IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received February 9, 2022, accepted March 12, 2022, date of publication March 23, 2022, date of current version April 6, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3161845

Real-Time Scheduling for Optimal Energy Optimization in Smart Grid Integrated With Renewable Energy Sources

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This work was supported by the Taif University Researchers Supporting Project through Taif University, Taif, Saudi Arabia, under Grant TURSP-2020/331.

ABSTRACT Load scheduling, battery energy storage control, and improving user comfort are critical energy optimization problems in smart grid. However, system inputs like renewable energy generation process, conventional grid generation process, battery charging/discharging process, dynamic price signals, and load arrival process comprise controller performance to accurately optimize real-time battery energy storage scheduling, load scheduling, energy generation, and user comfort. Thus, in this work, the virtual queue stability based Lyapunov optimization technique (LOT) is adopted to investigate real-time energy optimization in a grid-connected sustainable smart home with a heating, ventilation, and air conditioning (HVAC) load considering unknown system inputs dynamics. The main goal is to minimize overall time average energy cost and thermal discomfort cost in a long time horizon for sustainable smart home accounting for changes in home occupancy state, the most comfortable temperature setting, electrical consumption, renewable generation output, outdoor temperature, and the electricity costs. The employed algorithm creates and regulates four queues for indoor temperature, electric vehicle (EV) charging, and energy storage system (ESS). Extensive simulations are conducted to validate the employed algorithm. Simulation results illustrate that the proposed algorithm performs real-time energy optimization and reduces the time average energy cost of 20.15% while meeting the user's energy and comfort requirement.

INDEX TERMS Real-time, optimization, convex optimization, dynamic pricing, renewable energy generation, scheduling, energy storage, user comfort.

NOMENCLATURE

Abbreviations	Explanation
AI	Artificial intelligence.
ACO	Ant colony optimization.
ABC	Artificial bee colony.
AEP	Annual energy production.
BES	Battery energy storage.
DR	Demand response.
EMS	Energy management system.
ESS	Energy storage system.
EV	Electric vehicle.
GA	Genetic algorithm.
HEMS	Home energy management system.
HVAC	Heating, ventilation, and air conditioning.
GA–PSO	Genetic algorithm particle swarm optimization.
LCoE	Levelized cost of energy.
LOT	Lyapunov optimization technique.
MINLP	Mixed integer non linear programming.
MILP	Mixed integer linear programming.

The associate editor coordinating the review of this manuscript and approving it for publication was Alexander Micallef.

NRFNA	Normalised reasoning-based fuzzy neural adaptive.
NMPC	Non-linear model predictive controller.
PAR	Peak to average ratio.
PV	Photovoltaic.
PSO	Particle swarm optimization.
PCC	Point of common coupling.
PHEVs	Plugin hybrid electric vehicles.
PG	Peaker generator.
RES	Renewable energy sources.
RT	Real time.
TCLs	Thermostatically controlled loads.
Constants	**Explanation**
A	Thermal conductivity in general ($kW/^{\circ}F$).
C_{pv}	PV panels' total irradiance area (m^2).
$D^{\max}$	Q_t max queueing delay (hour).
$e^{\max}$	HVAC system power (kW).
ε	Inertia factor.
N	The total amount of time slots available.
η	Efficiency of thermal-conversion (heating).
R	EV charging tolerant delay (hour).
$T^{\min}$	Comfort range's lower bound ($^{\circ}C$).
$T^{\max}$	Comfort range's upper bound ($^{\circ}C$).
$T^{out\,\min}$	Outdoor minimum temperature ($^{\circ}C$).
$T^{out\,\max}$	Outdoor maximum temperature ($^{\circ}C$).
τ	Time slot duration (hour).
$u^{c\,\max}$	ESS max charge power (kW).
$u^{d\,\max}$	ESS max discharge power (kW).
$v^{\max}$	EV max charge power (kW).
ω	System time-constant (hour).
θ_{pv}	The efficacy of PV generation.
γ	Thermal cost-coefficient ($RMB/(^{\circ}F)^2$).
Indices	**Explanation**
t	Single time slot index.
Variables	**used**
a_t	Q_t queue arrival rate (kW).
B_t	Electricity buying cost (RMB/kWh).
e_t	HVAC input power at slot t (kW).
G_t	ESS stored energy level (kWh).
g_t	Buying/selling energy relating smarthome (kW).
H_t	Indoor temperature virtual queue ($^{\circ}F$).
K_t	ESS control virtual queue (kWh).
L_t	Lyapunov function.
pwt_t	Wind generation output (MW).
ρ_t	Intensity of solar irradiance (W/m^2).
Q_t	Energy queue for EV (kW).
r_t	PV panels' generation output (kW).
S_t	Electricity selling cost (RMB/kWh).
T_t	Indoor temperature ($^{\circ}C$).
T_t^{out}	Outdoor temperature ($^{\circ}C$).
T_{t+1}^{ref}	The foremost comfortable temperature ($^{\circ}C$).
x_t	Q_t queue service rate (kW).
y_t	ESS Charge/discharge power (kW).
Z_t	EV charging delay virtual queue (slots).
Π_{t+1}	Home occupancy state at slot $t+1$.
$\Phi_{1,t}$	Cost of energy (RMB).
$\Phi_{2,t}$	Cost of thermal discomfort at slot $t+1$ (RMB).

I. INTRODUCTION

Due to budget and technological constraints, the main power grid cannot electrify the remote regions across the world. Thus, electrification of remote regions becomes possible with a microgrid's emergence. A microgrid is an integrated framework linking distributed generators, distributed energy storage, and controllable load within a limited and clearly defined region operating independently [1]. With the emergence of information and communication technology, the microgrid can be operated in two modes: grid-connected and standalone to solve energy balancing problems. On the record, residential sector consumers $31\%-41\%$ of the overall energy, which is major consumption. Thus, for effective energy balancing/energy optimization, an optimal controller infrastructure is required for charging/discharging activities scheduling, flexible load scheduling, energy flow control between microgrid and power grid [2]–[4].

On this note, in the literature, diverse research work has been conducted for real-time energy optimization in smart grids integrated with renewable energy sources and energy storage systems. For instance, in [5], a novel energy management framework with smart control and automation is introduced for household energy management. Similarly, many works are conducted for energy balancing either in grid-connected or stand-alone modes in both aspects like user-centric and utility-centric. The utility-centric energy optimization function is constrained to user commitment, spinning reserve, energy storage, renewable energy generation, power grid operation, demand response, etc. In contrast, the user-centric energy optimization function is constrained to appliances scheduling delay, battery storage management, energy cost reduction [6]–[9]. The particular discussion of related work is presented in section II, where challenges in the existing works are highlighted.

In this study, we emphasize on scheduling the load in a smart home that includes HVAC and EV charging because HVAC systems account for roughly half of a smart home's power usage, and EV charging falls under the flexible load's category. Consequently, the variation in price over time may be used to save money on energy. In particular, the smart home takes into account distributed generators and ESS. The goal of this research study is to reduce the overall cost of electricity-related to smart home appliances and thermal discomfort costs associated with residents over a long time horizon by taking into account variations in electricity costs, outdoor temperature, RES generating output, electrical demand, the foremost comfortable temperature level, and home occupancy state. To accomplish the goal mentioned above, we first solve the challenge of lowering the average projected total cost for a home equipped with an HVAC load. As time-coupled limitations and the prospective system characteristics are uncertain, solving the specified problem is complex.

A time average optimization problem may usually be solved using the framework of LOT [10], and an online energy management method may be constructed as in [11] and [12]. Current Lyapunov-based energy management algorithms aim to queue flexible load facility demand requests when the price of electric power is high and provided when the price of electric power is low. Unlike an EV load, the power consumption of an HVAC system is unknown at any given time and is impacted by a variety of factors, including the most comfortable temperature level, the lowest and highest internal temperature bounds, house occupancy state, and outdoor temperature. Also, the conventional Lyapunov based energy management methods do not apply to our scenario due to inherent limitations. Thus, a Lyapunov based energy management framework is developed that caters all virtual queues related to indoor temperature, EV charging, and ESS without predicting any parameter values or knowing HVAC power usage. In addition, the proposed method function utilizing LOT framework by establishing an interior temperature virtual queue without knowing the amount of HVAC power required at any particular for real-time energy optimization. The novel technical contributions of this work are highlighted as follows.

- A mechanism is established to reduce the estimated time-averaged total cost for a home equipped with HVAC load that accounts for variations in energy costs, environment temperature, RES output power, energy demand, the comfortable temperature setting, and home occupancy state.
- A real-time energy management technique is developed based on the LOT framework that without anticipation any system characteristics or knowing the HVAC power need perform optimal online energy. Also, a study is conducted which ensures viability and performance guarantee of the proposed framework.
- Extensive simulation results show that the proposed algorithm may efficiently decrease energy expenditures while sacrificing little in terms of thermal comfort, according to extensive simulation findings based on factual footprints.

The rest of this work is organized in the following manner. The related work is included in Section II. Proposed system model is discussed in Section III while problem statement and problem formulation are described in Section IV and Section V, respectively. The proposed algorithm is presented in Section VI. We do comprehensive simulations in Section VII. Section X concludes with findings and recommendations for further work.

II. RELATED WORK

Before performing energy management, renewable energy generation and load forecasting are of prime importance, which is catered in [13]–[15]. A lot of research work has been conducted in real-time scheduling for optimal energy optimization in smart grid. To better understand the existing literature regarding energy optimization in smart grid. The related work is classified into three categories: first-class demonstrate energy optimization microgrid centric techniques in grid-connected mode, the second class presents energy optimization microgrid centric techniques in islanded mode, and the third class investigates energy optimization user-centric techniques in islanded mode. Each category is given below in detail.

A. ENERGY OPTIMIZATION MICROGRID CENTRIC TECHNIQUES IN GRID-CONNECTED MODE

Several research studies have been conducted to solve the energy optimization problem in smart grids using microgrid-centric techniques in grid-connected mode. For example, in [16] proposed a bilevel strategy to address the issues of energy optimization using demand response (DR) programs for microgrids in grid-connected mode. This framework successfully simulates users' behavior and dissatisfaction at the initial optimization level to produce the optimum DR program for each user energy optimization. At the second level, grid restrictions are taken into account to prevent voltage and current deviations from their regulatory limitations. In [17], a game-theoretic methodology is proposed for optimizing power usage of power plants by scheduling individual thermostatically controlled loads (TCLs). The authors in [18] proposed a methodology for real-time energy optimization of the microgrid in islanded mode. The problem after modification and transformation is employed to utilize the LOT framework. The paper [19] proposed an optimum energy storage control strategy to optimize microgrid operation. A replacement methodology that mixes three completely different artificial intelligence techniques for energy demand optimization in a smart home is proposed in [20]. A control-based network model to arrange transmission and storage resources effectively in the presence of unpredictable energy sources is proposed in [21]. Authors in [22] proposed a linear and quadratic model for smart home energy management in grid-connected mode. The developed model uses a smart metering system with wireless connectivity to optimally control energy flow. In [23], a linear programming based mechanism is introduced for energy optimization of the microgrid in grid-connected. In [24], a game-theoretic method is proposed for energy management in smart grid. A hierarchical system model is developed for energy optimization, where numerous providers and prosumers work together to define the simplest pricing value and requests. The work in [25] uses a compromise programming technique to reduce the cost of cyber web power by considering energy sharing across many interconnected microgrids. In [26], artificial intelligence based strategy is introduced to resolve the energy management issue using RES plus battery storage in smart gird.

B. ENERGY OPTIMIZATION USER CENTRIC TECHNIQUES IN GRID-CONNECTED MODE

The research studies have been conducted in the literature on user-centric techniques to solve the energy optimization problem in grid-connected mode. For instance, authors in [27] proposed an IoT-based strategy in smart grid to perform energy optimization for the purpose of meeting the long-term energy demands of users. In [28], artificial intelligence is adapted to significantly increase the potency, reliability, and safety of electric cars in grid-connected mode. The paper in [29] investigated the use of an alternate direction method of multipliers in conjunction with a convex optimization strategy for smart grid load energy distribution. Authors in [30] developed mixed-integer nonlinear programming (MINLP) to overcome self-scheduling drawbacks. In [31], heuristic optimization methods like a genetic algorithm (GA), ant colony optimization (ACO) algorithm, and particle swarm optimization (PSO) algorithm to tackle the energy management issue in the presence of that in the availability of PV generating resources and BES. In [32], a hybrid genetic algorithm particle swarm optimization (hybrid GA–PSO) approach is developed to minimize the energy cost by matching generation and load demand. Authors in [33] proposed an energy scheduler and distributed storage strategy to increase user satisfaction level while lowering consumer energy consumption. A dynamic energy management method based on a set of thresholds that take into account RES and storage is proposed in [34] for energy optimization in grid-connected mode. To achieve a better match between renewable generation and demand, a prediction model is also included in the home energy management system. The paper [35] introduced a fuzzy analytical hierarchy process technique for handling the energy management problem in user-centric grid-connected mode. A blockchain-based predictive energy mercantilism framework is developed in [36] for distributed energy resource period support, day-ahead dominance, and generation planning. The purpose is to support user-centric energy optimization in grid-connected mode. In [37], dispersed divisions with a time period stratified charging/discharging approach are developed to provide coordination of charging/discharging between EVS and power grid.

