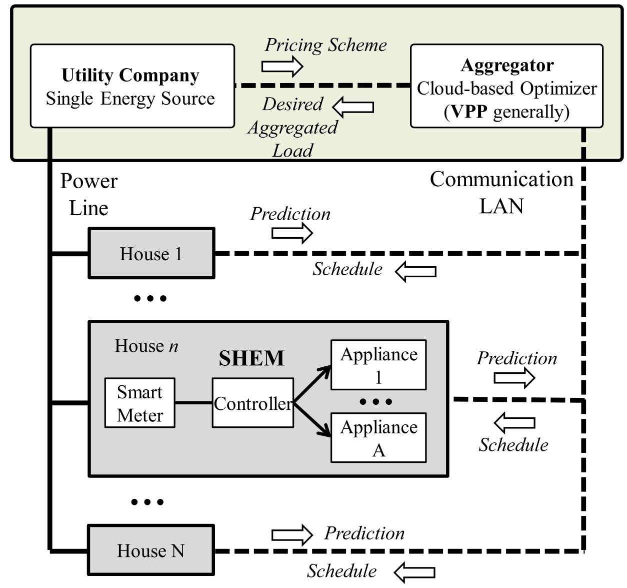

Fig. 1. Simplified block diagram of the smart power distribution system modeled in this work.

Furthermore, assume that house n has its own set of $\mathcal{A}_n$ appliances whose loads are *shiftable*. Each of those appliances has assigned to begin with an energy usage scheduling vector:

$$\mathbf{x}_{n,a} \triangleq \left[x_{n,a}^1, \ldots, x_{n,a}^H\right] \tag{2}$$

where $x_{n,a}^h$ denotes the one-hour energy usage by appliance a at hour h. In that case, the total hourly energy usage by house n can be calculated with the following expression:

$$l_n^h = \sum_{a \in \mathcal{A}_n} x_{n,a}^h, h \in \mathcal{H} \tag{3}$$

Focusing on only house n, for any of it appliances a, we define the total daily energy usage $E_{n,a}$ of that appliance as:

$$E_{n,a} = \sum_{h=1}^{H} x_{n,a}^h \tag{4}$$

With the above notations, we can write the *energy balance* equation:

$$\sum_{h \in \mathcal{H}} L_h = \sum_{n \in \mathcal{N}} \sum_{\alpha \in \mathcal{A}_n} E_{n,a} \tag{5}$$

4.2. Cost model

Given the load across all houses at any hour, L_h, we define the energy cost function $C_h(L_h)$, which represents the total cost incurred due to generation and distribution of power at hour $h \in \mathcal{H}$. These days, utility companies practice energy dynamic pricing schemes that charge differently based on the time of use (TOU) during the day; and, typically, energy costs less during night time when overall energy usage is low and energy costs more during day time, and with even higher prices during peak hours when the power system may become congested and overloaded. In this paper, we assume a similar pricing scheme as described later.

Moreover, we also assume that the energy cost function C_h is *increasing* and *strictly convex*. The increasing property ensures that a larger energy usage costs more, which makes sense, and can be expressed as:

$$C_h(\hat{L}_h) \le C_h(\tilde{L}_h), \qquad \forall \hat{L}_h \le \tilde{L}_h \tag{6}$$

The strictly convex property will help simplify the solution for the optimization problem formulated later on and can be expressed as [57]:

$$C_h(\theta \hat{L}_h + (1-\theta)\tilde{L}_h) < \theta C_h(\theta \hat{L}_h) + (1-\theta) C_h(\tilde{L}_h) \tag{7}$$

for any $\hat{L}_h, \tilde{L}_h \geq 0$ and $0 < \theta < 1$ real numbers. A good example of a cost function that satisfies the above two properties is the quadratic function:

$$C_h(L_h) = a_h L_h^2 + b_h L_h + c_h \tag{8}$$

where $a_h > 0$ and $b_h, c_h \geq 0$. In this paper, for simplicity but without loss of generality, we will use $b_h = 0, c_h = 0$.

4.3. Load control via rescheduling

The primary mechanisms to achieve optimization in this paper are (1) Optimized offers of reschedules of the energy usage load without changing the total amount used and (2) Optimized offers of reschedules that also achieve energy usage reduction within a threshold agreed on by both the aggregator/utility and by house users. The algorithm (discussed later in this paper) that solves the optimization problem to find the best new schedules and possible amounts of energy load reduction for house user is executed by the aggregator (see Fig. 1) which could be owned by and representing the utility itself. The new schedules found by the centralized algorithm will essentially be altered versions of the energy usage scheduling vectors described by Eq. (2) for all appliances in all houses.

To keep our problem formulation simple and the solution practical, we assume that rescheduling of energy usage of any appliance a of any house n can only be done within a pre-specified interval of time, measured in an integer number of hours. This is particularly more so in the case of HVACs because one would want to heat or cool the house when it is the hottest or coldest times, within an interval of time of interest referred to as *peak hours*. We denote such an interval as the set of hours $\mathcal{PH} = \{\alpha_{n,a}, \ldots, \beta_{n,a}\}$, $\alpha_{n,a} < \beta_{n,a}$. For example, the peak hour interval of time for the HVAC system or appliance during a summer day could be from $\alpha_{n,a} = 12:00$ to $\beta_{n,a} = 17:00$ (i.e., 12PM to 5PM). Note that different appliances in a house can have different such peak hour intervals. Also, the span of such an interval can vary too, but, in this paper we will fix it at a length of three hours — as a minimum length that would give enough room for rescheduling to have an impact. However, the length of three hours can be different and easy to change in our framework described in the experiments section later on.

The two primary mechanisms to achieve optimization mentioned above allow us to investigate the problem addressed in this paper in three different scenarios:

Scenario 1: Energy usage by appliance a in house n is rescheduled within the peak hours $\mathcal{PH}$ interval, but, the total amount of energy usage in this interval, $E_{n,a}^{\mathcal{PH}}$, remains unchanged. In other words, the same power consumption is just redistributed. Thus, also unchanged remains the total daily energy usage by appliance a from house n, $E_{n,a}$.

Scenario 2: Energy usage by appliance a in house n, $E_{n,a}^{\mathcal{PH}}$, is rescheduled within the peak hours interval and possibly reduced with up to a maximum possible percentage, denoted as $y_{n,a}^{max}$. It is important to mention here that $y_{n,a}^{max}$ is a maximum limit amount, that the aggregator and the house users agreed on in advance. With how much actually the offered energy usage is reduced will depend on how the aggregator will set-up the penalty parameter and solve the game theory based optimization problem (explained later on).

Scenario 3: Energy usage by appliance a in house n is rescheduled within the peak hours interval and reduced with a fixed percentage, equal to $y_{n,a}^{max}$.

Note that in any of the above three scenarios, the optimization will just result into new versions of energy schedule vectors for all appliances. Thus, the new total daily energy usage $E_{n,a}$ by an appliance a after rescheduling can be rewritten as:

$$E_{n,a} = \sum_{h=1}^{H} x_{n,a}^h = (1 - y_{n,a}) E_{n,a}^{\mathcal{PH}} + E_{n,a}^{\mathcal{H} \setminus \mathcal{PH}} \tag{9}$$

where $y_{n,a}$ is the *actual* percentage that total energy usage of appliance a in house n during their peak hours ends up being reduced during the peak hours. This actual percentage represents a control variable that will be found by the aggregator (from solving the game theory problem presented later) and it will be offered to the house users through the DSM mechanisms. Again, in this work, we assume that the aggregator and the house users agreed in advance that whatever percentage reduction the aggregator suggests, the house user will accept it as along as it is within the pre-established limit for that house, e.g., $y_{n,a}^{max} = 0.15$ or 15% in this paper. Note that, according to the scenario definitions above, in *Scenario 1*, the aggregator desires to achieve $y_{n,a} = 0$, in *Scenario 2*, $0 \leq y_{n,a} \leq 0.15$, while in *Scenario 3*, $y_{n,a} = 0.15$. $E_{n,a}^{\mathcal{H} \setminus \mathcal{PH}}$ is the total energy usage outside the peak hours before rescheduling. $E_{n,a}^{\mathcal{PH}}$ is the total energy usage during the peak hours before rescheduling, and can be written as:

$$E_{n,a}^{\mathcal{PH}} = \sum_{h=\alpha_{n,a}}^{\beta_{n,a}} x_{n,a}^h \tag{10}$$

