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Energy Optimization: Smart Grid Integration with Renewable Energy

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Abstract

Energy optimization important problems in a smart grid setting, with user experience improvement, controlling battery energy storage, and load scheduling, are tackled in this paper. The efficiency of controllers in maximizing energy generation, user comfort, load scheduling, and real-time battery backup scheduling depends on system inputs, including dynamic pricing signals, load arrival dynamics, battery charging and discharging dynamics, and processes for producing renewable and conventional grid energy. To explore these issues, the virtual queue safety (LOT) based Lyapunov optimization approach is used in a grid-connected green smart home with an HVAC load. The main goal is to reduce the total time-averaged energy cost and the cost of thermal discomfort over a longer period. Variations in the number of occupants in the house, desired temperature circumstances, electrical consumption, output from renewable energy sources, outside temperature, and power prices are all considered in this optimization. The suggested method creates and maintains four queues for the electrical energy storage system (ESS), EV charging, and interior temperature. The algorithm's efficacy is verified through extensive simulations. Simulation results show that the suggested strategy satisfies the user's energy and comfort needs while achieving real-time energy optimization and a 20.15% decrease in the time-averaged energy cost.

Keywords

Energy Optimization, Smart Grid, Renewable Energy, Lyapunov Optimization, User Experience, Battery Energy Storage, Load Scheduling, Virtual Queue, HVAC Load, Electric Vehicle Charging

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Introduction

The advent of microgrids has offered a workable answer to the financial and technical limitations preventing isolated parts across the world from being electrified. A microgrid is an autonomous power system that connects distributed energy storage, distributed generators, and regulated loads in a specific area. It is especially useful for locations that are not connected to the main power grid. Microgrids, which take use of technological advances in communication and information advances, provide grid-connected and independent operating modes, which efficiently solve energy balance issues[1].

The residential sector is a significant energy user, making up between 31% and 41% of the total energy demand in the energy landscape. As a result, the development of an ideal controller architecture becomes necessary for efficient energy optimization and balancing. Scheduling of charging and discharging tasks, adaptable load management, and management of energy flow through the mini and the power grid are made easier by this architecture[2].

Real-time optimizing energy within smart grids that include energy storage devices and renewable energy sources has been the subject of much study. For example, a revolutionary framework for managing residential energy has been presented that combines automation and smart control. These studies cover a wide range of topics, including utility- and user-centric energy balancing in standalone or grid-connected modes. Utility-centric optimization functions struggle with user commitment, generating reserve, storing electricity, renewable energy production, power grid management, and demand response. Conversely, user-centric optimization features address energy cost reduction, battery backup management, and appliance scheduling delays. This discussion's Section II lists the difficulties with the current works[3].

This research focuses on load scheduling in smart homes, specifically addressing electric vehicle (EV) charging and HVAC (heating, ventilation, and air conditioning) systems[4,5]. Because HVAC systems account for around half of the power consumption in a smart house, it is critical to maximize their performance. Concurrently, EV charging, which is categorized as a variable load, offers a chance to save money by taking advantage of power rates that fluctuate over time. Local generators and energy-storage systems (ESS) are integrated in the smart house paradigm. The main objective is to lower tenants' long-term energy expenditures related to thermal discomfort and lower the total cost of power consumption related to smart home products. This optimization process depends on a number of variables, including changes in energy prices, outside temperature, the production of Renewable Energy Sources (RES), electrical popular, the most pleasant temperature, and the occupancy status of the residence[6–10].

In order to address the problem of lowering the average estimated total price for a house which has an HVAC the load, the research struggles with the uncertainty that comes with time-coupled constraints and potential system features. Online energy management is designed in parallel to meet real-time needs, while Lyapunov Optimal Theory (LOT) offers a framework to handle time-average optimization issues. Conventional Lyapunov-based management of energy algorithms give priority to submitting requests for flexible load facilities during spikes in electricity costs and completing them during dips in prices. But a new strategy is required due to the unpredictable nature of HVAC system power usage, which is impacted by variables including the most comfortable temperature, interior temperature limits, occupancy status of the home, and exterior temperature[11].