C. ENERGY OPTIMIZATION MICROGRID CENTRIC TECHNIQUES FOR ISLANDED MODE

The literature research studies have been conducted to solve the energy optimization problem using microgrid-centric techniques in islanded mode. For example, authors [38] proposed unique normalized reasoning fuzzy neural adaptive (NRFNA) management technique for a double-stage grid-coupled PV system. In [39], a hybrid genetic ant colony optimization (HGACO) algorithm is developed to resolve the programming model for three scenarios: without PV system, with a PV system, and with PV/BES system. The paper [40] developed an energy optimization model by the combination of the genetic algorithm with game theory-based fuzzy logic. The purpose is to maximize profit by forecasting future power demands. An energy management model based on mixed-integer linear programming (MILP) is developed in [41] to optimize the operation of smart buildings for peak shaving. In [42], a novel optimization method known as bat algorithm to tackle the energy management problem of a microgrid in islanded mode. The paper [43] implements a multi-objective cuckoo search algorithm to evaluate the effects of utilizing BES on optimal performance of power system. Authors in [44] proposed a self-tuning controller based on fuzzy logic to address traditional controller parameter uncertainties, such as operating conditions, microgrid operational purpose modifications, and microgrid modeling uncertainty. The paper [45] proposed a technique for regulating active and reactive power flow in a renewable generating system operating in the islanded mode for point of common connection (PCC). In [46], an artificial neural network based model is developed for maintaining a better voltage profile with balanced reactive power levels across the grid network. A two-stage random p-robust optimum energy mercantilism management model is developed in [47] for microgrids that include PVs, wind turbines, diesel engines, and microturbines.

D. ENERGY OPTIMIZATION USER CENTRIC TECHNIQUES IN ISLANDED MODE

An extensive part of the literature is investigated the energy management problem using user-centric techniques in islanded mode. For example, in [48] a microgrid energy management system supported by a stochastic MILP based on input from random processes that characterize uncertain parameters is developed. The paper [49] proposed an adaptive optimum fuzzy logic scheme to build suitable day ahead fuzzy rules to solve energy management and energy dispatch problems. Authors in [50] proposed an artificial bee colony (ABC) algorithm for the calculation and scheduling of individual electrical load. A real-time energy optimization solution for EV coordinated microgrids is developed using the Lyapunov stochastic optimization technique in [51]. In [52], a non-linear model predictive controller (NMPC) technique for coordinating the operation of linked multi-node microgrids with energy storage capabilities is introduced. A hybrid model is developed for series-parallel plugin hybrid electric vehicles (PHEVs) energy optimization in islanded mode, using a rule-based genetic algorithm (GA). In [54], IoT and cloud computing based energy management framework is developed for energy optimization in islanded mode. A stochastic energy management algorithm that minimizes the overall cost value and identifies the optimal size of different parts like battery, electrolyzer, fuel cell, microturbine, PV unit, and WT.

The research works mentioned above are efficient in terms of energy optimization for all three discussed classes, which is summarized in Table 1 and also existing models are compared with our proposed model. Our work proposes to minimize energy consumption by processing appliance facility demand requests so that requests are queued when the price of electric power is high and provided when the price of electric power is low. In contrast, to the EV load, the HVAC load has an unknown power consumption at any given slot and is impacted by several factors, including temperature bounds like lowest and highest indoor temperature bounds, the state of the home, and the outside temperature. Although, the Lyapunov optimization methodology has previously been utilized to build an online energy management plan for a home having HVAC system, our research also addresses the following aspects.

- The energy storage system, the random home occupancy state, and the buying and selling of power are all considered.
- The algorithmic feasibility factors impacting system management are calculated explicitly.
- Our suggested method functions by establishing an indoor temperature virtual queue despite not knowing the amount of HVAC power required at any particular slot.
- The loss in energy value and the increase in thermal discomfort are considered.

III. SYSTEM MODEL

The smart home studied in this work is depicted in Figure 1. As can be seen, there is a bi-directional link between home and power grid. The smart house and the traditional grid can both access real-time electricity pricing and overall power consumption thanks to this two-way link. The smart home can both buy and sell electric power from the conventional grid in this way. In our smart house model, the following components are connected to DC/AC low voltage bus bar for exchanging energy.

- RES (PV + wind).
- ESS.
- HEMS.
- Loads (HVAC + EV)

The HEMS serves as the smart home's core controller, managing energy generation, storage, and consumption. The HEMS can gather system data (cost of electricity, electrical demand, home occupancy state, outdoor temperature, and RES generating output) and deliver commands to controlled systems via two-way communication. For loads, we have considered inflexible loads such as HVAC and flexible loads such as EV, while other home appliances are not considered in our work; however, their demand will be fulfilled by HEMS. The HEMS works in slotted time, which is defined as $t \in [0, T]$, with T being the time slots total number. For the comparable use of power and energy, the time slot duration τ is considered unity.

A. RES MODEL

Two different energy sources are considered for our proposed renewable energy model, i.e., the PV and wind energy models.

1) PV ENERGY MODEL

The renewable energy generated is taken from a rooftop PV system. The maximum allowable output of a PV system is assumed to be r_t at time slot t. Where rt might be calculated using the [56] model, which is demonstrated in equation (1).

$$r_t = \theta_{pv} C_{pv} \rho_t, \forall t, \tag{1}$$

Both the actual PV's and the power electronic inverter are simplified in the aforementioned equation. Where θ_{pv} denotes PV generation efficacy, C_{pv} denotes the area of PV panel available for irradiance (in m^2), and ρ_t indicates solar irradiance (in W/m^2).

2) WIND ENERGY MODEL

The wind energy profile was compiled by [57]. Vestas' V120-2.2 MW is based on more than 48 GW of 2 MW turbines that have been successfully installed. The 2 MW turbine is designed to produce greater energy in low to moderate wind conditions, with annual energy production (AEP) gains of up to 14%. The 2 MW turbine harvests more energy from available wind and sets a new bar for park level simple Levelized cost of energy (LCoE) performance because of its 19% greater swept area. The following criteria were taken into account when creating our wind profile:

Maximum power output = 2 MW.
Wind cut-in speed = 4 m/s.
Wind rated wind speed = 12 m/s.
Wind cut-out wind speed = 25 m/s.

However, these parameters will only be met if the following constraints are taken into account:

$$if\ v_{co} < v \parallel v < v_{ci}, then, pwt_t = 0 \tag{2}$$

$$if\ v \geq v_{ci} \,\&\&\, v \leq v_r, then, pwt_t = [(2 * 10^6) * 4]/12 \tag{3}$$

$$if\ v \geq v_r \,\&\&\, v \leq v_{co}, then, pwt_t = 2 * 10^6 \tag{4}$$

B. LOAD MODEL

We have considered two types of loads: an inflexible load such as HVAC and a flexible load such as EV.

1) HVAC MODEL

There are two operational modes of the HVAC system: heating and cooling. But in our work, we have only focused on heating mode. It is taken into account the energy consumption of an HVAC system that can automatically adjust its power level to keep the indoor temperature within a reasonable temperature range. Let e_t represent the HVAC real-time power usage. The energy requirement of the HVAC system fluctuates continuously according to (5),

$$0 \leq e_t \leq e^{\max}, \ \forall t, \tag{5}$$

where $e^{\max}$ is the HVAC maximum loading capacity [in kW] and e_t is the HVAC current energy requirement at time slot t [in kW]. It serves as an inverter in this system, allowing the HVAC system to continually alter its input

TABLE 1. Summary of existing literature: a comparison between existing and our proposed models. Abbreviations used in the Table are: RE=Renewable Energy, PG=Peaker Generator, GE = Grid Energy, ESS=Energy Storage System, TES=Thermal Energy Storage.

Ref.	Sources	Storage	Objective(s)
[16]	RE+GE	ESS	Minimizing discomfort + voltage and current regulation
[17]	RE+GE	ESS	Power consumption optimization
[18]	RE+PG	ESS	Aggregated cost minimization
[19]	RE+GE	ESS	Cost minimization
[20]	RE+GE	ESS	Minimizing operational cost
[21]	RE+GE	ESS	Optimally schedule transmission and storage resources
[22]	RE+GE	ESS	Cost minimization
[23]	RE+GE	ESS	Power balance + minimization of microgrid operational costs
[24]	RE+GE	ESS	Minimize the dependency on the GE
[25]	RE+GE	ESS	Cost minimization
[26]	RE+GE	ESS	Reducing operational cost
[27]	RE+GE	ESS	Energy optimization to meet longrun demands
[28]	RE+GE	ESS	Efficiency + reliability and safety of electric vehicles
[29]	RE+GE	ESS	Cost minimization
[30]	RE+GE	ESS	Modeling the lightning and self-scheduling
[31]	RE+GE	ESS	Reducing electricity cost
[32]	RE+GE	ESS	Reduce electricity bill value
[33]	RE+GE	ESS	Cost minimization + user comfort
[34]	RE	ESS	Cost minimization using real time pricing
[35]	RE+GE	ESS	Cost reduction + environment betterment
[36]	RE+GE	ESS	Optimal power flow and energy crowdsourcing
[37]	RE+GE	ESS	Optimal charging–discharging between grid and electric vehicle
[38]	RE+GE	ESS	Cost minimization
[39]	RE+GE	ESS	Minimizing electricity cost + reducing carbon emission
[40]	RE+GE	ESS	Gaining maximum profit + predicting future power demands
[41]	RE+GE	ESS	Cost reduction + peak shaving
[42]	RE+GE	ESS	Cost reduction
[43]	RE+GE	ESS	Cost reduction + effect of battery storage
[44]	RE+GE	ESS	Unravel parameter uncertainties of classic controllers
[45]	RE+GE	ESS	regulate the active and reactive power flow
[46]	RE	ESS	Balanced reactive power level across the grid
[47]	RE+GE	ESS	To reduce peak period load
[48]	RE+GE	ESS	Cost reduction
[49]	RE+GE	ESS	Cost reduction + develop appropriate day-ahead fuzzy rules
[50]	RE+GE	ESS	Estimation of individual electrical load
[51]	RE	ESS	Minimizing microgrid average cost without knowing future price
[52]	RE+GE	ESS	Cost reduction
[53]	RE+GE	ESS	Overcome the battery limitations
[54]	RE+GE	ESS	Generation of load profile for utility company and consumer
[55]	RE	ESS	Minimizes total cost
Proposed algorithm 1	RE+GE	ESS	PAR alleviation + minimizing total cost + EV and ESS charge/discharge optimization

power e_t, according to [58]. An HVAC system's indoor temperature dynamics may be calculated as follows (6) from [59].

$$T_{t+1} = \varepsilon T_t + (1-\varepsilon)(T_t^{out} + (\eta/A)e_t), \ \forall t, \tag{6}$$

where T_t and T_t^{out} signify the indoor and outdoor temperatures, respectively. Similarly, η denotes thermal efficiency of conversion system, A denotes thermal conductivity $\varepsilon = e^{-\tau/\omega}$; measured in unit $kW/^{\circ}F$; and ω denotes time constant of system. When the indoor temperature of a smart home changes within a range, such as $20^{\circ}C \sim 25^{\circ}C$, a person feels comfortable. We use the following constraint (7) to achieve this:

$$T^{\min} \leq T_t \leq T^{\max}, \ \forall t \tag{7}$$

The high and low ranges of the comfort range are represented by $T^{\min}$ and $T^{\max}$.

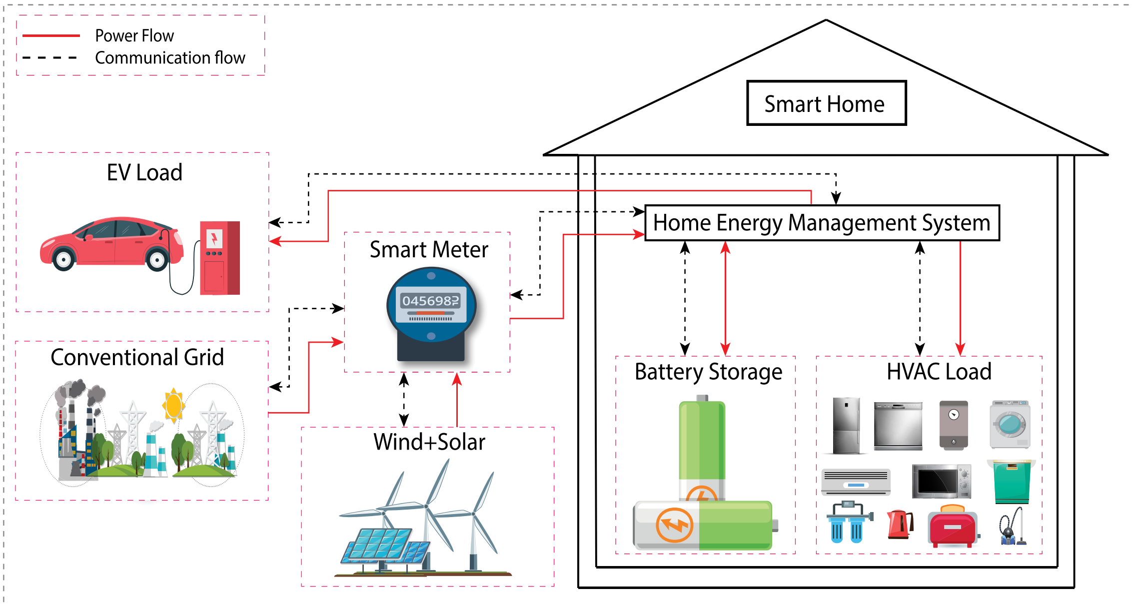

FIGURE 1. System model.

