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Classification of Energy use Pattern and Multi Objective Optimal Scheduling of Flexible Loads in Household

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ABSTRACT: The scheduling of flexible loads and multi-objective optimal load scheduling are an important optimization problem in the power system, which can bring significant economic benefits for all the market participants and environmental benefits for the society. By thoroughly considering flexible loads, the Convolutional Neural Network Algorithm (CNN) was applied to solve the proposed multi-objective optimization algorithm using MATLAB software. The effectiveness of the model and the proposed method is verified by a simulation. The simulation results show that the proposed algorithm can reduce the electricity cost while satisfying the residential electricity comfort. Flexible loads need optimal scheduling to establish a balance between energy supply and demand. The effect of optimal scheduling largely depends on the regulation characteristics of various flexible loads. One category of energy-consuming equipment may have multiple operational patterns in different types of households, and the energy use patterns of different households may also vary greatly with household income, job characteristics, resident age, and other demographic and social aspects. Therefore, there are significant differences between different households in the regulation characteristics of results. The core motivation behind this approach is to enable users—regardless of age—to shift their energy usage in a way that aligns with their daily routines and preferences, ultimately making energy consumption more convenient and efficient.

KEYWORDS: Flexible loads, Optimal Scheduling, Convolutional Neural Network (CNN), Feasibility and Effectiveness

I. INTRODUCTION

Over the past few decades, global energy consumption has increased significantly, leading to a range of critical issues such as energy shortages and environmental degradation. In response, the integration of renewable energy sources (RESs) into smart grid infrastructures has emerged as a promising solution to mitigate pollution and combat global warming. RESs offer numerous advantages, including reduced environmental impact, substantial potential for scalability, and comparatively low operational and maintenance costs. The growing depletion of conventional energy resources, coupled with the rising demand for electricity, has accelerated the adoption of RESs in modern power systems. However, the inherent variability of RESs, due to their direct dependence on climatic and weather conditions, introduces significant operational uncertainties. To address these challenges, microgrids incorporating both RESs and energy storage systems (ESSs) have been proposed as effective strategies for storing surplus energy and enhancing grid stability. Since RESs are typically non-dispatchable and exhibit limited load-following capabilities—particularly in residential energy applications—the implementation of Home Energy Management Systems (HEMS) plays a crucial role in optimizing energy usage. HEMS serve as a critical interface between consumers and demand response (DR) programs, enabling users to manage their energy consumption in real-time while accounting for dynamic electricity pricing, household device demands, renewable generation forecasts, battery storage limitations, and grid constraints. The primary objective of the energy scheduling problem addressed by HEMS is to minimize overall energy costs amidst uncertainties in supply, demand, and pricing, all while maintaining user comfort. Moreover, beyond environmental concerns, power distribution system operators are increasingly prioritizing cost-efficiency and operational performance, underscoring the importance of intelligent energy management solutions.

Recently, the issue of reducing energy consumption has been increasingly respected by researchers, mainly due to the economic benefits and long-term environmental sustainability. Most of the proposed solutions to address this important





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issue include some viewpoints. Accurate and up-to-date information on energy consumption is one of the most important requirements for implementing all energy-saving solutions. Therefore, the determination of energy consumption is a fundamental feature of energy efficiency management. Increasing attention and clarity to identify smarter and more efficient methods for the use of electrical energy is one of the main focuses of research on electrical engineering at present. Energy models for specific devices are an alternative to energy monitoring because these models provide the ability to measure and estimate the total energy consumption. Following a report from the electricity consumption in the USA, at least 30% of electricity in residential consumptions is wasted. Based on the aforementioned reasons, users have a significant role in developing the power grid efficiency. Therefore, selecting and designing an optimal scheduling scheme to control appliances is necessary for managing their energy consumption. However, optimal providing of the scheduling scheme for household appliances is a challenging subject. This addresses several focused research works for the home energy management system (HEMS) to assist the users in solving this issue. Several works have been done about scheduling some particular devices, like air conditioning, chillers, water heater. Han et al.(2020) presented a technique for providing smart home device standard practices to manage load demand in a smart energy based environment. They used ZigBee devices for generating the IoT based management system. The capability of the method is proved by applying it to a real tested. Zhang et al. (2016) developed a hybrid system based on machine learning, optimization, and data structure design, for designing HEMS and demand response (DR) to meet the real-life requirements. A method based on learning the demand response was proposed for variable loads with special attention to home heating, ventilation, and air conditioning (HVAC). Simulation results were applied based on the MATLAB platform. Shakeri et al. (2017) presented a control algorithm for use in managing and battery storage of thermal appliances. The proposed system guaranteed the energy Consumption of the household appliances at a level less than a particular value. The photovoltaic system and battery system were also used for decreasing the pollution and costs of the house. Simulation results showed that the presented system decreases the power consumption price up to 20% a day.Shakeri et al. (2018) designed another HEMS structure to control and schedule the electrical appliances. The system was applied to hardware and was tested on a testbed house. In the worst-case test, the primary implementation reduced up to fifteen percent of the electricity cost. Paper is organized as follows. Section II describes related work. Proposed systems and Design Methodology are presented in Section III. and IV. Section V presents experimental results showing results of load scheduling. Finally, Section VI presents the conclusion and future direction of work.