A novel Lyapunov-based energy management paradigm is created in response. This system does not need forecast of the values of parameters or HVAC power use information, and it can handle virtual queues relating to interior temperature, charging of electric vehicles, and ESS[12]. The suggested approach, which operates inside the LOT framework, creates a virtual queue for interior temperature without requiring real-time energy optimization to know how much HVAC power is required at any one time[13].

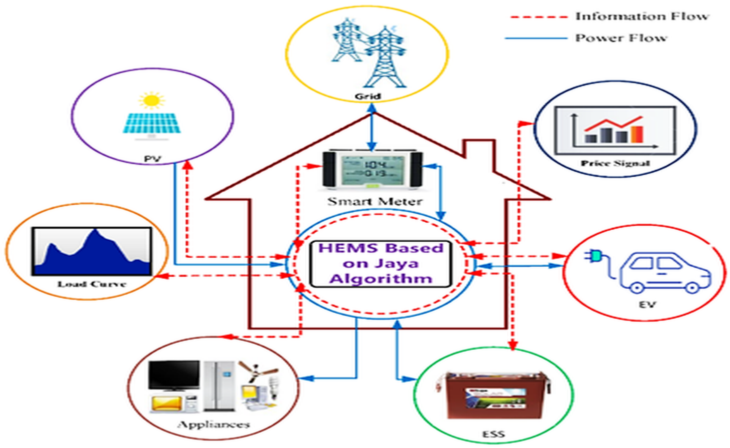

Figure 1. Classification of The System

RES output power, consumption of energy, pleasant temperature settings, house occupancy states, and variances in energy prices are among the key technological contributions[14,15]. Another is a way to lower the anticipated time-averaged overall expense for a residence with an HVAC load. Furthermore, a real-time energy optimization method based off the LOT foundation is presented, which carries out optimum online energy planning without requiring knowledge of HVAC power requirements or anticipated system features (figure 1). The suggested framework's effectiveness and feasibility are confirmed by an extensive investigation[16,17].

The effectiveness of the suggested method in reducing energy costs while eliminating trade-offs when it comes to of thermal comfort is shown by extensive simulation results. These results, which came from thorough simulation studies, confirm the usefulness and practical application of the created Lyapunov-based energy management system[18]. Essentially, the study provides a sophisticated and all-encompassing method of tackling the intricate problems linked to energy optimization in smart homes with HVAC loads, opening the door for long-term and reasonably priced electrification solutions based on microgrids[19,20].

Literature Review

Grid-Connected Mode Energy Optimization: Microgrid-Centric Approaches

Numerous studies have attempted to address the problem of energy optimization across smart electricity networks by using grid-connected microgrid-centric strategies. Demand response programs and microgrids are one creative way to solve problems with energy optimization[21–25]. This bilevel concept was presented in a research. This technique optimizes demand response systems by simulating user behaviour and discontent and takes grid constraints into account to avoid voltage and current aberrations.

Another work introduces the use of game-theoretic methods to schedule individual thermostatically controllable loads in order to optimize electricity utilization of power plants. In a separate research endeavour, real-time energy efficiency of microgrids in the islanded state is investigated via a modified and transformed issue using the LOT framework[26,27]. Furthermore, a microgrid operation-optimal energy storage management plan combining three different artificial intelligence techniques is proposed.

We provide linear and polynomial models for grid-connected energy administration in smart homes that include wireless smart metering systems for the best possible energy flow control. In order to lower the cost of cyber web power, other works use artificial intelligence tactics and compromise programming approaches to provide game-theoretic and linear programming mechanisms for energy optimization[28].

Grid-Connected Energy Optimization: User-Centric Approaches

Numerous strategies have been investigated in the field of user-centric methods for grid-connected mode energy optimization[29]. In order to satisfy long-term energy needs, an IoT-based approach for smart grid optimization of electricity is put forward. In grid-connected mode, artificial intelligence is used to improve the safety, dependability, and efficiency of electric automobiles[30].

Research examine how heuristic optimization techniques like particle swarm optimization, ant colony maximizing efficiency, and genetic algorithms may be used to solve energy management problems. In order to reduce energy expenses, hybrid algorithms based on genetics are designed to balance load demand and generation. In order to promote user-centric efficiency of energy in grid-connected mode, fuzzy analytical hierarchy technique methodologies and powered by blockchain frameworks are proposed for tackling energy management difficulties.