2) ELECTRIC VEHICLE MODEL

The EV is linked to the smart home through a DC/AC bus. The EV will send charge requests to the HEMS as it is connected. When the EV is connected in for charging, three tuple charging requests (s, c, E) are sent to the HEMS controller over the communication line, similar to [60]. For the EV, a three tuple request is provided, which includes the intended charging time s, the intended charge completion time c, and the total energy E necessary to completely charge the EV. To deal with the temporal variability of dynamic pricing, EVs electricity demand should be met so that EVs are charged when the price of electric power is low, and EVs charging is postponed when the price of electric power is high. To achieve this criterion without exceeding completion time, we use the following queue relating energy Q_t is defined in Eq. (8).

$$Q_{t+1} = \max[Q_t - x_t, 0] + a_t, \ \forall t \tag{8}$$

where x_t and a_t are the energy queue's service and arrival processes, respectively. As the Lyapunov optimization technique framework could turn a long-term optimization problem into multiple online subproblems via queue stability management, the energy queue Q_t was established, which contributes to online EV charging scheduling as in [61]. $x^{\max}$ defines the highest value of x_t where $x^{\max} \geq a^{\max}(a^{\max} = \max x_t a_t)$ because it keeps the queue Q_t steady. We have (9), the following constraint demonstrates that not to provide energy demand bigger than Q_t.

$$0 \leq x_t \leq \min\{x^{\max}, Q_t\}, \ \forall t \tag{9}$$

Since EV charging power is restricted, the EV will add the most of $v^{\max}$ electricity demand to Q_t, where $v^{\max}$ is EV's maximum charging power. Multiple time slots are required when $v^{\max} < E$ to complete the submission of net electricity demand E. EV delivers the electricity same as in [61], according to the following equation (10):

$$a_t = \begin{cases} v^{\max}, & s \leq t \leq s+k; \\ E - kv^{\max}, & t = s+k; \\ 0, & otherwise, \end{cases} \tag{10}$$

where $k = \lfloor e/v^{\max} \rfloor$. The following constraint (11) is used to make the average length of Q_t finite,

$$\lim_{T\to\infty} \sup 1/T \sum_{t=0}^{T-1} E\{Q_t\} < \infty \tag{11}$$

We impose the following constraint (12) since (11) is insufficient to assure that the charge completion time is not exceeded.

$$D^{\max} \leq R, \tag{12}$$

where $D^{\max}$ signifies the queue Q_t maximal queueing delay, and R signifies the tolerable EV charging service delay $(c - s - k)$.

C. ENERGY STORAGE SYSTEM MODEL

Let G_t represent the stored energy level in a smart home-connected ESS. The battery's accumulated energy level fluctuates over time with the operation (i.e., charge and discharge) according to the equation (13), ensuring that the amount of charge within the device does not surpass its capacity boundaries.

$$G^{\min} \leq G_t \leq G^{\max}, \ \forall t, \tag{13}$$

where $G^{\max}$ and $G^{\min}$ represent the ESS maximum and lowest capacities, respectively. ESS charge or discharge power at slot

t is determined by y_t defined in the constraint (14), which is specified as follows.

$$-u^{d\max} \leq y_t \leq u^{c\max}, \ \forall t, \tag{14}$$

where $u^{c\max} > 0$ and $u^{d\max} > 0$ are the charge and discharge maximum powers, respectively. The battery is charging when $y_t > 0$, discharging when $y_t < 0$, and idling when $y_t = 0$. The dynamic of the energy stored in the battery may be simulated in the same way as the ESS models in [62]–[64].

$$G_{t+1} = G_t + y_{t,} \ \forall t, \tag{15}$$

where G_t is the stored energy of the ESS at time slot t. We assumed that the battery's vampire loss (power leakage) is modest for the purpose of simplicity and so excluded it from the battery dynamics.

D. POWER BALANCING

The power trade between the smart house and the conventional grid is expected to be g_t at time slot t. Energy will be acquired from the grid when $g_t > 0$, and sold to the grid when $g_t < 0$. The real-time energy balancing is formulated as:

$$pwt_t + g_t + r_t = e_t + x_t + y_t, \ \forall t, \tag{16}$$

IV. PROBLEM STATEMENT

Previously, several works have used either heuristic or meta-heuristic methodologies to achieve the objective of energy management in smart grids. Existing studies have been done in islanded mode or grid-connected mode for microgrid central or central consumer approaches, as described before in the related work section. In the islanded mode, only the integration of RES in the microgrid is considered, but in the grid-connected mode, both the conventional grid and RES are connected to achieve energy management goals. On the other hand, the current works lack the flexibility to meet many objectives at once. As an example, some works have just met the cost-cutting goal without considering the level of consumer comfort. While some have focused on voltage and current regulation, others have focused on optimal charging-discharging between the grid and the EV. Many studies have been done on energy management techniques. However, none have taken into account real-time online energy management techniques. In our research, we used Lyapunov optimization, which is based on the online convex optimization energy management technique. Our research was conducted in a grid-connected manner, which implies that we evaluated both RES and the conventional grid as sources for our load in a smart home and ESS as a storage medium. Similarly, our work is predicated upon the reduction of the total cost, PAR alleviation, thermal discomfort cost associated with HVAC and EV load, optimizing the charging power of EV, and the charge/discharge power of ESS. The load is scheduled in such the simplest way to fulfill the energy demand of consumers. And for that, we have taken the dynamic behavior of inputs like uncertainties in cost of electricity, changing of outdoor temperature, RES generating output, home occupancy state, and energy consumption. To make it more clear different scenarios are compared using a convex technique based on Lyapunov optimization and without convex technique, and the output results from both scenarios showed efficient problem tackling capability of the proposed model with dynamic inputs.

V. PROBLEM FORMULATION

According to the models discussed in system model section the price of electric power related to buying and selling is modeled as:

$$\Phi_{1,t} = \left(\frac{B_t - S_t}{2} |g_t| + \frac{B_t + S_t}{2} g_t \right) \tag{17}$$

where $B_t \in \left[B^{\min}, B^{\max}\right]$ denotes the buying price of the electric power at slot t and $S_t \in \left[S^{\min}, S^{\max}\right]$ denotes the selling price of the electric power. It is assumed that for all t the selling prices are or less than or equal to buying prices, i.e., $B_t \geq S_t$. This condition prevents the smart home from greedily buying the electric power from the conventional grid and then reselling to grid at higher prices. This condition has already been considered by [63] and [65] in prior studies. And it's evident from (17) that simply the variable g_t is needed to represent the buying and selling of electric power. And this will be more cleared by the following conditions that when $g_t \leq 0$, then $\Phi_{1,t} = S_t g_t$ while if $g_t > 0$, then $\Phi_{1,t} = B_t g_t$. According to [66] the thermal discomfort cost for the residents at slot t is given by equation (18):

$$\Phi_{2,t} = \gamma \Pi_{t+1} (T_{t+1} - T_{t+1}^{ref})^2, \tag{18}$$

where γ is the cost coefficient having the unit $\$/(°F)^2$, and it is related to the importance of discomfort cost; T_{t+1}^{ref} represents foremost comfortable level of residents at $t+1$ which in our case is considered to be $22.5°C$. And Π_{t+1} is a binary variable which denotes the home occupancy state at $t+1$ (where 1 indicates occupancy and 0 indicates vacancy). When $\Pi_{t+1} = 0$, this shows that there is no occupant at home, then $\Phi_{2,t}$ would also be zero as a result. The final resident, who will depart the house at slot t, may decide on the value of Π_{t+1}. The criteria stated above were for human interaction. However, without human interaction, the smart devices with sensors particular settings applied, such as to signal departing or entering the home, can be used instead, according to [67]. To minimize the total energy and thermal discomfort costs, we formulated the problem using the models discussed above, and it is given as follows.

$$(P1) \ \min \lim_{N\to\infty} \sup \frac{1}{N-1} \sum_{t=0}^{N-2} E\{\Phi_{1,t} + \Phi_{2,t}\} \tag{19a}$$

$$s.t. \ (2) - (6), (8) - (13), \tag{19b}$$

Where E is the expectation operator that will act randomly on buying and selling of electricity prices B_t/S_t, renewable generation output r_t/pwt_t, outdoor temperatures T_t^{out}, electrical demand of EV a_t, the foremost comfortable temperature level T_{t+1}^{ref}, home occupancy state T_{t+1}^{ref}; the decision variables related to $P1$ are x_t, e_t, g_t and y_t.

VI. PROPOSED METHODS

In this section, the proposed method for online energy is discussed. The detailed description is as follows.

A. PROPOSED ALGORITHM FOR REAL-TIME ENERGY OPTIMIZATION

Two difficulties were encountered when attempting to solve $P1$. To begin, the following constraints (6), (8), and (15) add temporal couplings, implying that present decisions influence future decisions. Second, future variables like the price of electric power and outdoor temperature are unclear. Some approaches, such as dynamic programming [68], is used to address the problem of time reliance or temporal coupling. However, they suffer from (the curse of dimensionality). The LOT framework was frequently used to address the issues mentioned above as in [69] and [70]. Suppose existing Lyapunov-based energy management algorithms are taken into account. In that case, it can be shown that they seek to queue up power demand requests from appliances (e.g., EVs) and service them when the price of electric power is low. The energy/power requirement of an EV is predetermined, but the energy/power requirement of an HVAC load is determined by a variety of parameters, including home occupancy state, indoor temperature, foremost comfortable temperature level, and outdoor temperature. As a result, we must alter present algorithms to cope with HVAC load. The following is a summary of the suggested algorithm key idea:

- The virtual queues related to ESS, EV charging delay, and indoor temperature are constructed.
- According to the LOT framework, the drift plus penalty term is obtained.
- Upper bound of the right side of drift plus penalty term is reduced.

A real-time energy management algorithm based on the technique mentioned above without forecasting characteristics or knowing the HVAC power demands for any system. It is crucial to remember that virtual queues ensures that constraints (7), (12), and (13) are all met. The suggested approach will not violate the constraints ((7), (12) and (13) if such queues are efficiently stabilised. Three minor assumptions concerning system parameters are made to make the system controlled, i.e.,

$$T^{out\max} \leq T^{\max}, \tag{20}$$

$$\frac{\eta}{A}e^{\max} + T^{out\min} \geq T^{\min}, \tag{21}$$

$$T^{\max} - T^{\min} > \psi, \tag{22}$$

where $T^{out} \in \left[T^{out\min}, T^{out\max}\right]$, $\psi = (1-\varepsilon)\left(T^{out\max} - T^{out\min} + \frac{\eta}{A}e^{\max}\right)$. Because the highest temperature in winter is lower than the most pleasant temperature levels, which is first assumption and commonly observed for heating mode winter (e.g., Figure 8 indicates that $T^{out\max}$ is around $10°C$,, whereas $T^{\max}$ is around $25°C$). The second assumption demonstrates that temperature decline may be adjusted by infusing the HVAC system's maximum power (any HVAC system necessitates this). In practise, the final assumption might be readily satisfied by setting parameters as in [71], [72]. $T^{\max} = 23.5°C$, $T^{\min} = 20°C$, $\varepsilon = 0.96$, $T^{out\max} - T^{out\min} = 10°C$, $\eta = 1$, $A = 0.14kW/°F$, $e^{\max} = 10kW$, also $\psi = 4.8571°F < T^{\max} - T^{\min} = 6.3°F$. In principle, the control parameter $V_1^{\max}$ the $d > 0$, according to (22).

1) CONSTRUCTING VIRTUAL QUEUES

A virtual queue H_t, which is the altered form of indoor temperature, is defined as follows to ensure the workability of constraint (7):

$$H_t = T_t + \Gamma, \tag{23}$$

where Γ is constant term defined in Section VI - B. While the dynamics of H_t may be calculated using the formula in equation below,

$$H_{t+1} = \varepsilon H_t + (1-\varepsilon)(\Gamma + T^{out} + \frac{\eta}{A}e_t), \tag{24}$$

The above equation is determined by integrating (6) and (23). To meet the criteria of (12), the Z_t is delay aware virtual queue, which is mathematically modeled as:

$$Z_{t+1} = \begin{cases} [Z_t - x_t + \xi]^+, & Q_t > x_t, \\ 0, & Q_t \leq x_t, \end{cases} \tag{25}$$

Where $[\diamond]^+ \triangleq \max\{\diamond, 0\}$; ξ is the fixed parameter, representing the virtual queue Z_t arrival rate when $Q_t > x_t$,, while x_t is the service rate of queue Z_t. As in [73], equation (12) may be assured if the queues Z_t and Q_t have finite upper limits. The maximum queueing is calculated as: $D^{\max} = \lceil (Q^{\max} + Z^{\max})/\xi \rceil$. The existence of upper bounds will be demonstrated in the next section.

