Energy Efficiency Optimization for Smart Homes

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***Abstract*— Energy consumption has increased at an unprecedented rate as a result of the increasing integration of smart devices in residential settings. In response to the demand for smart homes to use energy sustainably and efficiently, this research suggests a novel strategy that maximizes energy efficiency by utilizing data mining techniques. We create a complete framework that analyzes and models human behavior, appliance usage patterns, and environmental conditions by utilizing the abundance of data created by smart home devices. Our method makes use of sophisticated data mining algorithms to glean valuable insights from the gathered data, allowing for the detection of patterns in energy consumption and the forecasting of future usage trends. The suggested solution incorporates these insights even more to create an intelligent energy management system that can optimize energy use in real time while preserving user comfort and preferences. The creation of a dynamic optimization algorithm that adjusts to shifting circumstances and guarantees steady increase in energy efficiency over time is a significant contribution of this research. Through thorough simulations and real-world trials, we assess the efficacy of the suggested approach and show notable savings in energy use without sacrificing user pleasure. Our research shows how data mining may improve smart home energy efficiency and open the door to a more ecologically friendly and sustainable residential infrastructure. By offering a scalable and flexible response to the urgent problem of energy optimization, this research advances the field of smart home technologies and advances the realization of smarter and more environmentally friendly living environments.**

Keywords—Smart Homes, Energy Efficiency, Artificial Intelligence, Machine Learning, Clustering, Classification, Optimization

I. INTRODUCTION

As there are more smart home appliances than ever before, they are expected to consume a significant amount of energy in smart homes. This is due to the launch of many new home appliances that help users live a better life [1]. In fact, the cost of the smart home devices needed to support modern and ever-changing technologies is borne by this comfort [2]. Dishwasher, refrigerators, microwaves, and smart cars are just a few of these devices [3].

Over the past decades, the energy system has had to evolve due to energy issues and climate change [4]. As energy demand increases in the coming decades, this problem will become more difficult [5]. Due to the increasing demand for energy, energy efficiency has become a major challenge for the world. However, due to the complexity of systems and procedures, this can be difficult. One potential answer to this problem is to use data to predict energy efficiency. Many types of inefficiencies can be solved with data.

II. RELATED WORKS

Machine learning-based smart home services have attracted significant attention, with a range of research contributing to the understanding and implementation of smart living spaces.
One study focused on characterizing low-voltage electricity customers, using clustering and classification techniques to analyze historical data [6]. Research emphasizes the importance of data mining (DM) techniques, especially clustering algorithms such as K-medoids and K-means, in identifying consumption patterns and customer classification [6].
In the field of domestic energy management, a new method using deep reinforcement learning (DRL) was presented, aiming to optimize photovoltaic self-consumption and dynamic temperature set points to improve user comfort and energy savings [7]. Exploring energy consumption patterns and interconnections between devices in a smart city context using DM techniques contributes to a deeper understanding of consumer behavior and preferences [8]. This study was carried out on the basis of Moroccan energy consumption data, providing valuable information for the development of energy management systems. Machine learning techniques play a central role in optimizing energy use in smart homes [9]. The study evaluates different methods including deep, reinforcement learning and decision trees, demonstrating their effectiveness in identifying models and forecasting future consumption [9].
The development of models that predict the energy consumption of household appliances, including the use of long-term and short-term memory networks, demonstrates the

benefits of deep learning in prediction and optimization energy consumption [10].

Another paper explores the implementation of machine learning algorithms in a smart home context, using decision tree regression, random forest regression, additive tree regression, gradient boosting, regression historical gradients and deep neural networks for data analysis and prediction [11]. Finally, a study focuses on data mining and analysis to predict electrical energy consumption, classifying electricity consumers and using decision trees, random forests, Naïve Bayes classifiers and algorithms SVM for efficient data analysis and prediction [12].

Together, these diverse works highlight the transformative potential of machine learning to improve efficiency, sustainability, and user experience in smart home environments.