Microgrid-Centric Energy Optimization Methods for Islanded Mode

In island mode, microgrid-centric solutions are studied to handle the energy optimization problem. For new double-stage grid-coupled PV system, a novel normalized reasoning hazy neural adapt (NRFNA) management strategy is put forward. Algorithms for optimizing hybrid genetic ant colonies are created for a range of situations, including those with PV systems and those without.

The goal of the energy optimization models, which combine fuzzy logic based on game theory and evolutionary algorithms, is to predict future power needs and maximize profit. Other research employs cutting-edge optimization techniques for microgrid energy savings in islanded mode (figure 2), such as multi-objective hawk search algorithms and bat algorithms. Fuzzy logic-based self-tuning controllers are proposed to improve operational stability by addressing uncertainty in conventional controllers.

User-Centric Approaches for Energy Optimization in Island Mode

A significant amount of the research uses user-centric approaches in islanded mode to study energy management issues. Taking unknown factors into account, a stochastic MILP-supported microgrid control system is created. To address energy management or dispatch issues, constructed bee colonies algorithms and adaptive optimal fuzzy logic methods are suggested.

Lyapunov stochastic optimization approaches are investigated for real-time optimal energy solutions for coordinated microgrids of electric vehicles. For the purpose of coordinating connected multi-node

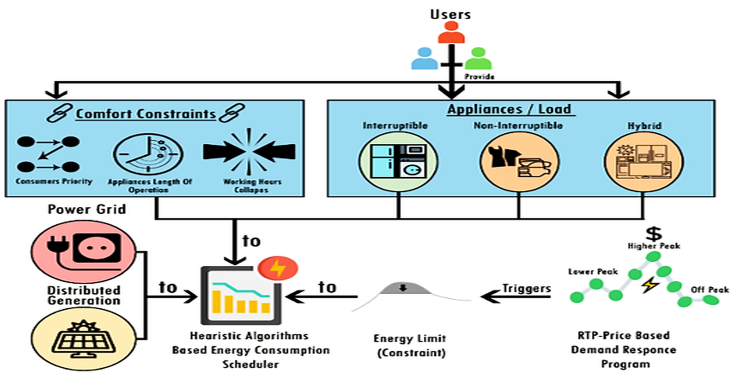

Figure 2. Workflow Methodology of The System

microgrids with storage capacities, non-linear model prescriptive controllers are presented. In islanded mode, series-parallel a plugin the combination electric vehicle are designed using hybrid models that include rule-based evolutionary algorithms. Energy management frameworks based on the Internet of Things and cloud computing are introduced. Stochastic algorithms are used to reduce total cost and determine ideal system sizes for different components.

The original material highlights extensive research efforts that effectively handle energy optimization throughout the relevant areas. By analyzing appliance resource demand requests and optimizing electric power use based on shifting costs, our suggested approach seeks to decrease energy consumption. Our study handles the uncertain energy demand of HVAC loads in a novel way, considering variables like temperature boundaries, home state, and exterior temperature, unlike the electric car load. The Lyapunov optimization approach is applied for online energy-usage planning, with explicit estimates of algorithmic feasibility aspects impacting system management. Our approach creates a virtual queue for interior temperature, considering the trade-off between increasing thermal discomfort and energy value loss, and accommodating HVAC power needs at each given slot.

Proposed Methodlogy

The analysed smart home, forms a mutually beneficial relationship with the electrical grid. The smart house and the traditional power grid may both obtain real-time energy price and total power usage thanks to this reciprocal connectivity. The smart house may purchase and sell electricity from the conventional grid thanks to this two-way communication channel. In order to facilitate seamless energy exchange, our model connects essential elements such as Energy Storage Systems (ESS), Renewable Energy Sources (RES), and Home Energy Management Systems (HEMS) with loads like Electric Vehicles (EV) and HVAC (heating, ventilation, and air conditioning) systems via a DC/AC low voltage bus bar.

The Home Energy Administration System serves as the central controller within a smart home system. It coordinates the complex dance of energy production, storage, and use (figure 3). The time slots in which the HEMS works are represented by the notation $t \in [0, T]$, where T is the total quantity of time slots. The time slot length τ is uniformly set to unity in order to guarantee equivalent power and energy consumption.