To ensure the functionality of (13), a virtual queue K_t, which is the shifted version of the ESS energy level G_t, is defined in (26):

$$K_t = G_t + \alpha, \tag{26}$$

where α is constant defined in Section VI - B). The K_t dynamics are as follows:

$$K_{t+1} = K_t + \alpha, \tag{27}$$

2) ACQUIRING DRIFT PLUS PENALTY TERM

The real energy queue Q_t, as well as the other three virtual queues, should be stabilized to meet (11). As a result, a Lyapunov function is defined below:

$$L_t = \frac{1}{2}({H_t}^2 + {Q_t}^2 + {Z_t}^2 + {K_t}^2) \tag{28}$$

We can define $\Psi_t \triangleq (H_t, Q_t, Z_t, K_t)$, and Lyapunov drift in (29):

$$\Delta_t = E\{L_{t+1} - L_t \,|\Psi_t\} \tag{29}$$

All assumptions are based on the changing behavior of the price of electric power, outdoor temperatures, renewable generating output, electric vehicle charging demand, the foremost comfortable temperature setting, home occupancy state, and control decisions. From (28) we have,

$$L_{t+1} - L_t = (\varphi_H + \varphi_Q + \varphi_Z + \varphi_K), \tag{30}$$

Where $\varphi_H = \frac{1}{2}({H^2}_{t+1} - {H_t}^2)$, $\varphi_Q = \frac{1}{2}({Q^2}_{t+1} - {Q_t}^2)$, $\varphi_Z = \frac{1}{2}({Z^2}_{t+1} - {Z_t}^2)$ and $\varphi_K = \frac{1}{2}({K^2}_{t+1} - {K_t}^2)$. And the upper bounds of $\varphi_H, \varphi_Q, \varphi_Z, \varphi_K$ are given as follows,

$$\varphi_H = \frac{1}{2}({H^2}_{t+1} - {H_t}^2) < \Omega_0 + \varepsilon(1-\varepsilon)H_t(\Gamma + {T_t}^{out} + \frac{\eta}{A}e_t), \tag{31}$$

$$\varphi_Q = \frac{1}{2}({Q^2}_{t+1} - {Q_t}^2) < \Omega_1 + Q_t(a_t - x_t), \tag{32}$$

$$\varphi_Z = \frac{1}{2}({Z^2}_{t+1} - {Z_t}^2) < \Omega_2 + Z_t(\xi - x_t), \tag{33}$$

$$\varphi_K = \frac{1}{2}({K^2}_{t+1} - {K_t}^2) < \Omega_3 + K_t y_t, \tag{34}$$

where$\Omega_0 = \frac{(1-\varepsilon)^2}{2} \max\left((\Gamma + T^{out\,\min})^2, (\Gamma + T^{out\,\max} + \frac{\eta}{A}e^{\max})^2\right)$, $\Omega_1 = \frac{(x^{\max})^2 + (a^{\max})^2}{2}$, $\Omega_2 = \frac{1}{2}\max(\xi^2, (x^{\max})^2)$, $\Omega_3 = \frac{(\max(u^{c\,\max}, u^{d\,\max}))^2}{2}$. When the function of total projected cost is added to (29), the drift plus penalty term is produced as follows:

$$\begin{aligned}\Delta Y_t &= \Delta_t + VE\{\Phi_{1,t} + \Phi_{2,t}\,|\Psi_t\} \\ &\leq \sum_{l=1}^{4}\Omega_l + E\{K_t y_t - (Q_t + Z_t)x_t\,|\Psi_t\} \\ &\quad + E\{\varepsilon(1-\varepsilon)H_t(\Gamma + T_t^{out} + \frac{\eta}{A}e_t)\,|\Psi_t\} \\ &\quad + VE\{\Phi_{1,t} + \Phi_{2,t}\,|\Psi_t\}\,,\end{aligned} \tag{35}$$

where V is a weight parameter that balances queue stability and net energy cost minimization.

3) UPPER BOUND MINIMIZATION

The Lyapunov based approach selects control actions to reduce the upper limits of the drift plus penalty term's right hand side. Algorithm 1 describes the proposed algorithm. $P2$ is a four-variable convex optimization problem that can be solved effectively using convex methods or tools. For clarity, $T_{t+1}|e_t = 0$ is used to indicate the value of T_{t+1} with $e_t = 0$. When the home is vacant, the HVAC power is zero in the next time slot, and $T_{t+1}|e_t = 0$ is still larger than $T_{\min}$, saving energy costs without harming home occupants thermal comfort.

The proposed algorithm can satisfy the constraints (6), (8), (15) by updating H_t, Q_t and K_t according to (24), (8), (27), respectively. Additionally, (5), (9), (14), (16) are included in $P2$. The remaining constraints (7), (11), (12), and (13) are not taken into account by Algorithm 1. The viability of the proposed algorithm for $P1$ will be demonstrated in the next section by demonstrating the constraints (7), (11), (12), and (13).

Algorithm 1 Smart Home Energy Management algorithm

For each time slot t *do*
At the initialization of slot t, check Ψ_t , T_t^{out}, B_t , S_t, r_t, a_t, T_{t+1}^{ref}, Π_{t+1}, pwt_t
Take g_t , e_t, x_t , and y_t as the solution to $P2$:

$$\begin{aligned}(P2)\ \min\ & K_t y_t - (Q_t + Z_t)x_t + \varepsilon(1-\varepsilon)H_t(\Gamma + T_t^{out} \\ & + \frac{\eta}{A}e_t) + V(\Phi_{1,t} + \Phi_{2,t}) \\ s.t.\ & (3),\ (6),\ (10),\ (13)\end{aligned}$$

If $\Pi_{t+1} = 0$ *and* $T_{t+1|e_t=0} \geq T^{\min}$
then, $e_t = 0$, $g_t = x_t + y_t - r_t - pwt_t$
End
Scenario 1:
Take output power of grid g_t only.
min $P2$
$g_t = x_t + y_t$
Scenario 2:
Take output power of PV and Wind r_t and pwt_t only.
min $P2$
$r_t + pwt_t = x_t + y_t$
Update H_t, Q_t, Z_t and K_t according to (24), (8), (25), (27);
End

B. FEASIBILITY OF THE PROPOSED ALGORITHM

Let $(y_t^*, x_t^*, e_t^*, and g_t^*)$ be the optimal solutions to $P2$. Now lemmas and theorems will prove that the proposed algorithm can satisfy constraints (7), (11), (12), and (13).

Lemma 1: The proposed algorithm has the following features for optimal HVAC operation decision where, $b_t = 2V\gamma\Pi_{t+1}(1-\varepsilon)^2\eta/A\left(T_t^{out} - \frac{T_{t+1}^{ref} - \varepsilon T_t}{1-\varepsilon}\right)$, $c_t = 2V\gamma\Pi_{t+1}(1-\varepsilon)^2\eta/A\left(T_t^{out} + \frac{\eta}{A}e^{\max} - \frac{T_{t+1}^{ref} - \varepsilon T_t}{1-\varepsilon}\right)$.

1) *If* $VS^{\min} + b_t > -\varepsilon(1-\varepsilon)H_t\frac{\eta}{A}$, $e_t = 0$.
2) *If* $VB^{\max} + c_t < -\varepsilon(1-\varepsilon)H_t\frac{\eta}{A}$, $e_t = e^{\max}$.

We came up with the following theorem 1 based on lemma 1.

Theorem 1: If the initial temperature $S_o \in \left[T^{\min}, T^{\max}\right]$, and the fixed parameters of proposed algorithm are $V \in \left(0, V_1^{\max}\right]$ and $\Gamma \in \left[\Gamma^{\min}, \Gamma^{\max}\right]$ then it ensures that $T_t \in \left[T^{\min}, T^{\max}\right]$ complete time horizon, where

$$V_1^{\max} = \frac{(1-\varepsilon)\,\frac{\eta}{A}d}{\left(B^{\max} - S^{\min}\right) + f}, \tag{36}$$

$$\Gamma^{\min} = \frac{VS^{\min} + b^{\min}}{-\varepsilon\,(1-\varepsilon)\,\frac{\eta}{A}} + \frac{h}{\varepsilon}, \tag{37}$$

$$\Gamma^{\max} = \frac{VB^{\max} + c^{\max}}{-\varepsilon\,(1-\varepsilon)\,\frac{\eta}{A}} + \frac{m}{\varepsilon}. \tag{38}$$

where in the above formulas,
$d = T^{\max} - T^{\min} - (1-\varepsilon)\left(T^{out\,\max} + \frac{\eta}{A}e^{\max} - T^{out\,\min}\right)$,
$f = 2\gamma(1-\varepsilon)^2\eta\left(T^{out\,\max} - T^{out\,\min} + e^{\max} + \frac{\varepsilon(T^{\max} - T^{\min}) + (T^{ref\,\max} - T^{ref\,\min})}{1-\varepsilon}\right)/A$,

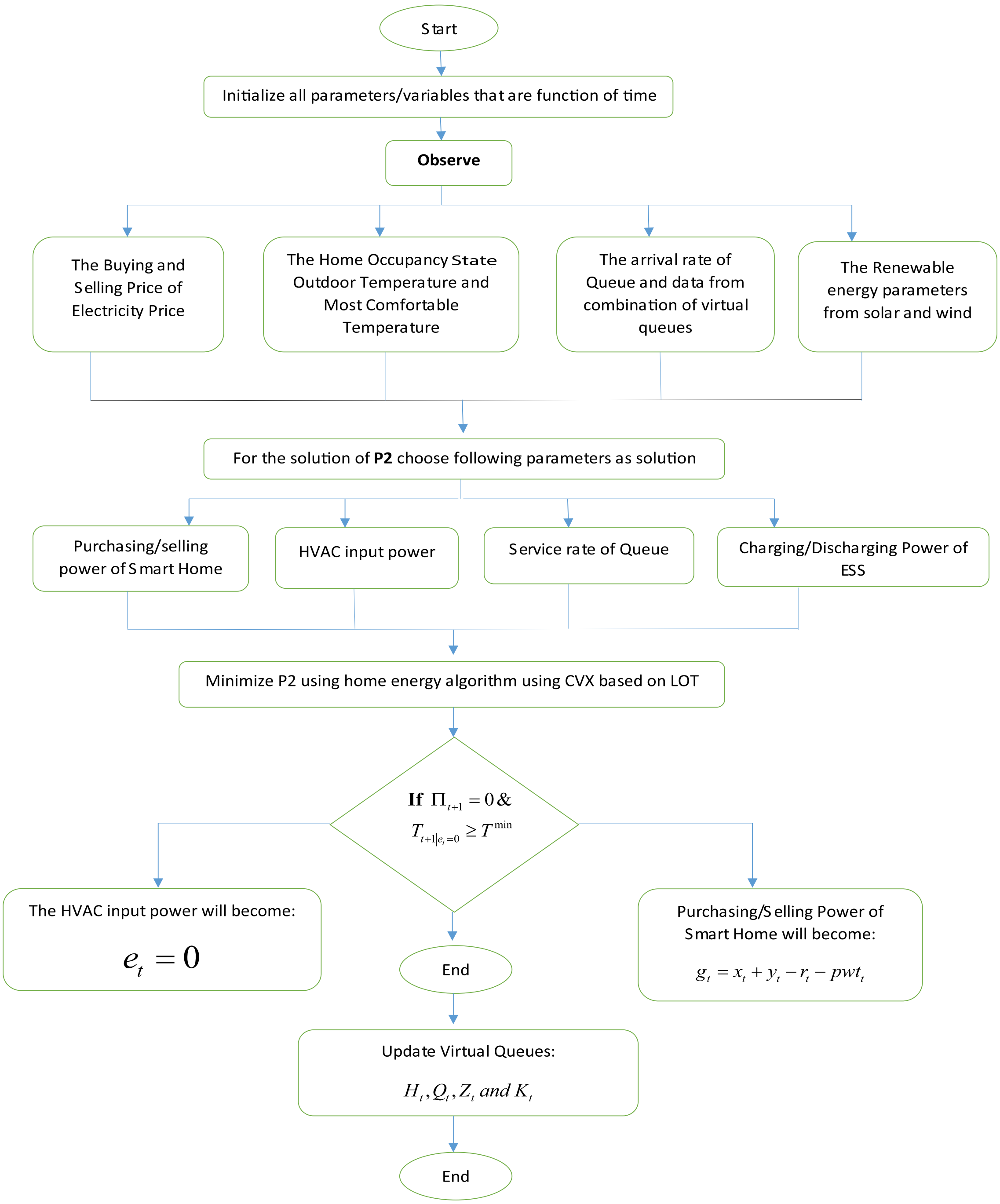

FIGURE 2. Scenarios implementation flowchart.

