International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 8, No. 2, 2021, pp. 26-30.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

A Smart Grid-oriented Energy Optimization System Using Renewable Energy Sources and Machine Learning

Manoj Bhattacharya [a], Anita Deshmukh [b]

[a] *Edge Computing Lab, Calcutta Digital Research Institute, India*.
[b] *Edge Computing Lab, Calcutta Digital Research Institute, India*.

Abstract

This study establishes a framework for implementing active demand-side control in houses inside smart grids that incorporate distributed Renewable Energy Sources (RES) production and energy storage systems. This methodology results in a decision-making mechanism that regulates the battery to minimize consumer energy expenses. It delays the development of the electrical grid when the peak loading period corresponds with the elevated daily electricity rate. The decision-making platform is a certified Neural Network (NN) trained with optimum data applicable in households fulfilling particular parameters, including location, power tariff, and consumption profiles aligned with standards certified by the nearby electricity company. Three consumption characteristics and energy production profiles were constructed and integrated to verify this process. The findings indicate that the Artificial NN (ANN) based decision-making mechanism manages the battery effectively to minimize the cost of electricity.

Keywords: Smart Grid, Optimisation, Renewable Energy, Machine Learning.

Received: 12 March 2021/Revised: 15 April 2021/Accepted: 7 May 2021/Published: 30 June 2021

Introduction

Due to population expansion and growth, energy demand is projected to increase by 4% by 2022. Conventional Power Grids (PGs) (Chen et al., 2017) fueled by fossil resources generate 63.6% of global electricity. These power generators emit a significant quantity of carbon, with the power generation sector and transportation contributing around 42% and 25% of carbon emissions. The Energy Information Administration (EIA) projects that the average energy bill for U.S. homes rise by 2.5% next year. The significant rise in demand and expenses will necessitate power generation from other sources, such as solar, heat, and wind energy. To address the exponential rise in energy consumption, mitigate carbon emissions, and lower costs, scientists have proposed novel power generation methods utilizing Renewable Energy Sources (RES). It is imperative to transform conventional power systems into smart grids to optimize the utilization of these RES. Smart Grid (SG) (IqtiyaniIlham et al., 2017) can satisfy increasing demands and integrate new RES concurrently. SG integrates contemporary communication systems with the current grid to optimize the utilization of the energy resources available on-site.

Implementing SG enables the establishment of Active Demand Side Management (ADSM) (Mohammad & Mishra, 2018) platforms in residential settings. ADSM integrates computerized controls with demand-side administration, which promotes consumer rationalization of energy usage, resulting in alterations to the consumer load curves without sacrificing comfort or disregarding their choices. The ADSM action is predicated on energetic criteria, such as energy pricing, the optimization of dispersed generation use, or power limitation. The execution of ADSM actions can yield advantages, including decreasing household power expenses, alleviating grid load during peak periods, optimizing self-consumption in residences with distributed power generation, and efficient energy utilization.

This study establishes an approach for the ADSM of families within SG to decrease the price of electricity for consumers and defer the necessity for spending on electrical grid growth when peak demand coincides with the highest power rates of the day using Machine Learning (ML) (Cui et al., 2020).

Background

Various strategies have been implemented for enhanced energy administration and load scheduling. Technological advances have resulted in a daily increase in power consumption. The literature has proposed numerous strategies for improved energy administration and load planning. Facilitating the user's ability to plan and transfer their consumption from peak hours to off-peak hours with Energy Management Controls (EMC) (Belila et al., 2018). The SG innovation enables users to decrease electricity expenses by incorporating RESs. The researchers examined a model constructed using Artificial Neural Networks (ANN) (Wu & Feng, 2018) to integrate RES to reduce costs and limit carbon emissions. The consumer's energy expenses are diminished by 30%. They overlooked incorporating base station and user convenience in their efforts. The researchers proposed both Genetic Algorithm (GA) and evaluated the outcomes. The findings indicated a decrease of 28% in bill cost and a 35.1% reduction in Peak Absorption Ratio (PAR), correspondingly. They have overlooked incorporating renewable energy sources into their research. The researchers proposed integrating Harris' Hawk optimization methods with Integer Linear Programming (ILP) to address the randomization issue and manage user appliances. The primary aims of the researchers were to examine costs and the trade-off techniques between user convenience and financial advantages.