A. Res Model

Photovoltaic (PV) and wind electricity are the two separate energy sources that are included in our suggested sustainable energy Source (RES) model.

1) PV Efficiency Model

The electricity produced from the solar panels on the roof system makes up a vital part of our ecologically conscious energy plan.

2) Model Of Wind Energy

The wind energy profile is based on more than 48 GW of 2 MW turbines and is taken from Vestas' V1202.2 MW. With an annual energy production boost of up to 14%, these turbines are intended for optimal energy production in low- to moderate-wind situations.

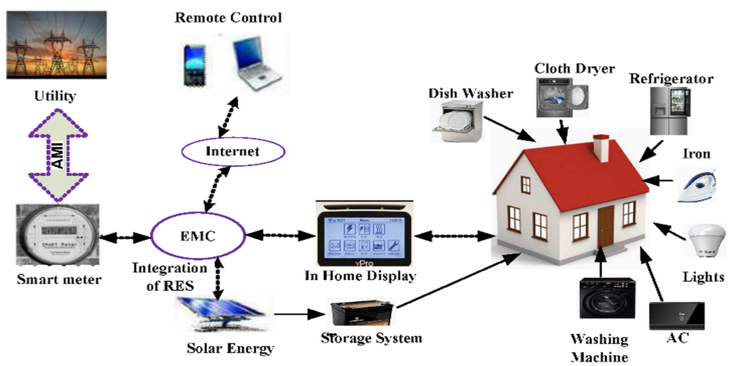

Figure 3. Approach of the System

B. Model of Load

The load model considers two different kinds of loads: flexible loads (such as electric vehicles; EVs) and inflexible loads (such as HVAC systems).

1) HVAC Type

There are two ways the HVAC system may function: heating and cooling. We only consider the heating mode for the objective of this investigation. The HVAC system's energy usage is predicted to automatically adjust the system's electric power level, represented as e_t, in order to keep the interior temperature within a tolerable range.

2) Model Of Electric Vehicle

Through a DC/AC bus, the battery of the electric car (EV) is connected to the smart house. When the EV gets connected for charging, charge requests are sent to a Home Energy Management Tool (HEMS). These requests allow the HEMS regulator to optimize electric vehicle charging depending on dynamic pricing, with each request having a three-tuple structure (start speed s, time to complete c, and energy consumption E). The idea is to delay charging the EV during times of significant pricing volatility and to charge it when power rates are low.

C. Model of Energy Storage System

The stored power amount (G_t) inside the digital home-connected Energy Storage Although it (ESS) is represented by the ESS model (figure 4). In order to maintain the device's charge within capacity limits, the energy level varies over time amid charge and discharge activities.

D. Equalizing Power

At time slot t, the power exchange between the smart house and the traditional grid is represented by the symbol g_t. When $g_t > 0$, energy is purchased from the grid, and when $g_t < 0$, it is sold back to the grid. The goal of real-time energy distribution is to maintain balance between energy production and consumption by optimizing the power exchange.

Proposed Methods

We explore a novel approach to online energy optimization in this section. By addressing issues with temporal connections and future variable uncertainty (table 1), the suggested method offers an immediate remedy for energy management.

Table 1. SYSTEM CHALLENGES AND THEIR REAL TIME SCHEDULING AND BENEFITS

CHALLENGE	SOLUTION: REAL-TIME SCHEDULING	BENEFITS
Unpredictable renewable energy generation	Dynamic resource allocation: Adjust energy sources based on real-time weather and demand forecasts.	* Reduced reliance on fossil fuels. * Increased grid resilience and stability.
Peak demand causing strain on infrastructure	Demand response programs: Incant consumers to shift energy use to off-peak hours.	* Lower energy costs for utilities and consumers. * Reduced strain on power lines and generators.
Inefficient energy storage and distribution	Distributed energy resources: Utilize local storage and microgrids for optimized energy distribution.	* Improved energy accessibility in remote areas. * Reduced energy losses during transmission.

Building Virtual Lines of Work:

The Energy Storage System (ESS), the electric vehicle (EV) charging delay, and interior temperature virtual queues are the first things the algorithm creates. The shifting nature of HVAC demands is accommodated by these virtual queues, which provide stability. We carefully develop the equations controlling the virtual queues, accounting for limited upper bounds on stability.