$h = (1-\varepsilon)\left(T^{out\max} + \frac{\eta}{A} e^{\max}\right) - T^{\max}$, $m = (1-\varepsilon)\, T^{out\min} - T^{\min}$, $b^{\min} = \min_t b_t$, $c^{\max} = \max_t c_t$, $T^{ref\max} = \max_t T_t^{ref}$, $T^{ref\min} = \min_t T_t^{ref}$.

Lemma 2: The proposed algorithm has the following properties for optimal EV charging decision:

1) *If* $Q_t + Z_t < VS^{\min}$, $x_t^* = 0$.
2) *If* $Q_t + Z_t > VB^{\max}$, $x_t^* = \min\{x^{\max}, Q_t\}$.

We came up with the following theorem 2 based on lemma 2.

Theorem 2: assume that $x^{\max} \geq \max\left[a^{\max}, \xi\right]$. If $Q_o = Z_o = 0$, the proposed real-time algorithm has properties as given below:

1) Q_t *is bounded by* $Q^{\max} = VB^{\max} + a^{\max}$, Z_t *is bounded by* $Z^{\max} = VB^{\max} + \xi$.
2) *Maximum queueing delay* : $D^{\max} = \left\lceil \frac{2VB^{\max} + a^{\max} + \xi}{\xi} \right\rceil$.

Lemma 3: The following properties are considered in optimal ESS decision of the proposed algorithm:

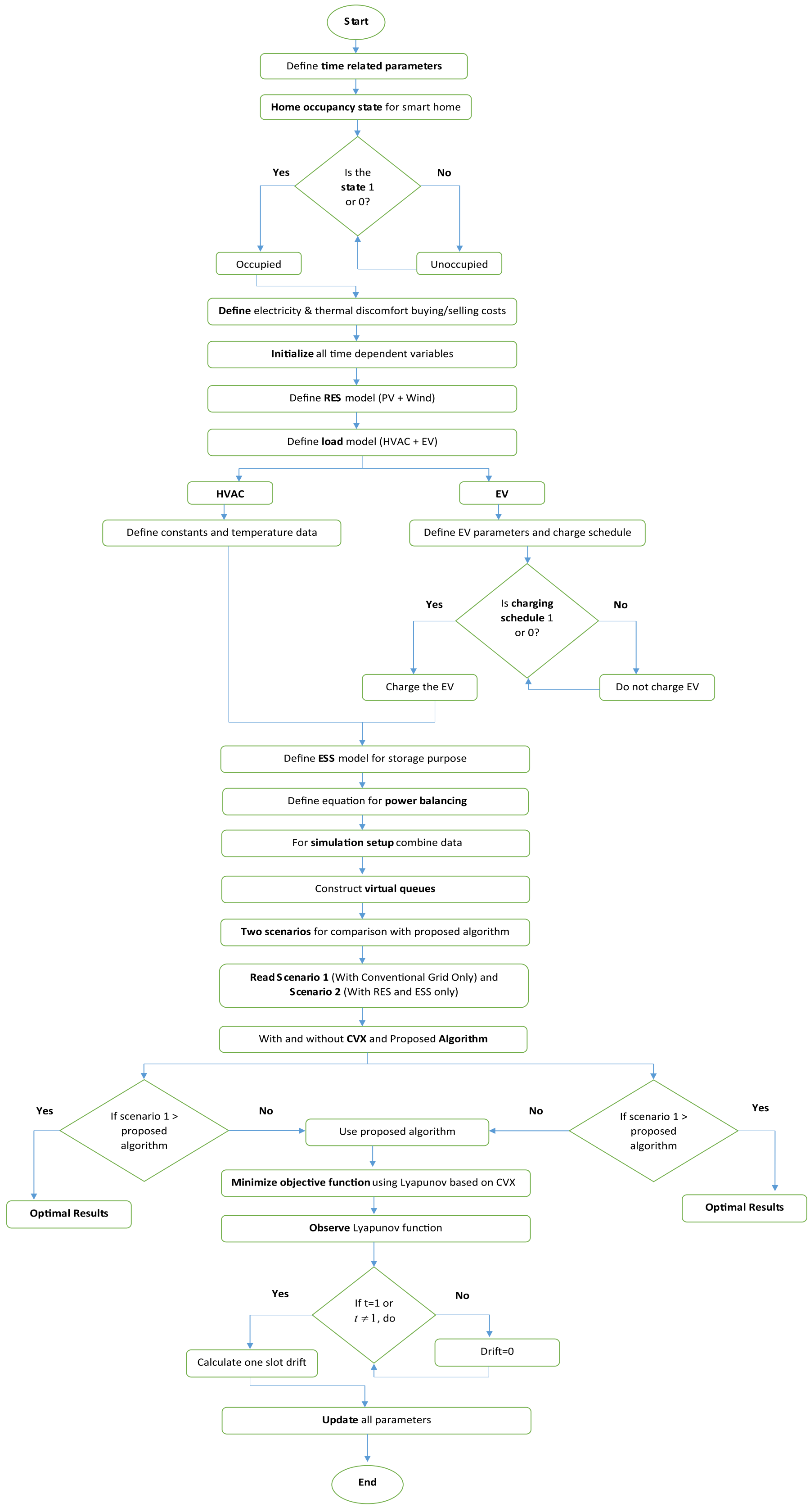

FIGURE 3. Flowchart presenting complete implementation.

1) *If* $K_t > VS^{\min}$, *we have* $y_t^* \leq 0$.

2) *If* $K_t < -VB^{\max}$, *we have* $y_t^* \geq 0$.

We came up with the following theorem 3 based on lemma 3.

Theorem 3: If we have the initial energy level $G_o \in \left[G^{\min}, G^{\max}\right]$, the proposed algorithm with fixed parameters $V \in \left(0, V_2^{\max}\right]$ and $\alpha \in \left[\alpha^{\min}, \alpha^{\max}\right]$ would offer the following guarantee, i.e., $G_t \in \left[G^{\min}, G^{\max}\right]$, for all slots, where

$$V_2^{\max} = \frac{G^{\max} - G^{\min} - \left(u^{c\max} + u^{d\max}\right)}{\left(B^{\max} - S^{\min}\right)}, \tag{39}$$

$$\alpha^{\min} = -VS^{\min} + u^{c\max} - G^{\max}, \tag{40}$$

$$\alpha^{\max} = -VB^{\max} - u^{d\max} - G^{\min}, \tag{41}$$

Theorems 1 − 3 shows that the constraints (7),(11), (12), and (13) may be met under the proposed algorithm. We may conclude that the proposed algorithm is workable for the original problem $P1$ because other constraints are explicitly considered in Algorithm 1. The efficacy of the proposed algorithm will be tested in the next section using real-world traces of outdoor temperature, cost of electric power, and renewable generation.

C. PERFORMANCE GUARANTEE

Theorem 4 will look at the proposed algorithm's performance guarantee.

Theorem 4: If buying or selling of electricity costs B_t/S_t, PV energy output r_t,the wind energy output pwt_t, outdoor temperatures T_t^{out}, foremost comfortable temperature level $T^{ref}{}_{t+1}$, electrical demand of EV a_t and the home occupancy state $T^{ref}{}_{t+1}$ are independent and identically distributed (i.i.d) over the slots then the following performance guarantee is offered by the proposed algorithm, i.e., $\lim_{N\to\infty} \sup \frac{1}{N-1} \sum_{t=0}^{N-2} E\{\Phi_{1,t} + \Phi_{2,t}\} \leq y_1 + \frac{\Theta}{V}$, where y_1 is the optimal value of $P1$.

As Θ is a complex function of V, the aforementioned optimality gap will not uniformly decrease as V rises. Θ becomes constant when $\varepsilon = 1$. If a greater value of V is given at this moment, the proposed algorithm will perform better.

VII. SIMULATION ANALYSIS

The performance of the suggested energy management method is evaluated in this section using extensive numerical simulations. CVX, a MATLAB package for disciplined convex programming [74], is used to construct the model. All simulations were performed in the MATLAB environment on a computer system with an Intel Core m3 7th Generation processor and 8 GB of RAM running Windows 10. First, the input data is acquired, and the proposed model's various control parameters are outlined. Second, the method is solved using the Lyapunov technique based on convex optimization, and third, the convex optimization results are obtained and compared with non-convex optimization to compare optimized and un-optimized outcomes. The study's performance metrics include PAR alleviation, overall cost minimization, and thermal discomfort cost for a smart home with HVAC as an inflexible load and EV as a flexible load, as well as optimizing EV charging power and ESS charging and discharging power. Two simulation scenarios have been created to demonstrate the clear comparability of our suggested algorithm which are as follows:

- With conventional grid only
- With RES and ESS only

The convex optimization saved cost by scheduling the inflexible load (HVAC) and flexible load (EV) at a low-price period, with positive values representing energy drawn from the grid and negative values representing energy supplied to the conventional grid from RES. We ran several simulations to determine the best scheduling for inflexible (HVAC) and flexible (EV) loads.

A. SIMULATION SETUP

Table 2 lists the key simulation parameters:

TABLE 2. Control parameters used in simulations.

Control parameters	Value
Time slot index (T)	744
Time slot duration (τ)	1 hr
Comfy temperature range's upper limit ($T^{\max}$)	$25°C$
Temperature setpoint for occupants in home (T_{ref}^{t+1})	$22.5°C$
Heating efficiency of thermal conversion (η)	1
Thermal conductivity (A)	$\frac{1}{15}kW/°F$
Initial temperature from Theorem 1 ($S_\circ$)	$22.5°C$
Weight parameter (V)	$\min\{V_1^{\max}, V_2^{\max}$
Γ	$\Gamma^{\max}$
The energy queue's arrival processes (α)	$\alpha^{\max}$
Selling price (S_t)	$0.9B_t$
Efficiency of PV generation (θ_{pv})	0.2
Solar panels' total irradiance area (C_{pv})	$0m^2$
Maximum ESS charge in ($G^{\max}$)	$20kWh$
Minimum ESS charge ($G^{\min}$)	$5kWH$
Max ESS discharging power = Max ESS charging power ($u^{d\max} = u^{c\max}$)	$1kW$
Factor of inertia (ε)	0.985
Maximum charging power of EV ($v^{\max}$)	$3kW$
Maximum HVAC input power ($e^{\max}$)	$8kW$

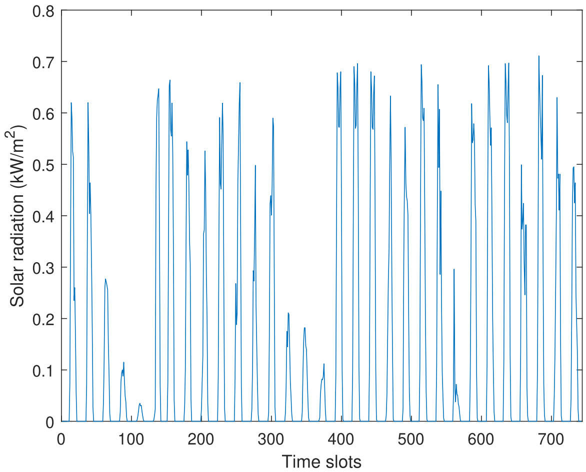

FIGURE 4. PV panels solar irradiance output.

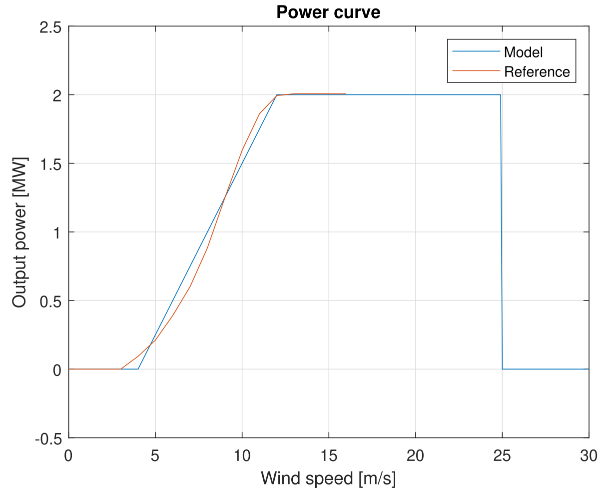

FIGURE 5. Wind turbine power curve.

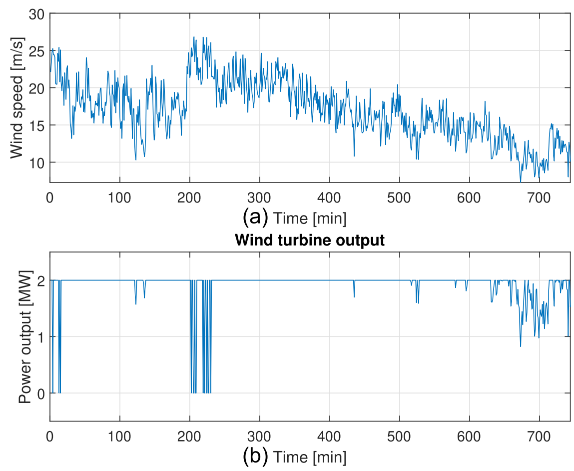

FIGURE 6. Wind speed and wind turbine output.