III. ENERGY EFFIENCY FOR SMARTHOMES WITH DATA MINING

III.I. Residential Demand Response (DR) Program within Home Energy Management Systems (HEMS)

Recently, more and more researchers have focused on residential demand response (DR) programs, this program plays a central role in motivating residential consumers to voluntarily reduce their everyday expenses consume electricity by effectively allocating available resources and managing their electrical appliances [13]. DR can be described as changes in consumers' electricity consumption patterns, which differ from their usual consumption patterns, due to factors such as changes in electricity costs over time or incentive programs. Incentives designed to encourage reduced electricity consumption during periods of high or potential wholesale prices system reliability concerns [14]. DR initiatives are widespread in Europe and the United States and aim to regulate timing, total power consumption, and immediate demand [15]. As part of the Demand Response (DR) program, customer feedback can be categorized into three options that take into account cost and customer behavior.The first option allows customers to reduce their electricity usage during important peak periods when electricity prices are high, although this option may temporarily affect their comfort level. In the second option, customers can adapt by shifting the operation of some household appliances from peak hours to off-peak hours to cope with rising electricity prices. The third option involves customers using local distributed power sources, leading to changes in their electricity consumption habits [16]. Customers participating in the Demand Response (DR) program can expect to save on their electricity bills by reducing consumption during peak periods. According to the United States Department of Energy, residential DR programs can be are classified into two main categories: incentive-based and price-based, as shown in Figure 1 [17].

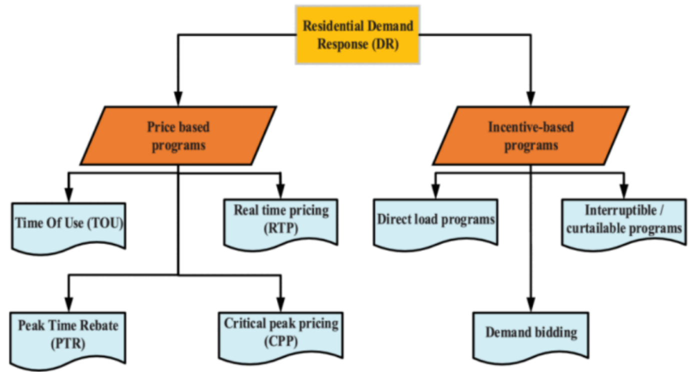

Figure1.
Classification of Demand Response Programs in Residential Settings

III.I.A Incentive-Driven Demand Response (DR) Program

Incentive program provides financial incentives to customers who participate in efforts to reduce and shift peak electricity usage. These customers receive a discounted rate or bill credit in exchange for their contribution to reducing demand. The program includes a variety of approaches, such as direct load control, decommissioning/mitigation programs, and demand-side procurement initiatives. In the case of direct load control, utilities can remotely manage customer devices by transmitting signals to turn them on or off without much notice, based on an agreement between the utility provider and the utility provider benefits and customers. This method is commonly used to control devices such as water heaters, air conditioning (A/C), and street lighting [18]. Under the Interruption/Load Shedding Program, utility providers and large industrial or residential customers will enter into mutual agreements regarding electricity rates. In an emergency, these customers will have their power cut off or switched to off-peak times. This reduction in electricity demand is facilitated by the transmission of demand-limiting signals from the utility, and in return, participants receive incentives. The main advantage of this scheme is its ability to contribute to network stability in emergency situations [19]. The demand bidding program, also known as the buyback program, operates on the basis of customer bids. Consumers submit bids specifying the amount by which they are willing to reduce their electricity load within the wholesale electricity market. Typically, the bidding process takes place a day in advance [20]. Customers have the flexibility to choose their bidding value in relation to the level of energy reduction, and they are rewarded when the actual energy savings align with specific criteria. Importantly, there are no financial penalties imposed if a customer is unable to meet the specified energy reduction requirement [21].