Authors have developed a sophisticated methodology for managing demand sides incorporating forecasting and a net-metering framework. Their goals were to decrease costs, PAR, and carbon emissions. Researchers have devised a load planning and energy administration model for Electric Vehicles (EVs) (Wu et al., 2015) integrated with the outside grid and chargers. In remote regions, where the expansion of electricity grids is prohibitively expensive and impractical, the small grid concept proves efficient and dependable. The authors have focused on the administration of storage and real-time load planning for RES-incorporated EVs. Their primary objectives were to reduce energy acquisition from the outside grid and charging stations, including parking locations, charging stations in public places, and home charging stations.

Their aims included minimizing delays, managing loads, reducing prices of on board photovoltaic systems, enhancing photovoltaic efficiency, decreasing battery degradation costs, and lowering annual carbon emissions. Researchers have developed a paradigm for the Internet of Things (IoT)-enabled smart homes for managing energy and load planning. Their primary goals were to mitigate peak generation and save costs while maintaining user comfort constraints. A new home Energy Management System (EMS) (Said et al., 2020) is proposed using ANN and an evolutionary method. They formulate a system for managing energy incorporating day-ahead demand responses and power consumption predictions in SG. Researchers have proposed a smart charging and discharging plan utilizing Linear Programming (LP) for EVs. User comfort, carbon emissions, and RES integration into the grid were

overlooked. Researchers have proposed a nano-grid idea to address high demand and mitigate blackouts. This model functions for home applications that disconnect low-priority connections. Their goal was to reduce system blackouts based on neighbouring levels. Comfort for users is excluded from the system's design.

Proposed Smart Grid-oriented Energy Optimization System

The suggested approach employs the price of power as an energetic criterion, primarily aiming to decrease electricity costs for consumers and secondarily to alleviate distribution system stress, which arises only when electricity rates are higher during periods of increased grid strain. The employed tools include solar photovoltaic production and energy storage, with the oversight of battery charge and discharge accountable for household ADSM. Fig. 1 illustrates the examined electrical framework, highlighting the presence of the battery converter controller. This approach encompasses the sale of power to the grid and employs optimization and ML as its strategy. This converter management includes the system for executing the ADSM, referred to as the Manager's Decision-Making System (MDMS) of the storage conversion, which can be set up according to the recommended strategy.