B. SIMULATION RESULTS

Renewable energy is defined as a blend of solar and wind energy. PV data is taken from Figure 4 [75], which shows the hourly solar irradiance of Golden city of the USA, in January 2017. The solar irradiance is shown over 744 slots, as can be seen readily. The intermittent nature of PV energy is demonstrated by the changes in the shape of rising and falling peaks in the Figure. The solar irradiance levels range from $0 - 0.7\,kW/m^2$. The wind energy profile was compiled by [57]. The 2 MW turbine is designed to produce greater energy in low to medium wind conditions, with (AEP) enhancements of up to 1414%. The 2 MW turbine harvests more energy from available wind and sets a new bar for park level simple Levelized cost of energy (LCoE) performance because of its 19% greater swept area. The power curve of a wind turbine with a given wind cut-in, wind rated, and wind cut-out speeds are shown in Figure 5. The cut-in wind speed is around 4 m/s, which is the speed at which the turbine begins to function. The wind turbine is then run at 12 m/s of rated speed constantly until the wind cut-out speed, which is 25 m/s, at which the turbine is commanded to shut down. Figure 6 shows the wind speed in m/s for 744 slots, along with power output generated by the turbine as the wind speed changes. Variations can also be noted in the output power generated, which is due to the wind energy source's intermittent nature. The electricity price of Nanjing, China is shown in Figure 7 for 744-time slots in simulations. The price signals fluctuate within the range of $0.35-0.55$ over the same time intervals, as seen in the graph. The outdoor changing temperature data affiliated with Nanjing, China in January of 2017 [76] for 744-time slots is represented in Figure 8. Outdoor temperature varies slightly more over time. The range in which the outdoor temperature changes can easily be observed in Figure, and it lies between $(-5) - (+15)\,^{\circ}C$. Similarly, Figure 9 shows the home occupancy state, with one (1) indicating that the home is occupied and zero (0) indicating that the home is unoccupied. For home, occupancy traces sports data related to step number January 2017 to estimate home occupancy states. If the total number of steps in an hour exceeds the threshold, the house is presumed to be unoccupied. Otherwise, the house is deemed occupied. The threshold has been set at 1800, which is 2 seconds per step [77]. When the EV is switched in for a charge, a three-tuple charging request (s, c, E) is sent to the HEMS controller through a telecommunication network. The EV proposes a three tuple request that includes the intended charge start time s, the intended charge completion time c, and the total energy E necessary to completely charge the EV. Assume that the EV's daily energy demand (E) is evenly distributed with parameters 4 and 18 and that energy demand (E) will have an equal probability of taking on a value in 42:

$$4kWh \leq E(t)_{t=s} \leq 18kWh \tag{42}$$

This is shown in Figure 10. While Figure 11 illustrates that EV charging starts at 7 pm every day and ends at 6 am the next morning, indicating that the EV is connected to the HEMS for charging while t is between 7 pm and 6 am. R = 5 for a tolerable EV charging delay in one hour. We determine the value of $\xi = (2VB^{\max} + v^{\max})/(R-1)$

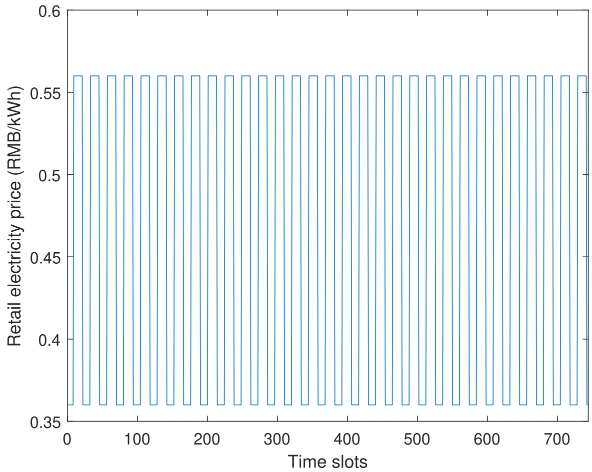

FIGURE 7. Electricity price signals.

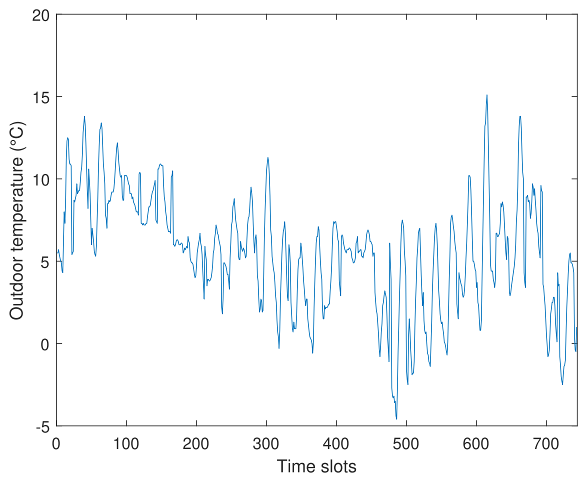

FIGURE 8. Outdoor temperature.

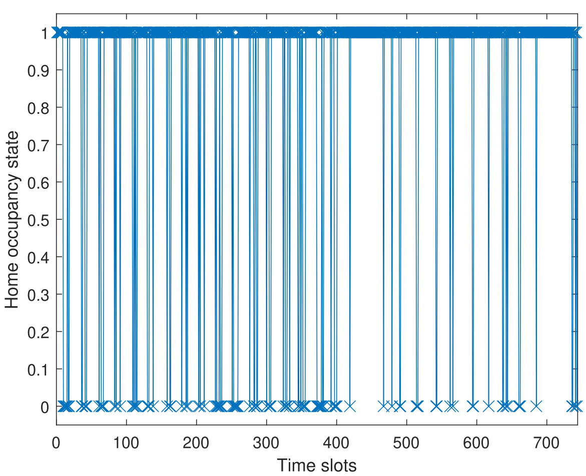

FIGURE 9. Home occupancy state.

using theorem 2. This results in a nominal charge time of $t_{EV,scheduleEV} = (24 + 6) - 18 = 12$ slots (hours), where the terms in brackets (24 + 6) shows the charge completion time at 6 a.m. the next day after the charge process starts. Since the EV's max charge rate is $v^{\max} = 3kW$, the

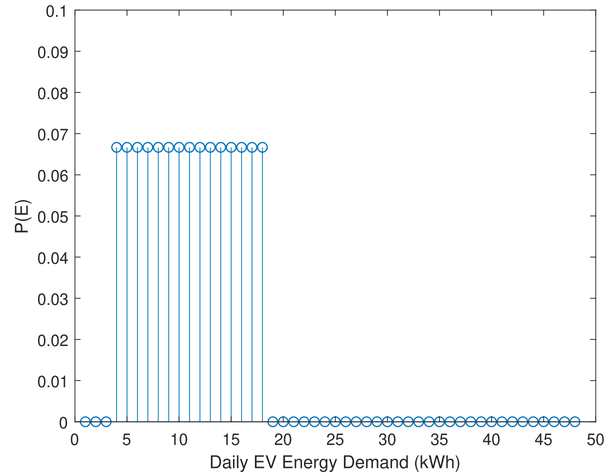

FIGURE 10. Evenly distribution of EV charge demand.

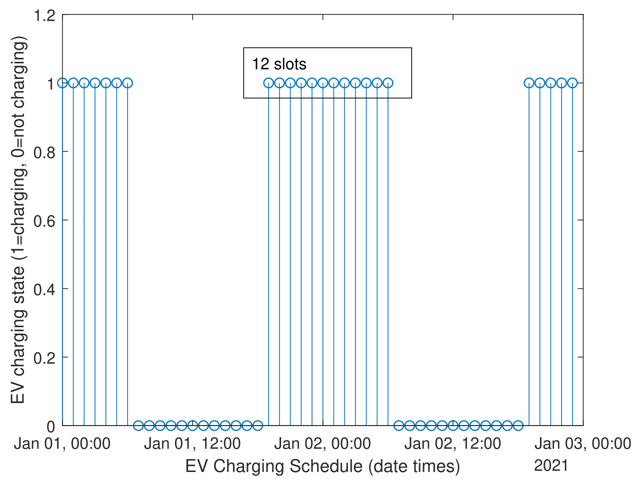

FIGURE 11. EV charge start and end time.

amount of time slots (hours) required to fully charge an EV when the battery is at its lowest point (i.e. when $E_t = E^{\max}$) is $t^{\max}_{EV,charge} = E^{\max}/v^{\max} = 18/3 = 6$ time slots. Given a maximum delay of $D^{\max} = 5$ slots and a maximum number of time slots required to charge the EV when it is at its lowest point of $t^{\max}_{EV,charge} = 6$ slots, the longest possible time required to charge the depleted EV batteries when delayed starting is allowed is $t_{EV,total} = D^{\max} + t^{\max}_{EV,charge} = 5 + 6 = 11$ slots (hours). As previously stated, the suggested model is developed utilizing the Lyapunov methodology with convex optimization. CVX is a convex programming tool in MATLAB. All of the constraints in a convex optimization problem are convex functions, and the objective function is said to be minimizing if it is also a convex function. The following four constraints are subjected to convex optimization in our work:

- Energy Demand of HVAC.
- Energy cost from the grid.
- Charging power of EV.
- Charge/Discharge power of EV.

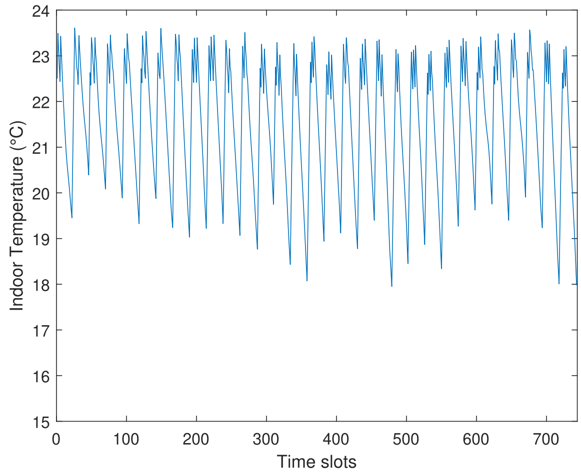

FIGURE 12. Indoor temperature.

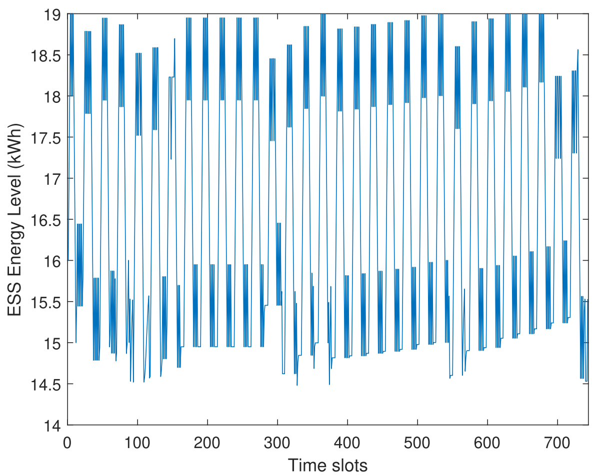

FIGURE 13. ESS stored energy level.

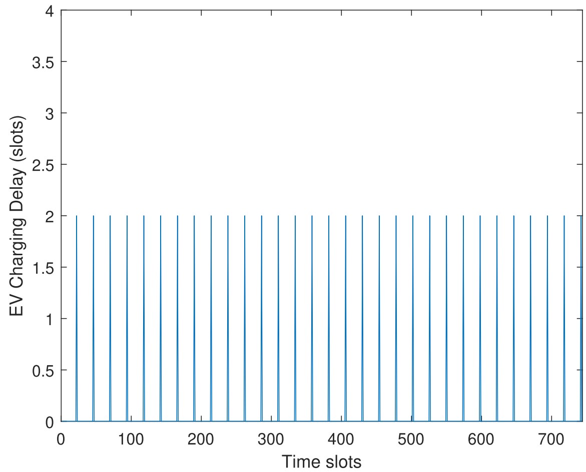

FIGURE 14. EV charging delay.

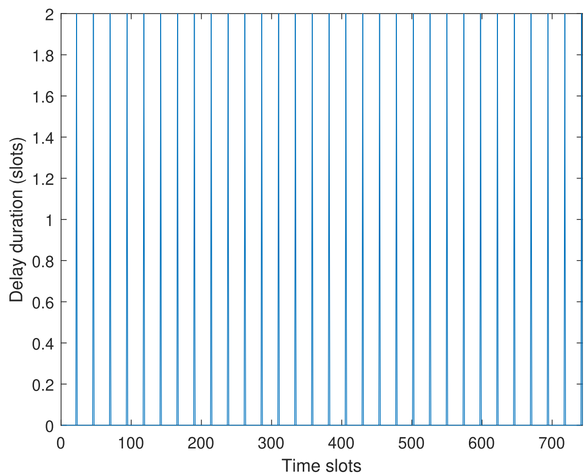

FIGURE 15. EV delay duration.