III.I.B Price-Based ProgramsType

Price-based programs offer customers financial incentives or discounts in exchange for reducing electricity usage during specific periods of time. These programs use different electricity pricing structures and use signaling mechanisms to help customers optimize energy consumption. Customers voluntarily adjust home electricity consumption based on time-of-day prices and track electricity costs in real time. These schemes offer different prices at different times of the day, including off-peak and peak periods, reflecting the required energy demand [22]. Time-of-Use (TOU) pricing is one of the most popular residential electricity pricing models and is currently used or considered by many utility companies around the world. TOU pricing divides electricity prices into different time frames, varying by season or time of day [23]. Power utilities leverage TOU programs by adjusting prices based on off-peak and peak time slots. Typically, electricity tariff rates are higher during peak hours and lower during off-peak hours, encouraging consumers to shift their energy consumption to times of lower pricing. Real-Time Pricing (RTP), often referred to as dynamic pricing, offers a unique pricing structure where each hour of the year corresponds to a distinct electricity price. This price fluctuates hourly within each time slot, reflecting the real-time condition of the utility's electricity price [24]. Many utilities view RTP programs as highly effective demand response (DR) initiatives due to their flexibility and widespread acceptance in the electricity market. Critical peak pricing (CPP) is structured to encourage end users to voluntarily manage and reduce their electricity demand or shift the operation of home appliances to off-peak times. RPC typically takes place several times a year, especially in the summer when energy demand increases significantly. Participating customers will receive notifications of higher prices during these critical periods. Many electricity retailers support CPP because it allows them to benefit from significant load reduction during critical demand periods. Off-peak pricing is a price-based scheme in which consumers receive a rebate proportional to the reduction in their energy consumption [25].

III.I.C Contrasting Residential Demand Response Programs

Table 1 provides a comparative overview of various Demand Response (DR) programs, outlining their respective advantages and disadvantages. These residential DR programs, as depicted in Table 1, offer consumers the opportunity to achieve cost savings, reduce electricity consumption, and diminish the need for substantial utility infrastructure investments. Customers engaged in DR can alter their electricity usage through several methods, including shifting energy consumption to different time periods, employing on-site standby generators for emergency back up to reduce reliance on the utility grid, and implementing load reduction sought by utility companies during a DR event, the challenge of meeting the expected comfort levels of end users, and the economic feasibility of program participation.

TABLE2 Comparison of Residential Demand Response Programs.

Residential DR program	Response and activation period	Advantage	Disadvantage
Real-time pricing	Electricity prices vary daily at the customer's end.	End user can reduce the electricity cost with respect to the price change in a day or month.	Customers who want to reduce electricity bill should instantaneously respond.
Time of use pricing	Electricity prices vary hourly at the end users.	Tariff prices are high during on-peak and low during off-peak, thereby encouraging customers to shift loads to reduce cost.	Tariff displays one price change with respect to time for all customers, and following the prices is compulsory for end users.
Critical peak pricing	Electricity prices change any time at the customer's end.	End users receive notification for a short period to earn discount.	Customers should curtail or shift home devices for a certain period.
Direct load program	Prices change any time occur at the utility side.	The utility offers special discounts for shifting of appliances.	Utility should curtail or shift certain devices so as to balance power consumption with authorization from the customers.
Curtailable programs	Prices change any time at the customer's end.	Customers respond within a limited period to obtain discount rates.	Customers should curtail or shift home devices for certain periods of time.
Demand bidding	Prices change any time at the customer's end.	The utility offers special discount offers for shifting of appliances.	Customers should curtail or shift home devices for a certain period of time.

III.II.SMART HOME INTELLIGENT HOME ENERGY MANAGEMENT SYSTEM

Smart homes represent the application of smart residential buildings, offering great promise for energy savings while reducing greenhouse gas emissions and energy consumption.

Smart homes not only save electrical energy but also provide many benefits including increased security, high comfort levels, and improved home automation and energy management.

Several smart technologies make integrating a smart home energy management system (HEMS) easier with various functions in the home, including automatic control, connection to utilities via smart meters and reduction of energy consumption.

These smart technologies enable customers to manage home appliances, optimize power consumption, and schedule home appliances during critical peak hours to respond to demand response signals (DR).

III.II.A Implementations of Intelligent Home Energy

Management Systems through Smart Technologies In the realm of intelligent Home Energy Management Systems (HEMS), numerous research endeavors have leveraged smart technologies to craft hardware components and control algorithms for HEMS. In one particular study [26], the power outlet was designed to monitor energy consumption at predetermined intervals; This outlet will cut off power when the monitored power drops below the demand threshold. The power socket is compatible with various domestic loads. Additionally, a hardware-based HEMS was created and amalgamated with a rule-based algorithm and Demand Response (DR) program within a laboratory setting [27]. The rule-based algorithm integrated into the Home Energy Management (HEM) control unit oversees the management of four loads, prioritizing them according to homeowner preferences.