II. RELATED WORK

The methods that seek to integrate smart home into DR programs on the purpose of peak demand reduction and system load curve modification become even more important. Therefore, in recent years, these programs have played an important role in energy management programs and numerous researches have been carried out on HEMS considering DR programs. Zeng et al. (2018) innovatively proposes a low- carbon real-time electricity price (LCEP) mechanism, which effectively reflects the external characteristics of renewable energy, and an energy management optimization strategy based on mixed linear integer programming is proposed to intelligently control all flexible resources in the family. Making full use of the flexibility of demand side resources to integrate with the grid brings economic benefits on the user side owing to the overall lower power price. The results substantiate that the LCEP mechanism not only provides a good signal to alleviate RESs restrictions but also maximizes the profits of demand side with RESs grid integration.

I. A type of residential complexes (RCs) integrates with distributed energy resources generation system and electric vehicles (EVs) is proposed by Barhagh et al. (2020). Operators of RC energy systems equipped with local generator sets can benefit from a DR program to reduce operating costs. The problem of optimal operation of a grid-connected EV energy system is examined in the presence of real-time pricing of a DR program. In this reference, a mixed- integer linear programming (MILP) model for optimal operation of energy systems integrated into RCs is presented. The simulation results indicate that the total expected cost of RCs is reduced by 37.31%.Wang et al. (2021), a heuristic method has been exploited for load demand management based on the generated power and the appraised market-clearing price. The model takes the utilization of renewable energy resources and the fluctuation of the power grid into consideration and the results demonstrate that demand response has highly cut the expenditure of electricity bill and maintain the balance of the power grid. The power system load serving entities pay special attention to voltage stability improvement and valley fillings and peak shavings of load demand profile.Gupta and Verma (2021) is proposed for residential consumers using Battery Energy Storage Systems (BESSs) as a key component for demand side management. The results show that centralized control of power dispatch from energy storage devices minimizes the





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use of node voltages and makes a great contribution to load curtailment optimization and social welfare maximization. A simulation model that reflects the flexibility requirements of power system and the assignment of Time-of-use (TOU) pricing to maximize the profits of power suppliers and the stability of the grid is described in Ref. Kumamoto et al. (2020). The results indicate that it is profitable to adopt TOU pricing for energy costs reduction by obtaining flexibility from users. Teki et al. (2021), a solar photovoltaic system with battery storage is modeled, which is beneficial for peak load shaving and grid stability utilizing particular control and energy management. This energy management contributes to integrate solar photovoltaic power into the grid network and reduces peak loads about 47.14% and the peak efficiency of the system scales between 90% and 94%...A two-stage stochastic programming has been presented in Ref. Zeynali et al. (2020) targeting on reducing the electricity procurement cost. Normal residential households. In this study, a proper analytical battery degradation cost model according to cost function is proposed and future battery storage cost reductions on the HEMS is investigated which results in total economic benefits.

II.

Khemakhem et al. (2019), presents a double layer supervision strategy is proposed to flatten power load profile in a residential scenario with the method of implementing a demand response algorithm and Plug-in Electric Vehicle power management, which contributes to flatten the fluctuations in demand and achieve the near optimal power. An interactive building power demand management strategy based on genetic algorithm is adopted to facilitate the optimization of the grid by Xue et al. (2014). In this paper, building thermal masses are also integrated into the model of the building, which contributes to a significant relief of grid power fluctuations. An article Ref. Elma and Selamogullari (2015) mainly focused on reducing peak demand and residential appliances shifting is developed by innovating the method of voltage control which is integrated into a new HEM algorithm to increase the energy efficiency. A hybrid algorithm, Genetic Binary Particle Swarm Optimization (GBPSO), is innovatively proposed by Javaid et al. (2017), the results show that GBPSO based HEM controller has a good performance on cost reduction and Peak-to-Average Ratio curtailment. Shakeri et al. (2018) a novel control algorithm for the HEMS considering battery storage system is demonstrated to apply in any conventional houses, which achieves up to 15% of electricity cost reduction and maximization of comfort index. Shirazi and Jadid (2015) represents a technique which can conduct optimal scheduling of residential energy consumption automatically resulting from home automation system shortage and lack of response to time- varying pricing of users. The results demonstrate that the model proposed and an appropriate scheduling load consumption can reduce energy costs and ensure residents' comfort as much as possible.A heuristic Forward-Backward Algorithm (F-BA) in minimization of energy costs of thermal appliances considering comfort index is proposed by Golmohamadi et al. (2019). This paper also presents a Peak Flatten Scheme in response to peak demands that emerged in the power system and optimizes the power distribution on the bus by shifting the power load from the weak lines to alleviate congestion, which contributes to economic benefits and the stress of the power grid relief.