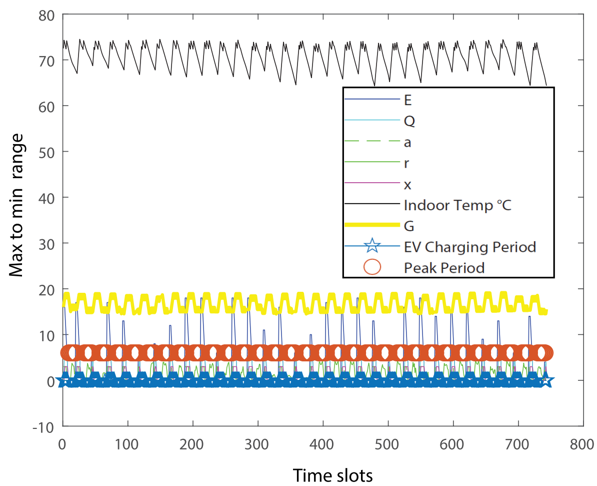

FIGURE 16. Combined figure.

The following baseline was used to determine the validity of our proposed algorithm. Baseline-1 (**B1**): As used earlier in [78], [79], our (**B1**) also maintain the foremost comfortable temperature level T^{ref}_{t+1} for the customers by drawing the power:

$$e_t = \max(0, \min(e^{\max}, A/\eta(((T^{ref}_{t+1} - \varepsilon T_t)/1 - \varepsilon) - T^{out}_t))) \tag{43}$$

when the home is occupied. We set $e_t = 0$ when $\Pi_{t+1} = 0$ and $T_{t+1_{et=0}} \geq T^{\min}$. Our baseline meets EV charging demand quickly by ignoring ESS.

1) Algorithm feasibleness: We examine the usual ranges of ESS energy level, EV charging delay and indoor temperature using theorems 1-3 to ensure that our algorithm is practical.

Algorithm Feasibility: We can observe clearly from Figures 12, 13, 14, and 15 that the indoor temperature and ESS energy level under the proposed method constantly fluctuate within typical limits. We can also observe that the EV charging delay is less than R = 5. These criteria support the applicability of the algorithm to the original problem **P1**. When the home is occupied, (**B1**) preserves the temperature at the foremost comfortable level, whereas when the home is unoccupied, (**B1**) turns off the HVAC system, but only if the next time slot does not result in a temperature below $T^{\min}$. The optimal results of EV energy demand (E), EV energy

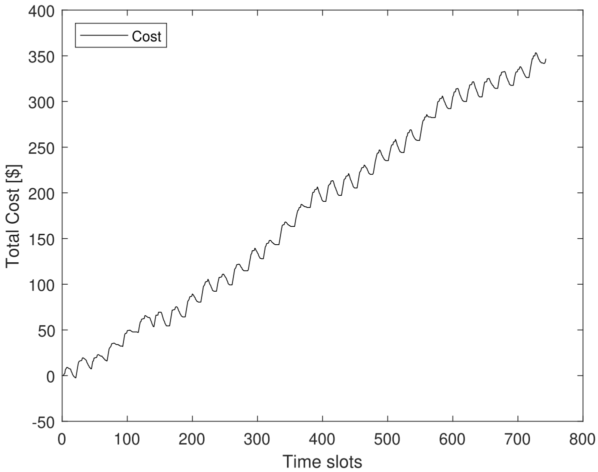

FIGURE 17. **Total cost.**

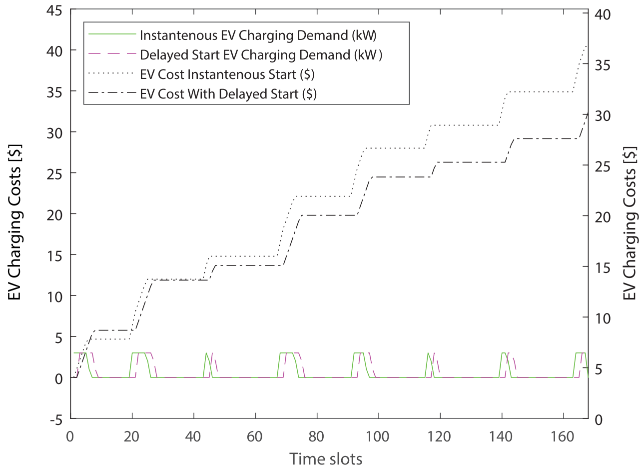

FIGURE 19. **EV charging cost.**

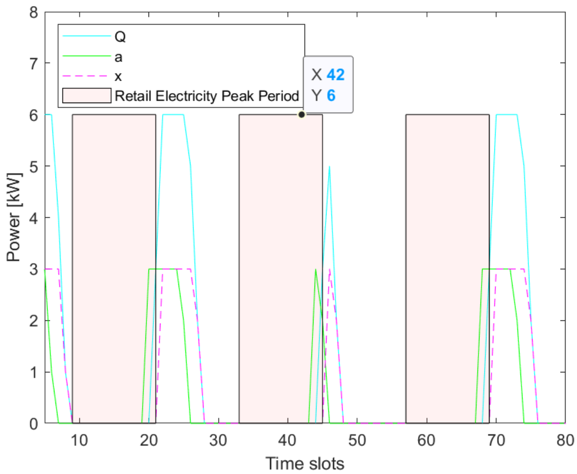

FIGURE 18. **Power (kW).**

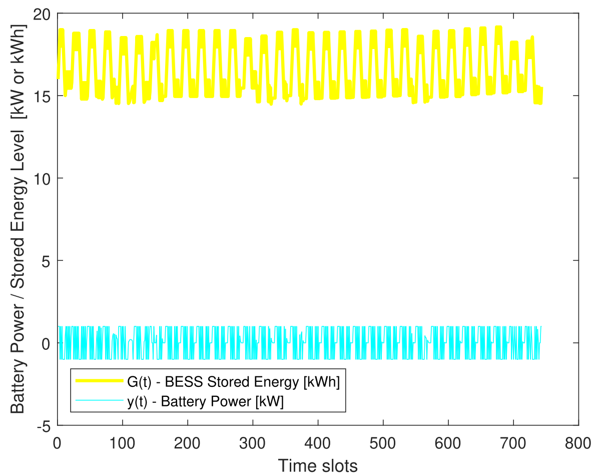

FIGURE 20. **Battery power and stored energy level.**

queue (Q), the arrival rate of Q (a), generation output of PV (r), generation output of wind pwt_t, the rate of queue Q (x), and stored energy level of ESS (G) are displayed for 744 slots in Figure 16. Figure 17 depicts a clear tradeoff between the RES and the conventional grid, with positive peaks indicating energy drawn from the conventional grid and negative peaks indicating energy provided to the conventional grid, lowering the total cost. The relationship between retail electricity price and EV energy's arrival and service rate is depicted in Figure 18. The cost and EV charging demand are compared in Figure 19. It can be observed that instantaneous EV charging demand has a high-cost effect, such that it raises the cost, but delayed EV charging lowers the cost. When $S_t = 0.9B_t$, an analysis of power flow within HEMS is performed.

Both the battery power in kW and the stored energy level in KWH vary within typical ranges, as shown in Figure 20. Figure 21 plots the four virtual queues versus the total number of time slots. The virtual queues that were employed were:

- $H(t)$ Shifted version of indoor temperature Tt.
- $Z(t)$ Delay-aware virtual queue.
- $K(t)$ Virtual queue related ESS energy level Gt.
- $Q(t)$ Actual energy queue to keep three virtual queues stable.

The plot of the Lyapunov function after all four virtual queues have been provided to the function is shown in Figure 22. A Lyapunov function is an aggregate summarising function that, as the system grows, consistently lowers toward a minimum value, providing a straightforward technique for checking stability. This theory is based on the assumption that if a system is not already at equilibrium, the energy inside it will naturally tend to diminish until it does. The Lyapunov function is a scalar assessment of overall network congestion when applied to queueing systems. In the context of energy queues in a smart home, the Lyapunov function measures the amount of energy backlog or queued energy demand. The graph shows that the Lyapunov function steadily decreases towards the lowest value, indicating stability. Figure 23 depicts the achievement of the goal of lowering the peak to average ratio. The PAR was around 24 when the Lyapunov technique was not used, but it was lowered to 17 when the Lyapunov approach was used. When $S_t = 0.9B_t$, the study of power flow within HEMS is shown in Figure 24.

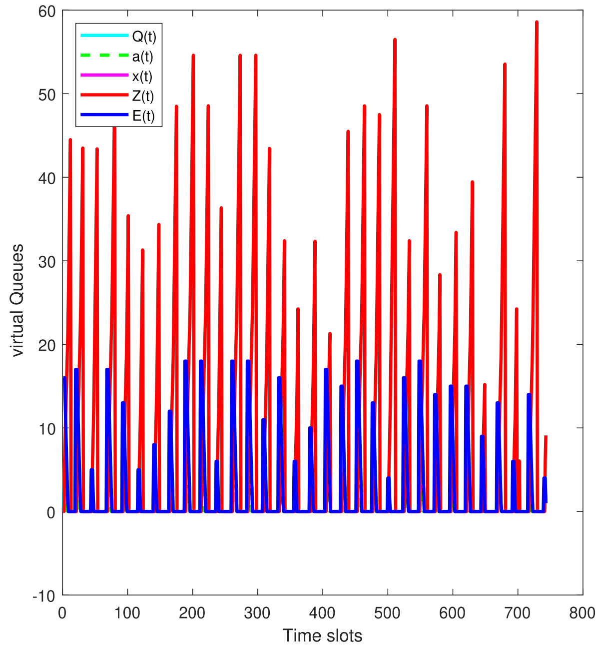

FIGURE 21. Virtual queues.

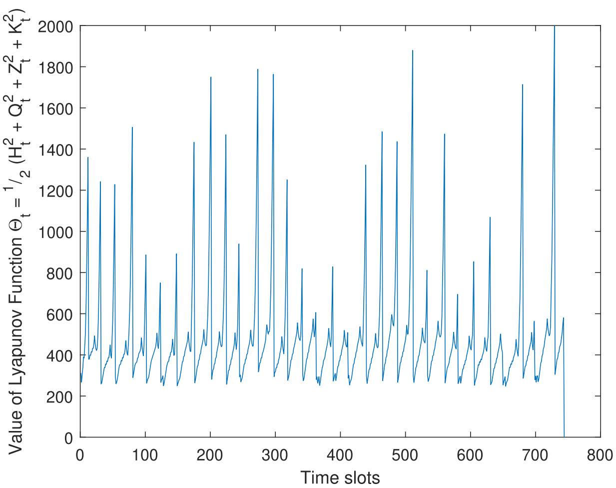

FIGURE 22. Lyapunov function.

The diagram depicts the smart home's power use and gives a unique view into the underlying linkages. The technology exports the majority of the electricity generated to the grid. It's also evident that when solar or wind power is poor, the system prefers to charge the EV and operate the HVAC.

VIII. SCENARIO 1: WITH CONVENTIONAL GRID ONLY

We only analyzed the grid as a source for supplying the loads in scenario 1, and no renewable energy sources were examined. Only grid energy is utilized, as seen by the positive peaks in the cost graph, indicating that only buying takes place and no negative peaks, indicating that no energy from renewable sources is utilized. Further, we have applied two conditions, Lyapunov technique based on convex optimization, and Lyapunov technique without convex optimization explained as follows:

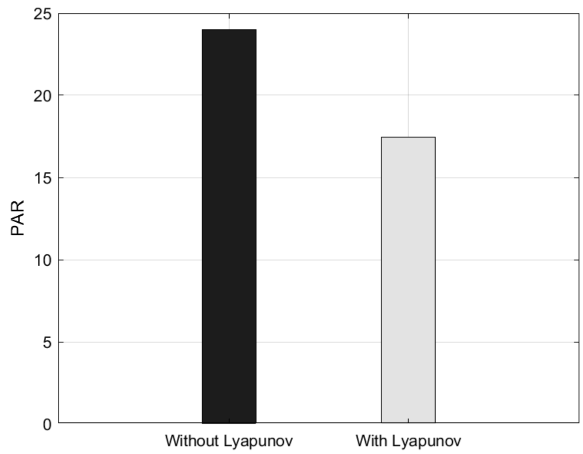

FIGURE 23. PAR comparison of load with and without Lyapunov.

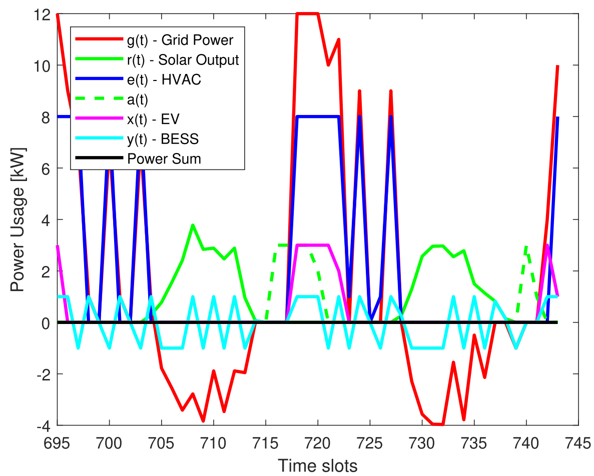

FIGURE 24. Power usage (kW).