Acquiring Penalty Term Plus Drift:

To stabilize the three artificial queues and the actual energy queue, a Lyapunov factor is developed. Next, the Lyapunov drift—a measure of the Lyapunov function's change—is computed. The drift + penalty component, which is essential for minimizing energy costs, is derived from the drift equation by adding the whole predicted cost.

Maximum Boundary Decrease:

The program chooses control actions in a deliberate manner in order to reduce the maximum drift plus penalty period. The technique guarantees effective and efficient solution-finding by defining the optimization issue and offering a convex approach.

Algorithm Performance:

A step-by-step explanation of the suggested Smart Home management of energy algorithm is provided, along with the reasoning behind each time slot's decisions. The system takes into account a number of circumstances, including EV charging and HVAC operating optimization. The algorithm's capacity to adjust to real-world settings is ensured by the constant monitoring and updating of constraints.

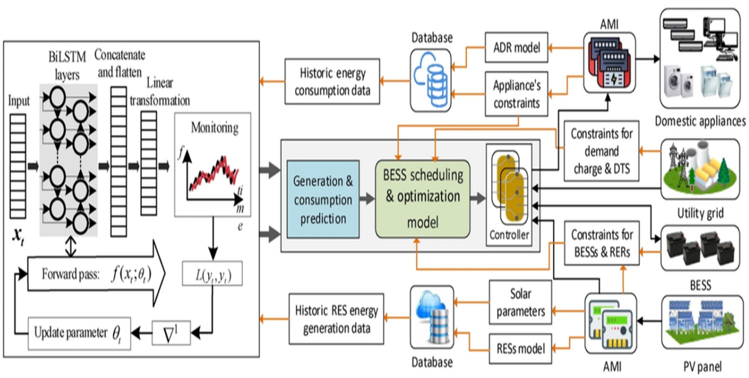

Figure 4. Implementation of The System

Surveillance Evaluation:

The suggested algorithm's viability is supported by the introduction of lemmas and theorems, which show how well it can adhere to restrictions on HVAC operation, electric vehicle (EV) charging, etc Energy Storage System choices. Because the parameters of the method are well-defined, performance is guaranteed in a range of circumstances.

Discussion

In a smart grid context, the research study tackles important energy optimization issues with a particular emphasis on load scheduling optimization, battery energy storage management, and user experience enhancement. The goal of the research is to limit temperature discomfort over a long length of time and lower overall time-averaged energy expenditures in an electrically linked green smart house with an HVAC load by using the Lyapunov optimization technique. The suggested approach considers factors including dynamic price signals, load dynamics, and natural energy sources while creating simulated waiting lists for battery storage, EV (electric vehicle) charging, and interior temperature.

In order to maximize energy use and balance, the suggested algorithm—which has its roots in Lyapunov Optimizer Theory—incorporates virtual lines, penalty conditions of sale, and drift calculations. Comprehensive simulation findings validate the approach's potential for real-world implementation in smart homes by demonstrating how well it reduces energy expenditures and temperature discomfort. The study advances knowledge on energy optimization in smart grids and provides insightful information for further study and useful applications in the area.

Conclusion

In this study, we looked at a sustainable smart house with randomized occupancy and HVAC load managing its energy dynamically. We describe an online handling energy algorithm utilizing the LOT framework, which operates without knowledge of the HVAC power needs or system parameters. Unlike existing Lyapunov-based energy management techniques, this algorithm efficiently reduces the time-averaged predicted overall cost as well as the thermal discomfort cost without requiring the submission of unidentified HVAC system electricity requests to an energy queue.

Our extensive simulation findings, based on real footprints, confirm the effectiveness of the suggested approach. Different scenarios were also created in order to make a comparative study of the results easier. Future studies will examine online HVAC controls in commercial buildings, with an emphasis on occupant comfort in the heat. These controls will include real-time circulation of airflow rates across each zone or room. Furthermore, we want to look at how end-user happiness in residential buildings is affected by the total HVAC load. This entails keeping overall power reduction/increase needs within specified limits while reducing the average level of discomfort caused by heat in houses during demand response events.

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