Bidirectional communication is established between the loads and the HEM controller to transmit actual current, voltage and power data from the devices. In addition, the hardware prototype of the smart home energy management system “HEMS”; Developed using machine learning algorithms along with sensor technology and communication capabilities to help homeowners reduce overall electricity costs and manage loads intelligently. Automatic power outlets are used to monitor the energy consumption of household loads for energy management purposes. Furthermore, a hardware architecture has been established for a home energy management system (HEMS) to regulate air conditioning units through smart thermostats [28].This control is made easier through pre-programming the thermostat, which reduces energy consumption during demand response (DR) and improves temperature control. Additionally, the HEMS hardware controller was built in the laboratory of Politehnica University in Bucharest [29]. The HEMS controller algorithm is used to collect energy consumption data, allowing activation or deactivation of various residential appliances and rescheduling of indoor loads operating during typical off-peak hours through household appliances. The user interface software implementation, integrated into HEMS, runs on the Android operating system, allowing the owner to benefit from this functionality. The HEMS controller algorithm is used to collect energy consumption data, allowing activation or deactivation of various residential appliances and rescheduling of indoor loads operating during typical off-peak hours through household appliances. The implementation of user interface software, integrated with HEMS, was executed within an Android OS, granting homeowners convenient access to load characteristics and the ability.

Possibility to remotely control the activation and deactivation of the device. Furthermore, efficient hardware and control algorithms have been developed for HEMS to automatically manage several home appliances, ensuring that the overall energy consumption of home appliances remains within the limits predetermined deadline [30]. HEMS uses intelligent techniques to minimize energy consumption costs through real-time control, stochastic scheduling, and continuous monitoring [31].

With real-time control, HEMS directly manages specific devices. Stochastic planning involves using stochastic dynamic programming to calculate the total cost of energy consumption and identify a set of home appliances for control. Real-time monitoring displays controllable indoor loads in real time and schedules based on their characteristics. However, the implemented smart algorithm is complex, requires significant computational resources, and operates at lower speeds. To solve this problem, customized software solutions for HEMS have been developed to enable device control and consumption monitoring. The software is Linux-compatible, runs on Raspberry PCs, and uses JavaScript, Python, and HTML for programming. It integrates a graphical user interface for HEMS, designed and developed on a PC using a communication protocol. This interface is capable of displaying, processing and collecting real-time energy consumption data while also providing remote control of home appliances. The main goal of this system is to inform end users about their energy consumption habits by providing them with this information. An important aspect of smart technology in home energy management systems (HEMS) is the ability to integrate energy storage and renewable resources into the energy consumption equation. In [32], an embedded system was created to integrate photovoltaic (PV) and energy storage sources into a smart home. This system effectively manages the smart energy needs of a smart home by deploying photovoltaic panels and batteries. The photovoltaic generator, combined with a grid-connected inverter, is the basic component of HEMS, which uses a self-learning feedback mechanism to establish an intelligent energy consumption management system. Synergy between photovoltaics and other smart devices creates greater comfort, economically sound customer strategies, and energy balance.

III.II.B Implementations of Scheduling Controller Techniques in Home Energy Management Systems (HEMS)

HEMS helps reduce overall energy consumption by efficiently programming home appliances while maintaining customer comfort. Typically, household loads are planned to minimize peak energy demand and reduce electricity costs by taking advantage of dynamic hourly electricity rates [33]. Through the use of an optimal scheduling controller, customers participating in a Demand Response (DR) program can effectively reduce their electricity costs by adjusting electricity consumption during peak and shifting peak load operations to off-peak hours.

Optimal scheduling strategies include activating and deactivating programmable home appliances such as washers, water heaters, dryers and electric carts, air conditioners as well as non-programmable home appliances such as lights, televisions ,ovens, printers, computers and microwaves, with the ability to ability to control them at any time [34].Various schedule control methods, such as rule-based systems, artificial intelligence (AI), and other optimization techniques, are used to create optimal equipment schedules based on energy consumption.