At this time, we introduce a new definition, which will be used in formulating the main problem addressed in this paper. We define the vector $\mathbf{x}_n$ as the vector formed by stacking up energy usage scheduling vectors $\mathbf{x}_{n,a}$ (given be Eq. (2)) for all appliances $a \in \mathcal{A}_n$ for house n. Similarly, $\mathbf{y}_n$ denotes the vector formed by stacking up $y_{n,a}$. It is important to note that the notation order of x_n and y_n in Eq. (11) does not matter. With this notation, then, we can define further the *feasible set* of new energy usage schedule points and percentage reductions for house user n as:

$$\boldsymbol{XY}_n = \left\{ \begin{aligned} & \mathbf{x}_n, \mathbf{y}_n | \sum_{h=\alpha_{n,a}}^{\beta_{n,a}} x_{n,a}^h = (1 - y_{n,a}) E_{n,a}^{\mathcal{PH}}, \\ & S\left(y_{n,a} E_{n,a}^{max}\right) + E_{n,a}^{mean} \leq x_{n,a}^h \leq E_{n,a}^{max}, \forall h \in \mathcal{PH}, \\ & x_{n,a}^h = x_{n,a}^h, \forall h \in \mathcal{H} \setminus \mathcal{PH} \\ & 0 \leq y_{n,a} \leq y_{n,a}^{max} \end{aligned} \right\} \tag{11}$$

where $E_{n,a}^{max}$ and $E_{n,a}^{mean}$ are maximum and mean energy usage values among all hours in the day, while S is a scaling factor, which is found empirically as 2 in our experiments. In the above equation, the first equality constraint simply says that the summation of all energy usage values during the peak hours should be less with $0 \leq y_{n,a} \leq y_{n,a}^{max}$ percentages from the summation within the same interval that we had before the rescheduling. The second inequality constraint places some lower and upper bounds on what the actual energy usage values should be inside the peak hours interval. The third constraint enforces for all energy usage values outside the peak hours to be left unchanged, their values remain the same as before rescheduling. The last constraint specifies lower and upper bounds on the aggregator control variable $y_{n,a}$, which all players (i.e., house users) will accept at the end of the game theory based solution presented later.

While the load model above is presented for $\mathcal{A}_n$ appliances for generality of the problem formulation later on, note that in the actual testcase studied later in the experiments section, we will focus on just one appliance, the HVAC. The initial energy usage scheduling vector in this case, containing 24 hourly energy usage values, will be estimated by each house SHEM using minimalistic LSTM models used to make day ahead predictions. These predictions are passed by each house to the aggregator, as indicated in Fig. 1.

5. The problem of energy cost minimization

In this paper, we focus on the problem of *energy cost minimization*. However, we will show later that indirectly, by solving the problem of energy cost minimization, we also provide a solution to the problem of *peak-to-average ratio (PAR) minimization*. The problem of energy cost minimization is that given initial values for all energy usage scheduling vectors $\mathbf{x}_1, \ldots, \mathbf{x}_N$, we want to find a new optimal set of energy usage scheduling vectors and acceptable values for the aggregator control variables $\mathbf{y}_1, \ldots, \mathbf{y}_N$, from among the corresponding feasible set defined by Eq. (11) for any user n, characterized as the solution to the following convex minimization problem:

$$\underset{\mathbf{x}_n, \mathbf{y}_n \in \mathbf{XY}_n, \forall n \in \mathcal{N}}{\textbf{minimize}} \quad \sum_{h=1}^{H} C_h\Big(\sum_{n\in\mathcal{N}} \sum_{a\in\mathcal{A}_n} x_{n,a}^h\Big) \tag{12}$$

In solving the above problem, we adopt the approach from [58] that presented a solution to a similar problem based on penalty functions. The penalty function solution was designed to deal with inequality constraints. In our case, the penalty function has an adjustable parameter under the control of the aggregator, who can set it to pursue its own objective. The way the penalty parameter is set by the aggregator directly affects the feasible region defined by Eq. (11). The addition of the penalty function transforms the problem from (12) into the following approximate problem:

$$\underset{\mathbf{x}_n, \mathbf{y}_n \in \mathbf{XY}_n, \forall n \in \mathcal{N}}{\textbf{minimize}} \quad \sum_{h=1}^{H} C_h\Big(\sum_{n\in\mathcal{N}} \sum_{a\in\mathcal{A}_n} x_{n,a}^h\Big) + \sum_{n\in\mathcal{N}} \sum_{a\in\mathcal{A}_n} y_{n,a} B \tag{13}$$

The second term in the above summation, is $y_{n,a}B$ the *penalty function* that is under the control of the aggregator through the control parameter B. The penalty function is a continuous function whose value on a variable $y_{n,a}$ is selected to increase (approach $y_{n,a}^{max}$) via B, which is set to very small number in *Scenarios 2, 3* or to a very large number in *Scenarios 1*. The aggregator will have different objectives in the three scenarios. These objectives need to be translated into reduction of energy usage during peak hours such that $0 \le y_{n,a} \le y_{n,a}^{max}$ as discussed earlier. The new approximate problem from (13) is not exactly equivalent to the problem (12), but as the penalty function always approaches zero during the minimization process (i.e., a very small number), it becomes a good approximation. In our case the penalty function will satisfy that because the aggregator manipulates the penalty function by having either $y_{n,a}$ (in *Scenario 1*) approach zero or controlling B (in *Scenarios 2, 3*) towards very small values close to zero. In the next section, we provide a game theory based solution approach to this problem formulation and then present an algorithm for deriving the actual solution in each of the three scenarios.

6. Game theory based approach

In this section, we present a game theory based algorithm for solving the problem of energy cost minimization presented in the previous section. Similarly to [26], before presenting the solution, we need to present a discussion about pricing (i.e., cost) and billing (i.e., tariffs charged by the aggregator/utility to the customers), which will help arrive at a relation of the billing of any given house user with respect to the total cost.

Recall that the cost of energy usage for a given hourly load $C_h(L_h)$ described by Eq. (8) is the price of generation and distribution of power to customers. However, the aggregator/utility must bill the customers an amount that is at least as much as cost of generation and distribution (usually more in order to make some profits too). Thus, the first relationship between *effective cost* of energy and *billing to customers* can be described by the following relationship:

$$\sum_{n\in\mathcal{N}} b_n \ge \sum_{h=1}^{H} C_h\Big(\sum_{n\in\mathcal{N}} l_n^h\Big) \tag{14}$$

where b_n is the bill amount charged to house user n at the end of the day. The above expression relates the total daily billing amount across all N houses to the total daily effective cost of generation and distribution (incurred by aggregator/utility or energy providers). To simplify notation, let us introduce the following definition, which is simply a reformatting of the above expression:

$$k \triangleq \frac{\sum_{n\in\mathcal{N}} b_n}{\sum_{h=1}^{H} C_h(\sum_{n\in\mathcal{N}} l_n^h)} \ge 1 \tag{15}$$

It is important to mention that at the extreme, $k = 1$, case in which the billing system is said to be *budget balanced*; it is the situation where houses are only charged or billed the actual cost and that the aggregator/utility does not make any revenue. When $k > 1$ the utility makes profit. It is also important to recognize that Eq. (14) is an aggregated relation over all N houses. It gives the aggregator/utility an expression for the total bill with respect to the total effective cost for a normal mode of operation of the power system. However, it does not provide details about how individual houses are billed in relation to each other. We can though fill that lack of information with a common sense new *assumption of proportionality*, expressed as:

$$\frac{b_n}{b_m} = \frac{\sum_{h=1}^{H} l_n^h}{\sum_{h=1}^{H} l_m^h}, \forall n, m \in \mathcal{N} \tag{16}$$

which essentially says that houses are billed proportionally to their total daily energy usage. The above expression really only says that if house n consumes more than house m, then, house n should be billed higher than house m. The relationship could be in the simplest case a linear relationship (i.e., bill double for a double amount of energy); though, one can use more complex billing strategies where a house can be charged premiums usage goes above an upper limit. However, in our case the proportionality depends on the cost of energy at each hour of the day, which in turn is dictated by the actual convex cost function from Eq. (8).