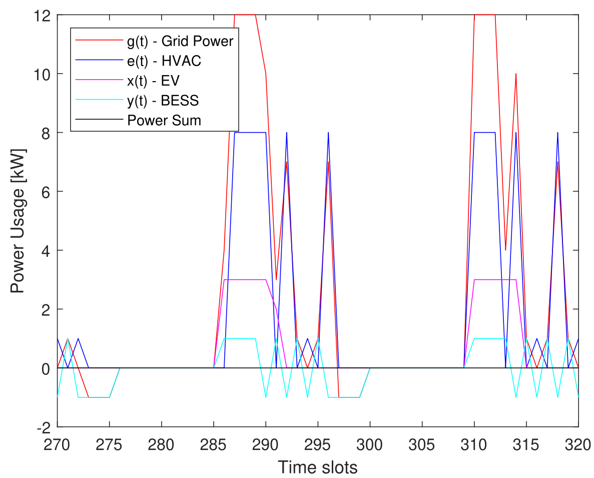

FIGURE 25. Scenario 1: Power usage with only grid with convex optimization.

A. LYAPUNOV WITH CONVEX

Figures 25 and 26 show the results produced when the method was run using the Lyapunov technique based on online convex optimization. Figure 25 shows that the grid

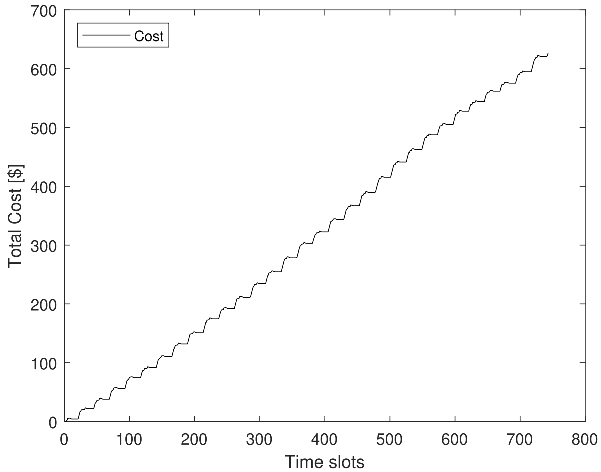

FIGURE 26. Scenario 1: Cost with only grid with convex optimization.

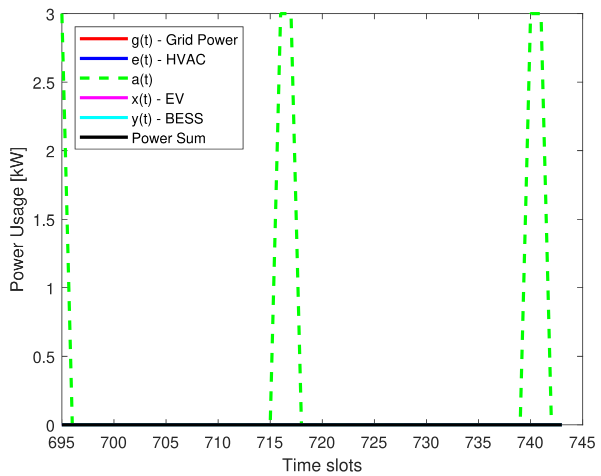

FIGURE 27. Scenario 1: Power usage with only grid without Convex.

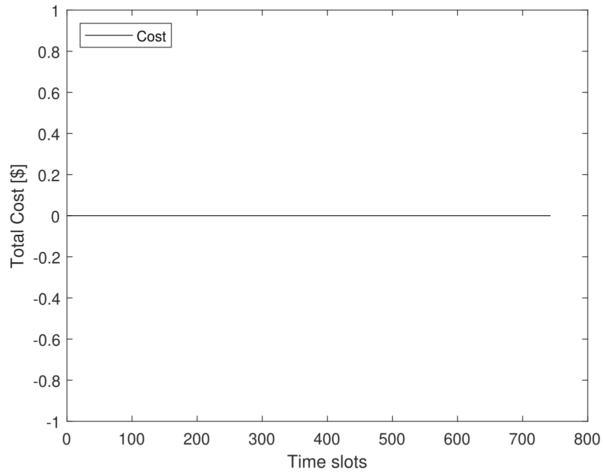

FIGURE 28. Scenario 1: cost with only grid without convex.

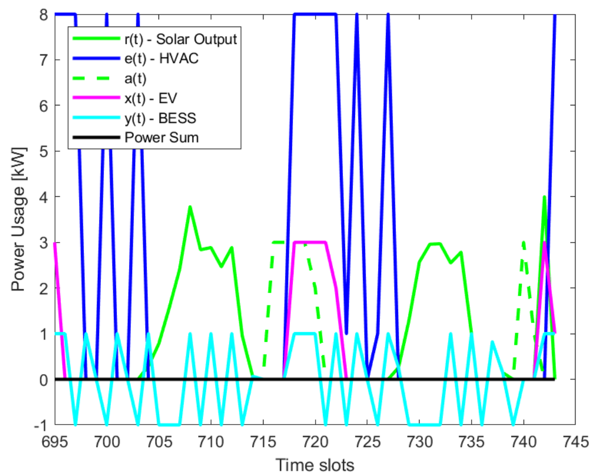

FIGURE 29. Scenario 2: Power usage with only RES and ESS.

generates 12 kW of energy, whereas our load, i.e., HVAC and EV, consumes 8 kW and 3 kW, respectively. The battery energy storage system, on the other hand, uses 1 KW of power. We can see the greater cost in Figure 26 since we have not included any renewable energy sources and the only source supplying our demand is the conventional grid. As a result, we may infer that this scenario is unfeasible owing to the high cost, which is prohibitive for consumers.

B. LYAPUNOV WITHOUT CONVEX

In this condition, when we removed the online convex optimization technique from the Lyapunov Optimization technique, we got the following results represented in Figure 27 and Figure 28. When we removed the online convex optimization technique from the Lyapunov optimization technique in this case, we received the findings shown in Figures 27 and 28. Figure 27 shows that when the convex optimization was removed from $e(t)$, $g(t)$, $x(t)$, $and\ y(t)$, the major variables responsible for the optimised results, we received an unoptimized result for power consumption. The entire supply and demand process is disrupted when the convex optimization is removed, resulting in a disrupted demand and supply process. Because these variables are likewise cost-dependent, removing them resulted in our system having zero cost, as shown in Figure 28.

IX. SCENARIO 2: WITH RES AND ESS ONLY

Only RESs and ESSs are connected for supplying the loads in scenario 2, and the grid is not included as a source in this scenario. The power usage graph displays the amount of energy utilized. The cost is represented via a cost graph. Furthermore, we used two conditions: the Lyapunov technique with convex optimization and the Lyapunov technique without convex optimization, which are described as follows:

A. LYAPUNOV WITH CONVEX

Figures 29 and 30 show the results produced when the algorithm was run using the Lyapunov technique based on online convex optimization. Figure 29 shows that the energy generated by renewable sources is 4 kW, whereas

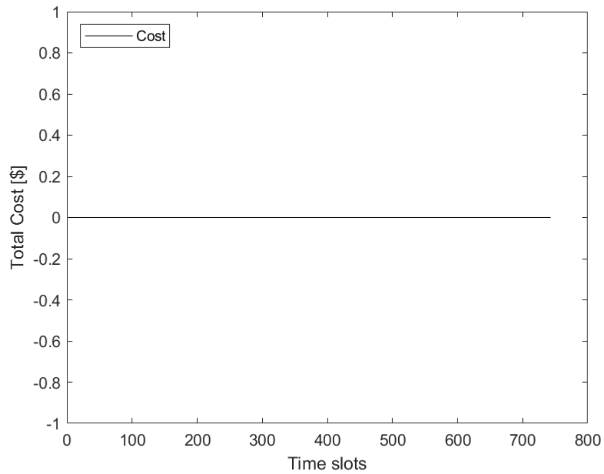

FIGURE 30. Scenario 2: Cost with only RES and ESS.

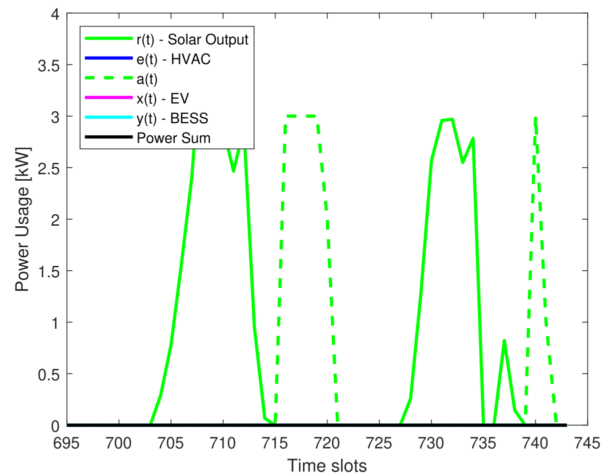

FIGURE 31. Scenario 2: Power usage with only RES and ESS.

our load, i.e., HVAC and EV, consumes 8 kW and 3 kW, respectively. The battery energy storage system consumes 1 kW of power. As a result, this conclusion specifies the supply and demand dilemma, in which supply is less than demand and loads suffer from a shortage of energy, rendering this scenario unsustainable. We reached zero cost because there was no conventional grid engaged, which implies there was no buying or selling of energy involved, as shown in Figure 30.

B. LYAPUNOV WITHOUT CONVEX

When we removed the online convex optimization technique from the Lyapunov optimization technique in this case, we received the results shown in Figures 31 and 32. We can see from Figure 31 that when the convex optimization was eliminated from $e(t)$, $g(t)$, $x(t)$, *and* $y(t)$, which were the major variables responsible for the optimised results, we received an unoptimized result for power consumption. As a result, the supply and demand dynamics are disrupted once more, rendering this situation untenable. Also, because

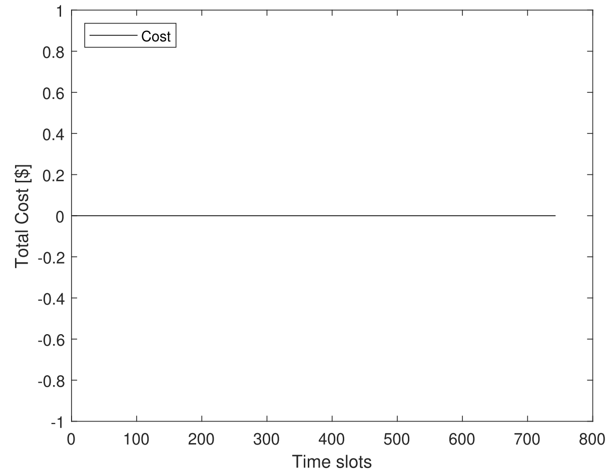

FIGURE 32. Scenario 2: Cost with only RES and ESS.

the convex optimization is not applied to the RES output, just RES output is accessible. The RES output is isolated power that loads may use within the smart home. In the Figure, we can observe that just the RES output is shown. Because these variables are likewise cost-dependent, removing them yielded a zero cost for our system, as shown in Figure 32.

1) EFFECT OF $T^{\min}$

The suggested method dynamically changes the HVAC power input based on current electricity prices and a wider temperature range, lowering energy costs. Range of temperatures ($T^{\max} - T^{\min}$) decreases as the $T^{\min}$ increases. Similarly, as compared to (**B1**), the proposed algorithm might save 36.3% percent on energy costs while sacrificing just a little amount of average temperature variation from the foremost comfortable temperature range.

2) EFFECT OF ε

Our proposed algorithm achieves lower energy costs with a greater value of ε because a greater ε results in less thermal depreciation over the same timescale. When ε is $\geqslant$ 0.98, the energy cost rises since small V tends to a limited temperature range.

3) EFFECT OF γ

When γ is between [0.002, 0.016], our recommended approach has the lowest total cost. As thermal discomfort cost of (**B1**) is the lowest and the corresponding energy cost is constant when γ is $>$ 0.02, (**B1**) obtains the best performance.

In conclusion, when a smart home resident is worried about both energy costs and thermal comfort, the recommended algorithm is an efficient way to operate the HVAC system.

X. CONCLUSION AND FUTURE WORK

This study looked at the energy management of a sustained smart home with HVAC load and randomized occupation.

Then, Without forecasting any system characteristics or knowing the HVAC power requirement, we offer an online energy management algorithm for the defined problem based on the LOT framework that helps in reducing the time-averaged estimated overall cost and thermal discomfort cost. Unlike other Lyapunov-based energy management algorithms, the proposed approach does not need to submit unknown HVAC system power requests to an energy queue. Comprehensive simulation findings based on factual footprints demonstrate the proposed algorithm's efficacy. Also, different scenarios are created to compare the results. We want to study online HVAC controls in a commercial building in the future, such as distributing the airflow rate within each zone or room in real-time while taking occupant thermal comfort into account. Furthermore, we intend to analyze the influence of HVAC load aggregate on end-user comfort in a residential structure, such as reducing the average thermal discomfort of these homes during a demand response event while still meeting the total power reduction/increase requirement.

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