III.III.A Rule-Based Scheduling Controller

Rule-based scheduling controllers work by defining behavior through conditional rules. In HEMS, the Rete algorithm is leveraged to manage energy consumption through smart sockets in the network [35]. The load is distributed to these smart stores for data collection and rule-based processing. Similarly, a rule-based approach involving "power on demand" is used to monitor electrical devices, where if/then rules are established based on the priority of the device suffered [36].The rule-based algorithm is designed to shift load to low-cost periods and reduce power consumption. The algorithm is highly flexible, capable of handling different device types and adapting to multiple operators, providing an effective solution to reduce energy costs and manage real-time price fluctuations. Additionally, a rule-based algorithm suitable for HEMS, considering demand response (DR) applications, has been developed to regulate home appliances [37]. However, it is important to note that a rules-based approach to equipment planning has limitations. It may not be suitable for extensions because it cannot be easily adapted or developed using rules. Additionally, managing large volumes of data, especially demand response (DR) strategies, can pose challenges, making real-time control of home appliances a daunting task complicated job.

III.B. HEM Schedule Controller Using AI Techniques

Recently, a variety of AI techniques have been used to develop programmable device controllers for residential consumers in smart homes. These AI-based HEM planning controllers leverage artificial neural networks (ANN), fuzzy logic control (FLC), and adaptive neuro-fuzzy inference systems (ANFIS). AI controllers involve programming software that simulates human decision making [38]. ANN, an information processing algorithm that models non-linear systems and reflects the activity of the human brain, has been used as an intelligent controller to manage household appliances. ANN-based solutions can be used instead of simulation tools to create quick solutions to control and predict problems. An advanced thermal control method based on ANN in civil buildings has also been developed to create a highly applicable thermal environment. The results show that the ANN control method can improve thermal comfort in residential buildings. In a study [39], ANN was used together with a genetic algorithm to weekly schedule appliances with optimized energy consumption in residential areas to reduce energy demand during peak times and maximize energy consumption usage of renewable sources. Moreover, another study [40] employed a Particle Swarm Optimization (PSO)-based ANN to enhance its performance by selecting the optimal number of neurons in each hidden layer and learning rates. In their work, the authors introduced a novel hybrid approach, combining the Lightning Search Algorithm (LSA) with Artificial Neural Networks (ANN) to predict the optimal on/off status of home appliances [41]. This hybridization of LSA with ANN aimed to enhance ANN's performance by determining the optimal values of neurons in each hidden layer and learning rate, thereby improving ANN's accuracy. In another study [42], a distributed algorithm-based ANN was employed to reduce the overall energy costs and operation delays in managing energy demand by making accurate energy management decisions. ANN technique is proven to be effective in managing energy consumption by controlling household electricity consumption. Fuzzy logic control (FLC) has found application in HEMS to manage home appliances with the aim of minimizing energy consumption and electricity costs. FLC is structured around four main stages: fuzzification, defuzzification, rule base, and inference engine. It is known for its simplicity of implementation, its suitability for linear and nonlinear systems based on language rules, and its independence from the need for mathematical models. FLC is used in the daily scheduling of air conditioning units, optimizing temperature schedules based on outdoor temperature forecasts and electricity prices.

DR is integrated into the smart home through the use of smart HEMS. Simulation results demonstrated the effectiveness of FLC in reducing energy consumption and planning the operation of air conditioning units effectively. Furthermore, FLC-based device scheduling for smart homes has been implemented in a previous study [43]. In this study, fuzzy techniques are used to model user comfort and predict prices, aiming to improve comfort levels while minimizing energy consumption in residential environments. Additionally, a high-resolution power consumption model for various houses using a fuzzy logic inference system is also presented [44]. In this study, a photovoltaic (PV) plant is integrated with HEMS to minimize the energy costs associated with the electricity consumption pattern of household appliances. The input parameters of the fuzzy logic system include device type and active occupancy, while the output represents the probability that each device will start up in the next minute. It is important to note that the development FLC has limitations as it only controls a select range of home appliances and does not take into account appliances that use a lot of electricity. Nonetheless, it contributed to the implementation of a real-time scheduling controller for residential appliances based on fuzzy logic within HEMS [45]. In this study, a system that included four home appliances equipped with batteries and photovoltaic panels was examined. The results demonstrated that the fuzzy logic controller (FLC) effectively reduced load demand by intelligently scheduling the operating times of home appliances, taking into consideration the energy supply from photovoltaic systems and batteries. Additionally, another research effort in [46] introduced an FLC for HEMS aimed at reducing energy consumption. However, this particular controller did not incorporate factors related to user comfort levels or demand response (DR) signals. Furthermore, three distinct control techniques were applied to schedule home appliances in [47], including FLC, continuous relaxation, and mixed-integer linear programming. Three types of Fuzzy Logic Controllers (FLC) were employed in this study: task-related FLC, heat-related FLC, and an FLC designed for battery control. The system that was developed utilizes these FLCs for the purpose of managing and supervising energy storage devices, heating, and power consumption. Another AI controller utilized in HEMS is the Adaptive Neural Fuzzy Inference System (ANFIS), an intelligent controller designed for scheduling and managing household loads to reduce power consumption. The ANFIS structure consists of multiple layers and doesn't require a mathematical model. An ANFIS-based controller was implemented. This controller integrates an intelligent lookup table and fuzzy subsystem, with input from output feedback, external sensors, and fuzzy subsystem. The proposed controller determines the optimal energy schedule based on dynamic pricing but does not focus on minimizing energy consumption. However, it ignores other factors such as user preferences and demand response (DR) strategies. Another intelligent inference algorithm based on ANFIS for HEMS is presented in [48]. This algorithm improves inference between devices, transmitting recycling schedules to ANFIS. The results indicate that the proposed ANFIS is better than the classic ANFIS.