With the goal of deriving a relation between the bill of any house n and the total aggregated cost in the entire system (for all houses), we extract b_m from Eq. (16) and do summation across all homes $m \in \mathcal{N}$:

$$\sum_{m\in\mathcal{N}} b_m = \sum_{m\in\mathcal{N}} \left(b_n \frac{\sum_{h=1}^{H} l_m^h}{\sum_{h=1}^{H} l_n^h} \right) = b_n \frac{\sum_{m\in\mathcal{N}} \sum_{h=1}^{H} l_m^h}{\sum_{h=1}^{H} l_n^h} \tag{17}$$

from where we can extract b_n, in which we can plug in order the expressions from Eqs. (15), (4), and (3) to arrive at:

$$b_n = \Omega_n \left(\sum_{h=1}^{H} C_h\Big(\sum_{m\in\mathcal{N}} \sum_{a\in A_m} x_{m,a}^h\Big) \right) \tag{18}$$

where, in order to simplify the final expression, we introduced the notation:

$$\Omega_n \triangleq \frac{k \sum_{a\in A_n} E_{n,a}}{\sum_{m\in\mathcal{N}} \sum_{a\in A_m} E_{m,a}} \tag{19}$$

Expression (18) is extremely important because it provides a means to estimate how much will be the bill for house n as a function of the schedule vectors of all houses in the entire system. It is a relation that connects how much a house is billed to the overall cost for all houses. In other words, the bill of a given house is *not independent*; rather, it depends on how much everybody in the system consumes cumulatively. This subtle observation is what really allows us to formulate the game theory presented next, which captures the interactions between the houses, where each house represents a player in the game.

Game of Rescheduling Energy Usage Controlled by Aggregator:

• *Players:* All house users in $\mathcal{N}$. Each house sends the aggregator once a day its day ahead energy usage schedule vector, obtained as prediction done by the local minimalistic LSTM models. The aggregator uses these predictions as the starting point for an iterative rescheduling inside a game executed by the aggregator with digital-twins for all houses; each digital-twin is modeled from the point of view of the house, and its interests are simulated in the game.

• *Strategies:* The aggregator reschedules energy usage on behalf of each house n and identifies new feasible vectors $\mathbf{x}_n$ such that to maximize the payoff for each house. Each time this is done, the energy usage schedule vectors of all other houses other than house n, denoted as $\mathbf{x}_{-n} \triangleq [\mathbf{x}_1, \dots, \mathbf{x}_{n-1}, \mathbf{x}_{n+1}, \dots, \mathbf{x}_N]$ remain fixed.

• *Payoff:* For each house n, we define the following payoff:

$$P_n\left(\mathbf{x}_n; \mathbf{x}_{-n}\right) = -b_n \tag{20}$$

where b_n is given by Eq. (18), which says that the meaning of payoff for house user n is the inverse of the bill charged by the aggregator/utility.

In the above game, the house users always prefer to receive offers new energy usage schedules that minimize their payments (i.e., bill) to the aggregator/utility. It was shown in [26] that the above game always has a solution as the Nash equilibrium and that it is the optimal solution. The energy usage schedule vectors $\mathbf{x}_n^*$ form a Nash equilibrium for the game if:

$$P_n(\mathbf{x}_n^*; \mathbf{x}_{-n}^*) \geq P_n(\mathbf{x}_n; \mathbf{x}_{-n}^*), \forall n \in \mathcal{N}, \mathbf{x}_n \geq 0 \tag{21}$$

7. Centralized algorithm to solve the game

In this section, we present an algorithm for solving the game formulation presented in the previous section. The algorithm is executed in a centralized fashion by the aggregator. The main reason for that (in contrast to the work in [26], which solves the game in a distributed fashion, at the level of each house) is to allow the aggregator to *control* the game such that to achieve desired target percentages $y_{n,a}$ in each of the three scenarios presented earlier. This control allows the aggregator to also possibly consider other objectives in addition to cost, such as line losses, balancing, congestion, etc.; however, that is not done in this paper, but, will be studied in our feature work. In addition, having the aggregator play the game on behalf of each house user serves as a sure enforcement of fair play — even though that is not necessary, as the players would not benefit from being untruthful. Finally, the centralized approach moves the computation to the cloud, which may offer shorter computational runtimes.

A simplified diagram that illustrates the centralized execution approach of the algorithm is presented in Fig. 2. It is important to observe that the algorithm solves the game in a way that preserves the perspective of each house (whose interest or objective is to reduce cost) as well as the *interaction* between users (as captured through Eq. (14) and (18)). This is achieved by having each house be part of the game as a virtual or digital-twin version of the actual house layer. These digital-twins are indicated in dashed lines in Fig. 2 and while they are constantly updated with information from the actual houses, their participation in the game captures the relationship or interaction among them, similarly to the approach in [26].

The pseudocode description of the proposed centralized algorithm is listed in Fig. 3. This algorithm is executed by the aggregator in the cloud. The algorithm is executed once per day; assumed to be done at midnight. At this time, all physical houses (that is their SHEMs) send their appliances' energy usage predictions for the next 24 h to the aggregator, i.e., to their virtual or digital-twin counterparts. These predictions represent the initial values of $\mathbf{x}_n$ and $\mathbf{x}_{-n}$, used in the first main iteration of the algorithm.

In each iteration of the algorithm, all houses are randomly placed in a list, and then, *processed* one by one from that list. Then, the aggregator solves on behalf of house n the following *local* maximization problem, to maximize the payoff for house n:

$$\underset{\mathbf{x}_n \in X_n}{\textbf{maximize}} \quad P_n\left(\mathbf{x}_n; \mathbf{x}_{-n}\right) \tag{22}$$

The above optimization problem is *local* to the house n in the sense that the only optimization variable for house n is the energy usage vector $\mathbf{x}_n$ during peak hours; the other energy usage vectors $\mathbf{x}_{-n}$ are

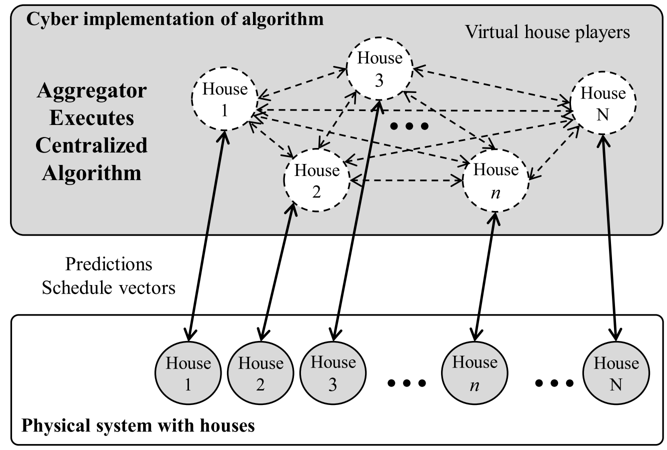

Fig. 2. The algorithm to solve the game is executed by the aggregator, in a centralized fashion, where all house users are implemented as digital-twins or counterparts of the actual houses.