III. PROPOSED SYSTEM

CNNs have been used to solve many problems in computer science with a high level of success, and have been applied in many fields in recent years. However, most of the designs of these models are still tuned manually; obtaining the highest performing CNN model is therefore very time-consuming, and is sometimes not achievable. Recently, researchers have started using optimization algorithms for the automatic adjustment of the hyper-parameters of CNNs. In particular, single- objective optimization algorithms have been used to achieve the highest network accuracy for the design of a CNN. When these studies are examined, it can be seen that the most significant problem in the optimization of the parameters of a CNN is that a great deal of time is required for tuning. Hence, optimization algorithms with high convergence rates are needed for the parameter optimization of deep networks. In this study, we first develop an algorithm called MOO-CNN, based on the multi- objective Optimization (MOOA) algorithm for parameter optimization of CNN or CNN-based methods. MOO-CNN is then compared with four different multi- objective optimization algorithms. This comparison is carried out using 16 benchmark functions and four different metrics, with 100 independent runs. It is observed that the algorithm is robust and competitive compared to alternative approaches, in terms of its accuracy and convergence. Secondly, the MOO-CNN algorithm is used in the parameter optimization of a CNN-based method, developed previously by the authors, for the segmentation and classification of medical images. In this method, there are three parameters that influence the test time and accuracy: the general stride (GS), neighbour distance (ND), and patch accuracy (PA). These parameters need to be optimized to give the highest possible accuracy and lowest possible test time. With the MOO-CNN algorithm, the most Appropriate GS, ND, and PA values are





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obtained for the test time and accuracy. As a result, it is observed that the MOO-CNN algorithm is successful, both in comparison with multi-objective algorithms and in the parameter optimization of a CNN-based method.

CNN architectures were first used in image classification problems, and various CNN-based architectures were subsequently developed for segmentation and detection problems. From examining this architecture, it can be seen that these models have extra parameters in addition to the basic CNN parameters, although these can be optimized in the same way. With this in mind, we aim to achieve parameter optimization for CNN-based methods. Our model has three parameters that significantly affect the test time and accuracy: the general stride (GS), which represents the stride value for the sub-images; the patch accuracy (PA), which represents the probability of sub-image classification; and the neighbour distance (ND), which refers to the neighbour distance for sub-images classified with low probability. When the parameter values are determined manually in this method, the best solution may not be obtained, and the optimal values of these parameters can only be finding by using an optimization algorithm. Detailed information on these parameters is given in Section 4. This problem is addressed in the first half of this study. Multi-objective optimization algorithms are used for parameter optimization due to the computational complexity and accuracy of performance of CNN structures. The most significant difficulty that arises in the design of CNNs or CNN-based architectures with these algorithms is the convergence time, and new algorithms with rapid convergence therefore need to be developed in order to Obtain the optimal solution. This problem is addressed in the second half of this study. As a solved problem, this study seeks solutions to two problems: the first is the development of a new multi-objective algorithm for the optimization of CNN parameters, while the second involves obtaining the optimal values in terms of the accuracy and test time for the three different parameters of a CNN-based method.



Figure 4.1 The flowchart of the proposed CNN-based MOO algorithm.





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IV. DESIGN METHODOLOGY

As per the proposed approach, the first step is to fetch the input datasets termed as "loads" which are stored in data.xlsx file in Microsoft Excel. These datasets are fluid in nature and can be edited at any point in time in the course of action. The data incorporates different types of electrical loads, which include both flexible and non-flexible categories. Some loads are flexible, like fans, lamps, and motors, while others, like air conditioners and water heaters, are classified as non-flexible because they have a fixed schedule due to their necessary nature. The data obtained undergoes preprocessing where preliminary filters are applied to remove noise or irrelevant background information. In this process, classifying data is done by organizing devices into groups using some initialization variables, and data validation is done using evolutionary techniques including selection, mutation, and crossover processes until the termination condition is met.