Table 4 provides a comparison of ANN, FLC and ANFIS controllers for HEMS.

ANN Controller	FLC Controller	ANFIS Controller
1. Mathematical model is not required	1. Mathematical model is not required	1. Mathematical model is not required
2. Complex design and implementation	2. Easy design and implementation	2. Moderately complex design and implementation
3. Normal structure	3. Simple structure	3. Complex structure
4. Can achieve good performance if appropriate activation function, training data, and number of nodes are selected	4. Can achieve good performance if proper parameters in the rule-based algorithm and type of membership functions are selected	4. Can achieve good performance if suitable training data and type of membership function are selected
5. Requires learning process when designing the controller	5. Requires no learning process when designing the controller	5. Requires learning process when designing the controller

The document highlights various limitations in using FLC and ANFIS in planning controllers. For example, FLC relies on appropriate variables in rule-based algorithms and membership functions, which are often determined by trial and error, which can be time-consuming. On the other hand, the challenge of the ANFIS controller involves the need for a significant amount of data as well as a lengthy training and learning process. Therefore, the ANN technique offers several advantages, including accurate predictions, strong real-time performance, the ability to effectively learn complex nonlinear functions during training, and generate insights. Valuable insight throughout the training process.

IV. State of Art Analysis

It's evident that recent advancements in smart home energy management systems (HEMS) have leveraged various Artificial Intelligence (AI) techniques]). The integration of AI-based controllers such as Artificial Neural Networks (ANN), Fuzzy Logic Control (FLC), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) into HEMS planning has been prominent. These controllers exhibit both strengths and limitations: while FLC offers simplicity and easy implementation, ANFIS requires extensive data and training. In contrast, ANN demonstrates exceptional predictive accuracy, real-time performance, and the ability to learn complex functions efficiently.

Moreover, the research signifies the ongoing shift towards self-learning AI approaches in HEMS, aiming to reduce user involvement in system settings while optimizing energy efficiency. It emphasizes the importance of AI-driven solutions in tackling the challenges of energy optimization, particularly in the context of smart homes.

In summary, recent studies showcase a pivotal role for AI-based controllers in advancing smart home energy management, offering promising prospects for more efficient and autonomous systems in the future.

V. Conculusion

The beginning of this study highlights the importance of energy optimization in smart homes. It then provides an overview of earlier studies on HEMS (Home Energy Management Systems). The field of smart home energy management has seen the application of several AI techniques. In-depth talks cover DR (Demand Response) tactics and strategies, including tariff initiatives. In order to build hardware and schedule control algorithms for intelligent HEMS, it also examines smart technologies. The study also discusses the development of HEMS scheduling controllers through the application of artificial intelligence techniques such as rule-based systems, ANN (Artificial Neural Networks), FLC (Fuzzy Logic Control), and ANFIS (Adaptive Neuro-Fuzzy Inference Systems). HEMS seems to be headed toward a future where user engagement in system settings is minimized by the integration of self-learning AI approaches.

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