Algorithm 1: Centralized Algorithm to Solve Game

```
For sufficient number of times Do
  Create random List with all houses
  While any house has new schedule from last main iteration Then
    For house n in List Do
      Initialize x_n, x_-n; 1st time based on SHEMs predictions
      Solve local problem (25) using Interior Point Method
      If x_n changed compared to current schedule Then
        Update x_n
      End
    End
  End
End
```

Fig. 3. Pseudocode description of proposed centralized algorithm to solve game of rescheduling energy usage.

kept fixed to their previous values when problem (22) is solved locally. Because Ω_n is fixed or constant (does not depend on the choice of $\mathbf{x}_n$) it can be dropped from Eq. (18). After dropping Ω_n, the above maximization problem can be converted into a minimization problem by multiplication with -1 as follows:

$$\underset{\mathbf{x}_n, \mathbf{y}_n \in XY_n}{\textbf{minimize}} \quad \sum_{h=1}^{H} C_h\Big(\sum_{m \in N} \sum_{a \in A_m} x_{m,a}^h\Big) \tag{23}$$

which, using Eq. (3), can be rewritten also as the following minimization:

$$\underset{\mathbf{x}_n, \mathbf{y}_n \in XY_n}{\textbf{minimize}} \quad \sum_{h=1}^{H} C_h\Big(\sum_{a \in A_n} x_{n,a}^h + \sum_{m \in \mathcal{N} \setminus \{n\}} l_m^h\Big) \tag{24}$$

It is important to note that the above observation that Ω_n is fixed and therefore dropped is true only in *Scenario 1* and *Scenario 3*. That is not the case in *Scenario 2*. However, for simplicity, we drop it also in *Scenario 2*, at the expense of the solution found later not being globally optimal (i.e., Nash equilibrium). In our experiments, we found that the rescheduling solutions found in this way in *Scenario 2* were satisfactory, even though they may not be globally optimal. Moreover, the error or distance of these non-optimal solutions from the global optimal solution is bound to be small because we work with relatively small $y_{n,a}^{max}$ values and small $\mathcal{PH}$ intervals (in Eq. (9)), which makes for the range of values for Ω_n (Eq. (19)) to be rather narrow. In addition, we assume that all house users are rational players in the game who agreed in advance to accept the reschedule and amount of energy reduction offered by the aggregator, because it is an incentive that guarantees minimization of their payments.

In solving the problem defined by Eq. (24), we again use a penalty function based approach and transform the problem into the following approximate minimization problem:

$$\underset{\mathbf{x}_n,\mathbf{y}_n\in XY_n}{\textbf{minimize}} \sum_{h=1}^{H} C_h\Big(\sum_{a\in\mathcal{A}_n} x_{n,a}^h + \sum_{m\in\mathcal{N}\setminus\{n\}} l_m^h\Big) + \sum_{a\in\mathcal{A}_n} y_{n,a} B \tag{25}$$

where $y_{n,a}B$ represents the penalty function, which will be set to act as a penalty applied to solution points (during solution space exploration by the proposed algorithm) that violate the aggregator objective, which is different in each of the three scenarios. Now, observe that the problem defined by Eq. (25) is essentially the same as the problem from Eq. (13). A subtle difference only is the fact that the problem (25) is *local* in the sense that its has as variables only local variables for house n; all other houses have their variables fixed to the values at the end of the previous main iteration of the algorithm. So, in a given iteration of the algorithm, solving the local problem (25) results into best new values for the local $\mathbf{x}_n$ for house n. This is done for all houses separately inside one main iteration of the algorithm; in other words, each house as a player in the game has its own local problem (25) solved in multiple iterations. Because the problem (25) is convex it can easily be solved with an interior point method (IPM) based approach [57]. To achieve the objective in each of the three scenarios, the key is to choose the appropriate value for the penalty parameter B. That is, in *Scenario 1*, it is desired to arrive to a solution that forces the control variable $y_{n,a}$ to approach to zero ($y_{n,a} \to 0.00$) — so that the total energy usage during the peak hours interval remains the same (recall that this scenario was done in [26]). To achieve that, the aggregator will set B to a very large positive value. We empirically found that a value that is at least as large as the largest energy usage value among all houses in the system leads to the desired result. In *Scenario 2*, it is desired for the total energy usage during the peak hours interval to be possibly reduced with a percentage less or equal to say $y_{n,a} \leq 0.15$ (we work with 15% in this paper, but this percentage can be changed). In *Scenario 3*, it is desired for the total energy usage during the peak hours interval to be reduced by an amount that approaches a fixed percentage such as $y_{n,a} \to 0.15$. To achieve that, in both *Scenarios 2, 3*, the aggregator will instead set a very small positive value for the penalty parameter B. This value was again found empirically, and a value equal to the inverse of the largest energy usage value among all houses in the system leads provided good results in practice. The difference between how the local problem (25) is then solved for *Scenarios 2, 3* is that in *Scenario 3* the feasible region is made larger than in *Scenario 2* by modifying Eq. (11) to replace the scaling parameter S with a much smaller value, (in practice an order of magnitude compared to *Scenario 2*) such that the feasible space is effectively increase. In this way, the feasible space includes much smaller values for $\mathbf{x}_n$ including those that result into a certain $y_{n,a} = 0.15$ for total energy usage during the peak hours interval for each house n. Once the local problem (25) is solved (Line 6 in Fig. 3) for a given house n, the schedule vector $\mathbf{x}_n$ is updated if it changed compared to its value from previous iteration (Line 8 in Fig. 3). The algorithm from Fig. 3 is an iterative algorithm, which is executed a *sufficient* number of times, that is until convergence to a solution with schedule vectors for all houses that do not change anymore between consecutive iterations.

8. Simulation results

8.1. Simulation tool

To conduct experiments, we have developed a custom simulation framework, which primarily integrates the GridLab-D tool [59], Julia optimization packages, and LSTM deep learning models developed in Tensorflow. These software components are integrated and executed from within a Python script. A simulation experiment is run from within this script in several stages: In stage one, the script passes information about a specific day (dd-mm-yyyy) as input to the GridLab-D tool, which also reads in the instrumented IEEE 13 node testcase. The GridLab-D simulates the testcase for 24 h; as result of the simulation, the hourly energy usage (both net and HVAC loads) for all houses is obtained. In stage two, the Python script passes the energy usage result to the LSTM prediction models of each house; in a practical deployment of our approach this would be done at the house sites, by their SHEM computer. The minimalistic LSTM models predict the HVAC energy usage (or more generally of any number of appliances with shiftable energy usage) for the next 24 h. The predictions are passed by the Python script in stage three to the aggregator component, which constructs the game theory based optimization problem that is solved by an implementation in Clarabel package in Julia (interior-point solver for convex conic optimization problems). Finally, the new best HVAC schedule vectors are sent back to all houses SHEMs, which in turn will generate their optimal DR signals – modeled by the GridLab-D tool – which continues the simulation for the next 24 h. The simulation framework can also be set to continue the simulation for the next 24 h with HVAC schedule vectors as the initial predictions, which serves as a reference or base for our comparison, with and without the proposed optimization. Then, the entire process is repeated every 24 h. A simplified diagram that describes this simulation framework is shown in Fig. 4.

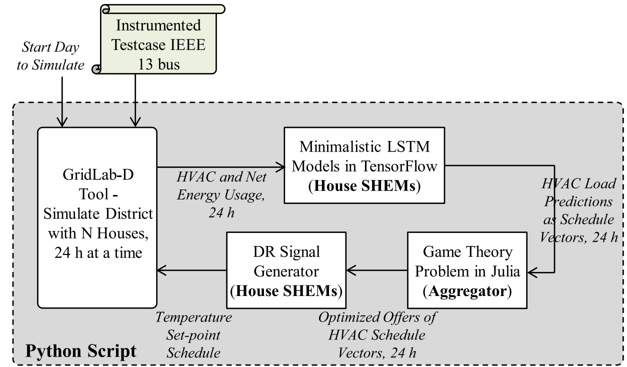

Fig. 4. Description of the simulation framework controlled from within a Python script.