The preprocessing step is followed by feature extraction, which includes the extraction of the refractive index, major axis, and minor axis of an object. While features such as absorption coefficient and electrical conductivity were considered, they needed more training data, and so were ultimately dropped due to the high value similarity across object types, making classification difficult. The model is trained in MATLAB and executable script ver_1_1 compiles the values from feature extraction into a model file. For testing, a different script ver_1_2 is run where the model with Multi-Objective Optimal Scheduling algorithm is loaded and validated. This testing phase provides results in both visual and coded outputs such as energy density, frequency response graphs, and probability density function (PDF) graphs. In general, the dataset is processed meticulously in order to improve its quality and trustworthiness by tuning the primary features which enable accurate classification and removing secondary features that increase confusion.



The daily electricity bill in the majority of earlier research on home energy management system optimization is set to a single objective optimization for consumers looking to optimize financial gains. In the future, humanized home energy management systems should also consider user demands in all areas. The HEMS selects various opening timeslots within the equipment's permitted operation duration after first taking the satisfaction index into account. Furthermore,

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the power purchase profile's peak and valley balance are taken into account; in light of grid stability and power consumption safety, the power purchase profile's fluctuation should be kept to a minimum. The proposed HEM model is validated in this section with one case study and two different scenarios for this case. This case analyzes two mathematical models of optimization objectives, and a multi-objective optimization model that meets multiple needs. The main aim of this case study is to analyze the peak load management and cost management for each scenario separately. The battery energy storage system is integrated in this case to obtain best multi-objective optimization results. With the peak-valley balance index as the sole optimization goal, scenario 1 depicts the balance between the power consumption and purchase profiles. Scenario 2 takes into account a multi-objective optimization model based on the peak-valley balance index, the satisfaction index, and the operational expenses. By moving FLs and TCLs from periods of high load demand to periods of low load demand, Scenario 1 attempts to reduce both the power consumption profile and the power purchase profile. As a result, this scenario's operating expenses may rise. Compared to Scenario 1, Scenario 2 is a compromised strategy that addresses three optimization goals. When scheduling the opening periods of all residential appliances in the first step, coefficients are assigned. The optimal load scheduling of all residential appliances with single optimization objective in Scenario 1. The opening time periods of optimization with battery integrated in the second step are on the basis of optimal load scheduling in the first step. The daily power consumption profile and the usage of photovoltaic power with peak-valley balance objective in Scenario 1 are depicted in Fig 5.1. It is clear that the multiple peaks of the power purchase profile have been reduced in the early morning. In Scenario 1, the battery has only two charge and discharge cycles, therefore, the power purchase profile in the evening is flatter, and there are no charge and discharge cycles in the early morning when the electric vehicle is being charged at a rated power. It is clear that the stationary of power purchase profile has been improved in the early morning in Scenario 1. Scenario 1 in case study with single optimization objective according to peak-valley balance index deals with the optimization problem of the fluctuation of the grid, this approach may not meet the optimal aggregated objective function values.







Figure 5..2 Lamp load





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Figure 5.3 Motor load



Figure 5.4 Other loads



Figure 5.5 Frequency response of lamp load



Figure 5.6 Frequency response of motor load





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Figure 5.7 Frequency response of other load







Figure 5.9 Energy vs rate





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V. CONCLUSION

As an important part of the smart grid, home energy management system (HEMS) is closely related to power usage, in which consumers are not only the users of the power grid, but also the suppliers of distributed power. In this paper, an intelligent HEMS with three adjustable strategies is proposed to maximize economic benefits and consumers' comfort. Besides, a novel objective function mainly focusing on satisfying users' needs is developed by innovating a triobjective model concerning different weight coefficients which is integrated into a new algorithm to reach a balance among the running costs, peak-valley balance index and the satisfaction index. Moreover, this project innovates historical weather data to predict the outcome of photovoltaic power. The benefits of HEMS with photovoltaic and battery energy storage system which is beneficial for peak load shaving and grid stability utilizing three different strategies are analyzed by two different scenarios. The simulation results demonstrate that the proposed model has highly cut the expenditure of electricity bill by 39.81% and maintain the balance of the power grid by reducing peak load by 50.37%, meanwhile, the index of users' comfort improves about 1.6 times. This study classified households according to the different energy use patterns of typical flexible load equipment. Based on this classification, a multi-objective optimal load scheduling model was built and implemented. By this, consumer can receive more favorable electricity rates in return for load flexibility and minimizing consumption during peak demand.

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