8.2. Experimental setup

We conducted simulations on an instrumented IEEE 13 node testcase, which has 15 houses attached to the 7 buses of the testcase. We provided details on our tool and the instrumented testcase in our recent conference paper [55], where we developed minimalistic LSTM models that predict the HVAC energy usage for the next day at an hourly granularity for 12 houses in the system. In the interest of space, we do not elaborate on the LSTM models here. Because we have already developed the minimalistic LSTM models that predict the HVAC energy usage for each house, in this paper we focus only on the HVAC as the major appliance for which we apply the proposed rescheduling approach. In other words, the HVAC load is the only load controllable via house-local SHEM DR signals. Note that HVAC represents by far the biggest consuming appliance in a typical residential home whose load is shiftable. However, the theoretical framework presented in this paper can be applied to multiple appliances whose loads are shiftable.

For simplicity we assume the quadratic cost function from Eq. (8). We also assume an TOU pricing scheme, available to the aggregator/utility, with three levels for 24 h [60] that uses: *Night-Sleep* period (22:00 to 7:00), *Day-Normal*∩*Night-Normal* period (7:00 to 12:00 and 18:00 to 22:00), and *Peak-Day* (12:00 to 18:00). For these periods the prices are: $\phi_{Night-Sleep} = 0.1$ cents/kWh, $\phi_{Peak-Day} = 0.3$ cents/kWh, and $\phi_{Day-Normal\cap Night-Normal} = 0.2$ cents/kWh. In addition, the distribution system is assumed to be budget-balanced case in which $k = 1$ (see Eq. (15)). In all three scenarios discussed earlier in this paper, house

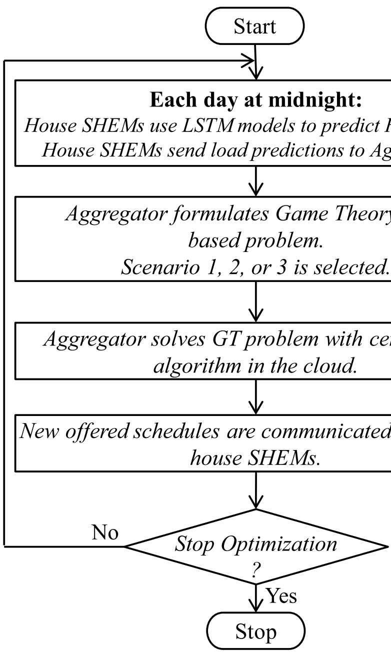

Fig. 5. Flowchart depicting the simulation experiments: every 24 h, each house predicts its own HVAC load, and then, the aggregator solves the game theory problem to find new schedules for HVACs within the peak hours interval.

users agree to honor the offered rescheduling found by the aggregator. Finally, we work with $y_n^{max} = 0.15$, but, this can be changed.

The rescheduling discussed in Section 4.3 and solved by the game theory based algorithm, always starts from a default energy usage schedule vector for all HVAC systems for all houses. That initial schedule is generated for each house by the local minimalistic LSTM models. These predictions are done automatically by the SHEM of each house and transmitted once per day to the aggregator from Fig. 1 — where they will represent the starting energy usage schedule vector for the optimization algorithm executed by the aggregator. Our custom simulation tool follows the flowchart in Fig. 5 where every day, at midnight, the aggregator receives the predictions from each house, then, it formulates the game theory problem (from Section 6) and solves it with the approach from Fig. 3. All houses are then sent back their offered new daily energy usage schedule vectors by the aggregator. These new schedules are assumed to be honored by their local SHEMs for generating optimal DR signals for the next 24 h. Then, the entire process is repeated for another day (i.e., 24 h) and so on as many days as desired.

8.3. Results in three scenarios

We present in Fig. 6 a brief comparison of the three scenarios (more details are provided in subsequent sections) to showcase the effectiveness of the proposed method. In *Scenario 1* (desired $y_n = 0$), the aggregator is only interested in HVAC load shifting during peak hours. As shown in Fig. 6.a, the total HVAC energy usage during peak hours intervals for each of the 12 houses remains unchanged after executing Algorithm 1 from Fig. 3. In *Scenario 2*, the aggregator wishes to both reschedule and reduce total HVAC energy usage during peak hours intervals by up to y_n^{max}, i.e., $0 \leq y_n \leq 0.15$. After executing the proposed algorithm in this scenario, the E_n^{PH} of each house during peak hours is reduced by various amounts, all less than 15%, as seen in Fig. 6.b. Finally, in *Scenario 3*, the new energy schedules from aggregator again both reduce and shift the total amount of HVAC energy usage during peak hours (E_n^{PH}) by 15% (maximum available option). As a result of executing the proposed algorithm in this scenario, the total HVAC

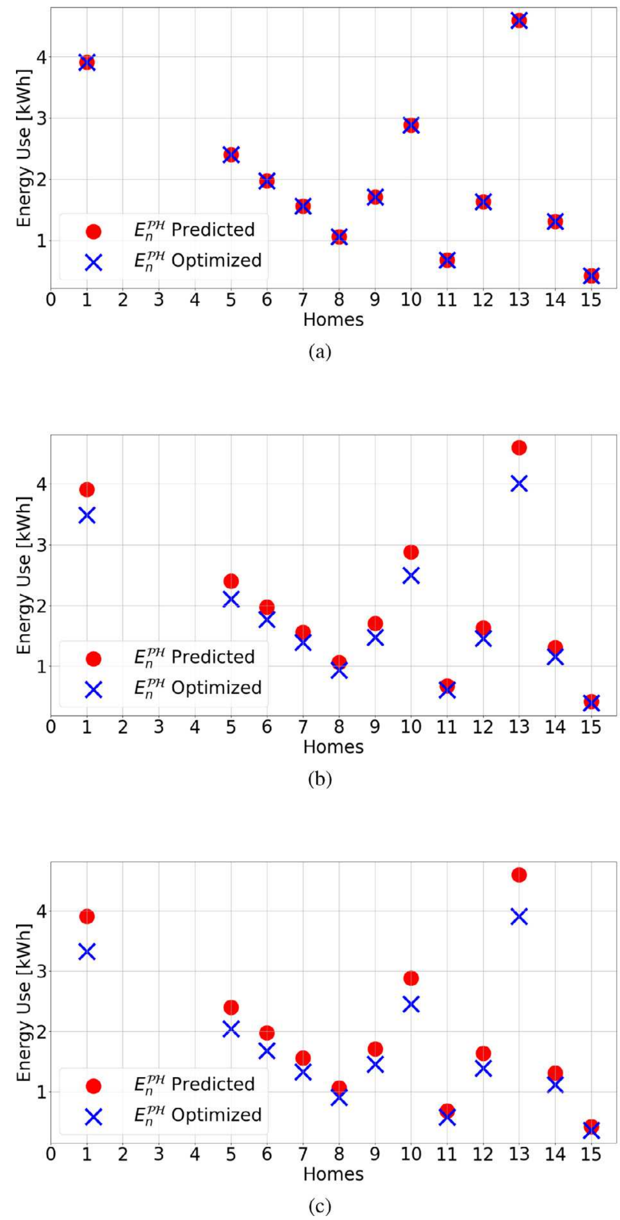

Fig. 6. Reduction of daily total HVAC energy usage during peak hours intervals in three scenarios ((a) is *Scenario 1*, (b) is *Scenario 2*, (c) is *Scenario 3*) on the same day as in Fig. 13.

energy usage during peak hours intervals for each of the 12 houses is reduced and shifted by the maximum amount as shown in Fig. 6.c.

8.3.1. Scenario 1

In this scenario (desired $y_n = 0$), the aggregator is only interested in HVAC load shifting within the peak hours interval. After executing the Algorithm 1 from Fig. 3, the daily total net energy usage (i.e., HVAC controllable load plus all remaining load in the house) for each of the 12 houses remains unchanged as shown in Fig. 7. However, because of the rescheduling within the peak hours intervals the total daily cost – from the aggregator point of view – is reduced. As an example, Fig. 8 shows how the total cost is reduced in 12 randomly selected days, one from each month of the year. We can see that for example for the day in May, the proposed optimization algorithm can reduce the total HVAC cost by 23% using only load shifting. As an example of how this is achievable, Fig. 9.a shows how peak energy usage is shifted for house 6 on a randomly selected day in May. On the same day, the total

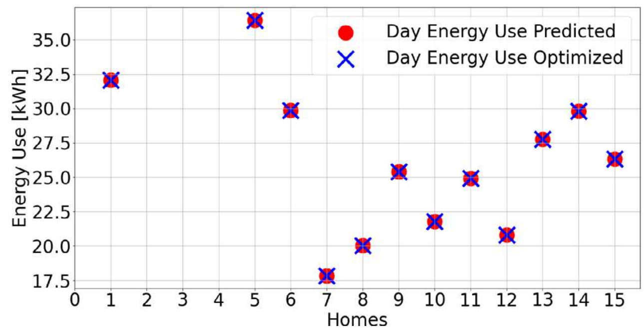

Fig. 7. Daily total net energy usage remains the same for each house in *Scenario 1*.

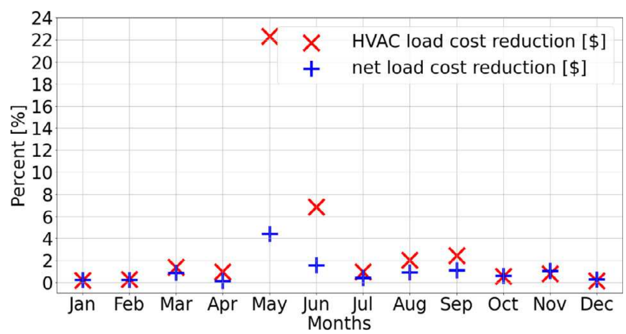

Fig. 8. Total aggregated cost reduction for 12 randomly selected days in *Scenario 1*.

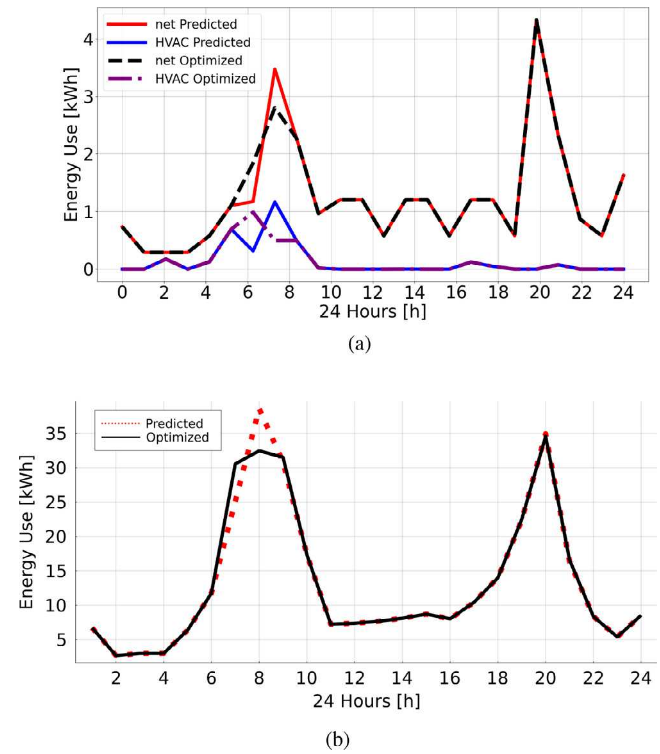

Fig. 9. (a) Houly HVAC and net loads for house 6 on a randomly selected day of May in *Scenario 1*. (b) Total aggregated net load in the entire system on the same day in *Scenario 1*.

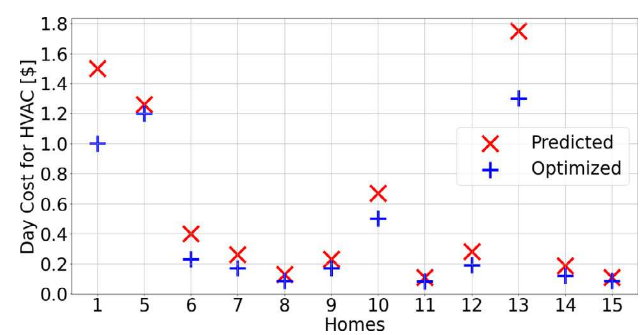

Fig. 10. Change in daily cost of HVAC energy usage for all 12 houses in *Scenario 1*; on the same day as in Fig. 9.

aggregated net load in the system changes as shown in Fig. 9.b. This total cost reduction is due to individual cost reduction for each house. This is shown in Fig. 10 that shows how the daily cost of HVAC energy usage (i.e., controllable load) changes as a result of applying the DSM' signal offered in this paper.

8.3.2. *Scenario 2*

In *Scenario 2*, the aggregator desires to reschedule (i.e., shift) but also to reduce the total amount of energy usage during peak hours interval $E_n^{\mathcal{PH}}$ (Eq. (10)) by up to y_n^{max}, i.e., $0 \leq y_n \leq 0.15$. After executing the proposed algorithm in this scenario, each house has its total HVAC energy usage within peak hours reduced with various amounts, all less than 15%, as shown for example in Fig. 11.a. As an example, Fig. 12 shows how the total cost is reduced in 12 randomly selected days, one from each month of the year. Because in this scenario the aggregator has more flexibility in reducing costs further by cutting down the total HVAC energy usage within peak hours, the reduction in total HVAC cost can be as much as 32% — as shown for instance in Fig. 13, which shows how peak energy usage is shifted for house 6 on a randomly selected day in May and how the total aggregated net load in the system changes on the same day. The individual daily HVAC load cost reductions for each house are shown in Fig. 14.

8.3.3. *Scenario 3*

In *Scenario 3*, the aggregator's new energy schedules offer to reduce and shift at the same time the total amount of HVAC energy usage during peak hours $E_n^{\mathcal{PH}}$; the offered reduction is with a fixed percentage amount y_n^{max}, in our case 15% (i.e., $y_n = 0.15$). As discussed earlier, this is achieved – especially in contrast with *Scenario 2* – by enlarging the region of feasible solutions for each local problem. After executing the proposed algorithm in this scenario, each house has its HVAC energy usages reduced during peak hours with essentially 15%, as shown for example in Fig. 15.a. As an example, Fig. 16 shows how the total cost is reduced in 12 randomly selected days, one from each month of the year. In this scenario, the aggregator has the most flexibility in reducing costs further by reducing 15% of the total HVAC energy usage within peak hours, the reduction in total HVAC cost can be as much as 36% — as shown for instance in Fig. 17, which shows how peak energy usage is shifted and reduced for house 6 on a randomly selected day in May and how the total aggregated net load in the system changes on the same day. On the same day, the individual daily HVAC load cost reductions for each house are shown in Fig. 18.

8.4. Peak to average ratio

In this section, we investigate how solving the problem of energy cost minimization, which is the primary focus of this paper, also indirectly improves the peak to average ratio (PAR). We do that because it has been shown in previous literature that a solution to the energy cost minimization problem can also be a solution to the problem of PAR minimization. The daily peak and average load levels are calculated with the following two expressions:

$$L_{peak} = \max_{h \in \mathcal{H}} L_h \tag{26}$$

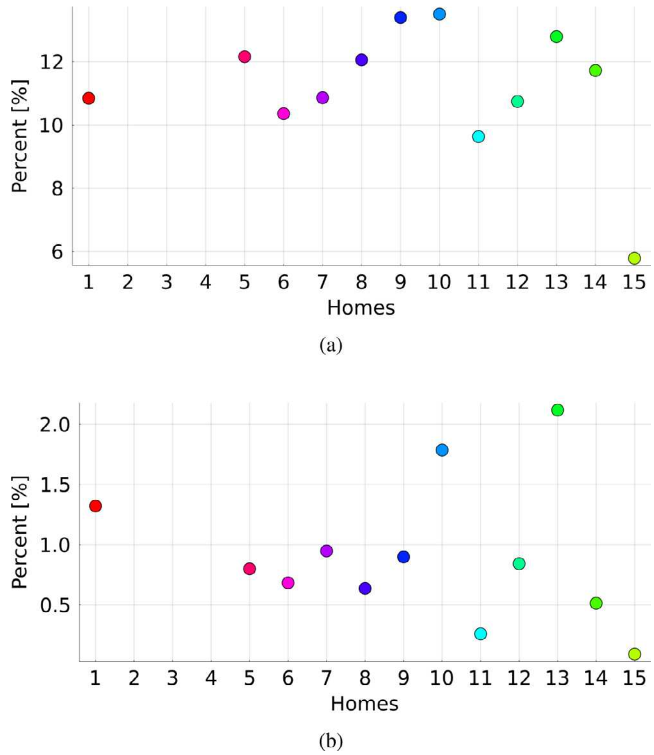

Fig. 11. (a) Reduction in total HVAC energy usage during peak hours only in *Scenario 2*. (b) Reduction of daily total net energy usage in *Scenario 2*.

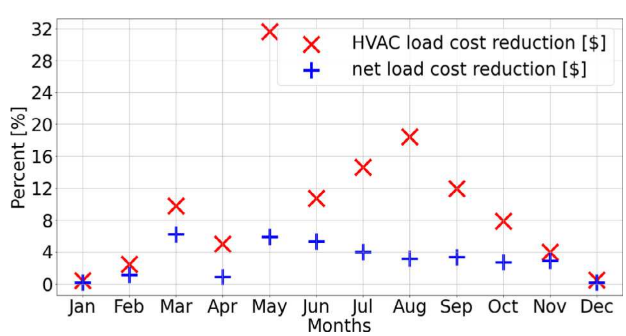

Fig. 12. Total aggregated cost reduction for 12 randomly selected days in *Scenario 2*.

$$L_{avg} = \frac{1}{H} \sum_{h \in \mathcal{H}} L_h \tag{27}$$

With these two definitions then, PAR can be calculated as:

$$PAR = \frac{L_{peak}}{L_{avg}} = \frac{H \max_{h \in \mathcal{H}} L_h}{\sum_{h \in \mathcal{H}} L_h} \tag{28}$$

Then, using the expressions from Eq. (1), (3), and (5), Eq. (28) can be used to derive the problem of PAR minimization in terms of energy usage scheduling vectors $\mathbf{x}_1, \dots, \mathbf{x}_N$ as:

$$\underset{\mathbf{x}_n \in \boldsymbol{XY}_n, \forall n \in \mathcal{N}}{\textbf{minimize}} \quad \max_{h \in \mathcal{H}} \left(\sum_{n \in \mathcal{N}} \sum_{a \in \mathcal{A}_n} x_{n,a}^h \right) \tag{29}$$

While solving the PAR minimization problem is not the main focus of this paper, we report here the results in terms of PAR reduction achieved by the solutions to the problem of HVAC energy cost minimization. The aggregate PAR percentage reduction in each of the three scenarios is shown in Fig. 19 for the 12 randomly selected days, one for each month, studied in the previous sub-sections. We observed that

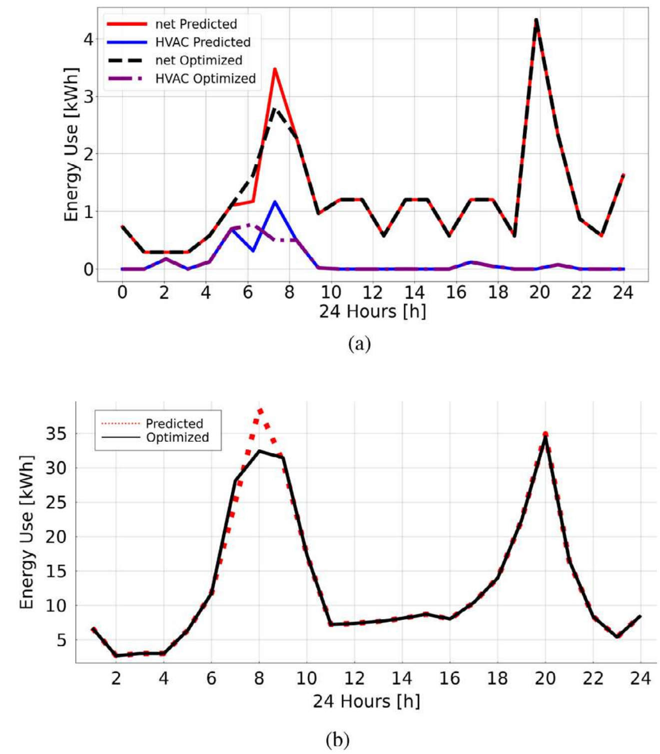

Fig. 13. (a) Houly HVAC and net loads for house 6 on a randomly selected day of May in *Scenario 2*. (b) Total aggregated net load in the entire system on the same day in *Scenario 2*.

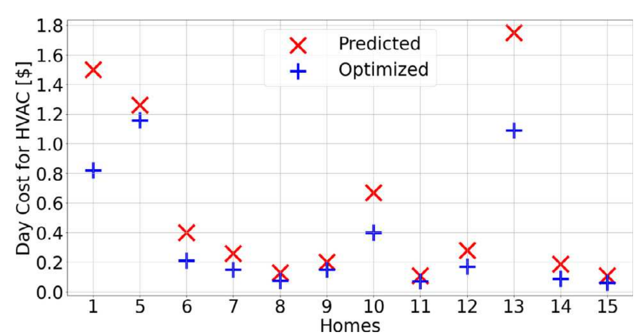

Fig. 14. Change in daily cost of HVAC energy usage for all 12 houses in *Scenario 2*; on the same day as in Fig. 13.

PAR was reduced by up to 8.25%, 10.10%, and 11.09% in *Scenario 1*, *Scenario 2*, and *Scenario 3*, respectively — confirming the results from previous literature.

9. Conclusion

We presented a novel cloud-based DSM optimization approach for the cost reduction of HVAC systems in residential homes. The proposed approach achieves optimization through scheduling of HVAC energy usage within permissible bounds set by house users. Hence, the main focus is on cost reduction via load scheduling of the HVAC system — as the major component of shiftable energy usage in residential houses. By shifting and reducing HVAC energy usage within permissible bounds set by home users, we solve the formulated problem using an iterative algorithm that is applied to three different scenarios set-up by the aggregator: (1) energy is only shifted within the peak hours, (2)

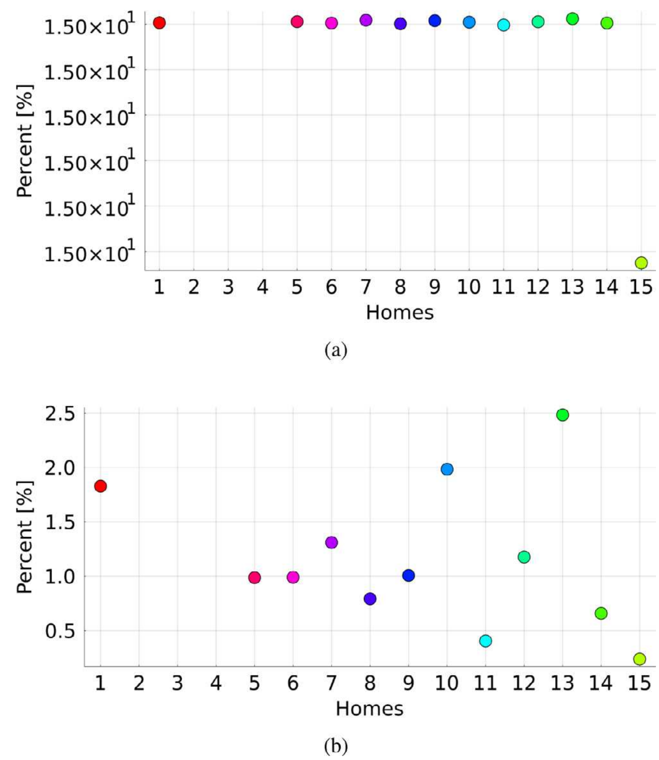

Fig. 15. (a) Reduction in total HVAC energy usage during peak hours only in *Scenario 3*. (b) Reduction of daily total net energy usage in *Scenario 3*.

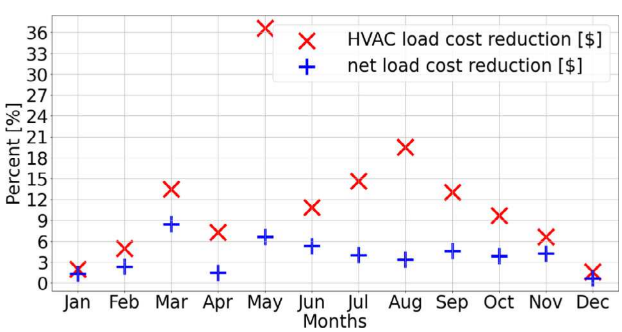

Fig. 16. Total aggregated cost reduction for 12 randomly selected days in *Scenario 3*.

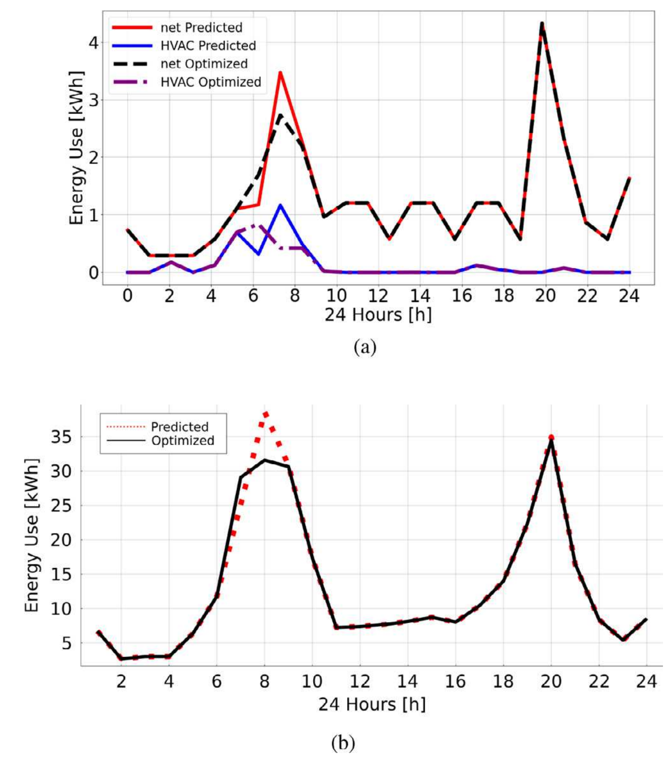

Fig. 17. (a) Houly HVAC and net loads for house 6 on a randomly selected day of May in *Scenario 3*. (b) Total aggregated net load in the entire system on the same day in *Scenario 3*.

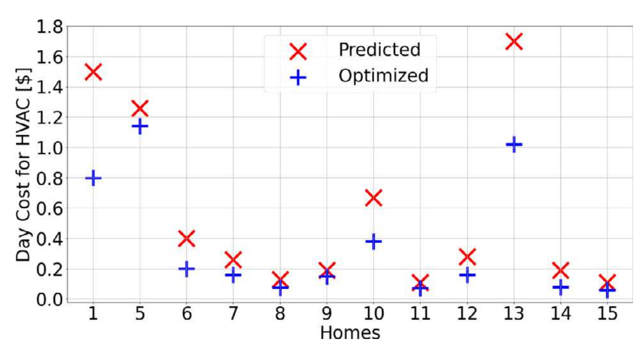

Fig. 18. Change in daily cost of HVAC energy usage for all 12 houses in *Scenario 3*; on the same day as in Fig. 17.

energy is both shifted and reduced with up to a certain percentage, and (3) energy is both shifted and reduced with a fixed percentage. The proposed algorithm is executed in a centralized fashion in the cloud, and it captures by design the relationship between house users in the budged-balanced system through a proportionality relation of the house users bills. The proposed algorithm is verified on an instrumented IEEE 13 bus testcase simulated multiple consecutive days with a custom simulation tool based on GridLab-D tool, which integrates LSTM models for 24 h prediction of HVAC energy usage and optimization libraries. Simulation results showed that HVAC energy cost can be reduced by up to 36% while indirectly also reducing the peak-to-average ratio (PAR) of the aggregated net load by up to 9.97%. We plan to extend the optimization framework and simulation tool presented in this paper by considering the case where the power system has multiple energy sources in the system and houses may have individual PVs, as well as energy storage systems such as fixed batteries and EVs that can be used to provide (even to sell energy back to the grid at peak hours) energy at high-price hours and can be charged at low-price hours, usually during the night. Another interesting direction is to include objectives other than cost reduction such as grid congestion avoidance, line loss reduction, and system stability.

CRediT authorship contribution statement

Rahman Heidarykiany: Conceptualization, Data curation, Formal analysis, Software, Visualization, Writing – original draft. **Cristinel Ababei:** Investigation, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

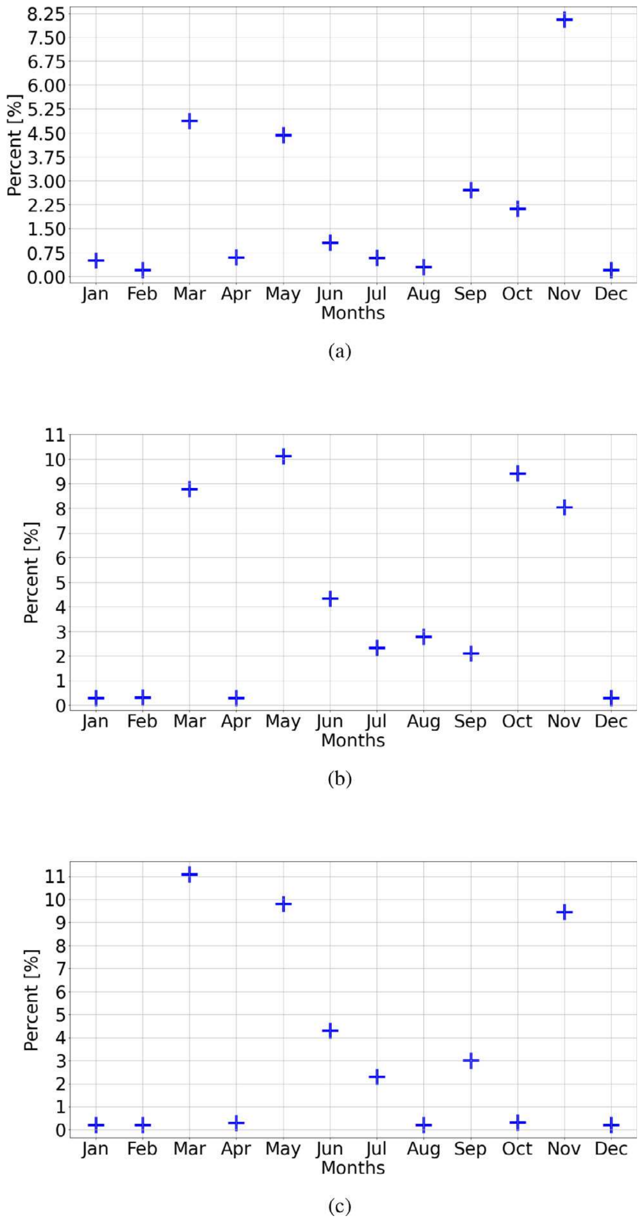

Fig. 19. Reduction in PAR of aggregated net load for 12 randomly selected days in each of the three scenarios.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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