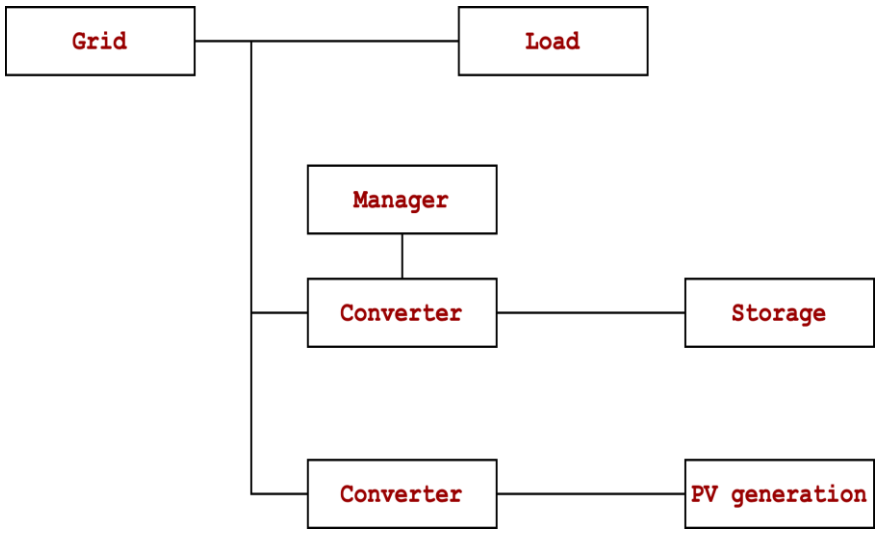


Fig. 1: System Architecture

Fig. 2 illustrates the schematic representation of the MDMS inputs and outcomes, where Psolar denotes the solar generation energy at instant k, Pcons represents the power of the client's load curve at time k, Tenergy indicates the price of electricity at right away k, and storage refers to the power from the batteries (either charge or release) at time k. The incoming data requires normalization, whereas the output necessitates denormalization. The normalization method facilitates the utilization of the MDMS by families exhibiting analogous features, situated in proximate regions, and possessing the same electricity tariffs.

This study presents the MDMS as a Multi-Layered Perceptron (MLP) Nonlinear Auto-regressive with External inputs (NARX) and ANN. ANNs learn from historical information and generalization outcomes within the range of values utilized during the training stage. The ANN was selected due to the time-dependent nature of the issue, which is the primary justification for its utilization in this study. The culmination of the MDMS setup is a constructed and verified NN, achieved via supervised instruction, wherein the outputs for certain input sets of information must be predetermined. Optimization determines how to transfer energy to and from the battery (Pstorage) to minimize the power cost.

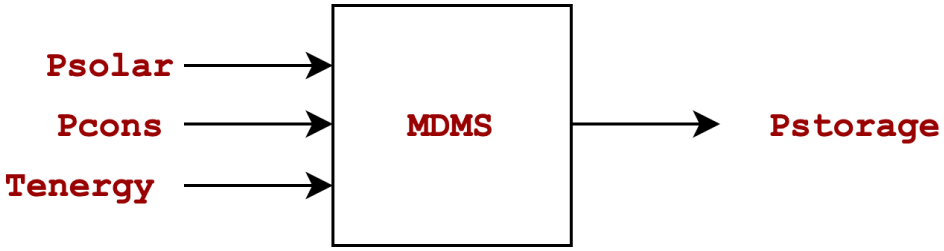


Fig. 2: MDMS Diagram

Optimization Procedure

The optimizing procedure was executed in Matlab. It employs the Dynamic differentiation optimization technique to minimize a function that assesses the consumer's electricity costs. The optimization technique employs the subsequent input data:

- Pre-determined daytime power tariff (Tenergy).
- A collection of photovoltaic production profiles throughout the day (Psolar). To enhance generalization from ANN instruction, it is essential to incorporate generation characteristics for both overcast and clear sky days.
- Daily power demand graph (Peons). Load ratios for various consumer profiles enhance the ANN's generalization ability.
- Optimum energy storage of the battery (Estorage) and its efficiency (Ustorage) The size of the battery is a crucial parameter for the optimal approach, as well as its storage effectiveness. Another factor influences the battery's duration; an extended storage time correlates with increased losses.
- Peak converter energy (Pconv) along with efficiency (Nconv). This equipment is responsible for charging and discharging the battery via AC-DC conversion. The converter's power influences the rate at which the battery can be charged or drained. The (dis)charging rate must never surpass the battery capacity. The converter's efficiency influences the frequency of charge and discharge cycles throughout the day; a more significant number of cycles results in increased energy losses. Decreased charge and discharge cycles enhance the battery's lifespan.

Training Procedure of ANNs

The NN method of training employs a supervised learning approach. This technique entails delivering the requisite outputs for each input signal sampling. Every training sample consists of the inputs and associated outcomes, representing the actions the neural network requires to learn. A neural network is deemed trained when the discrepancy between the expected output and what is generated by the system is tolerable. Post-training, an NN must generate legitimate outputs from the input information that differs from that utilized during the training phase, provided the data falls within the numerical range employed in the training phase.

Results

Three consuming profile arrangements, with the solar energy production profiles not utilized in the ANN training process, were presented to the MDMS. Fig. 3 illustrates the daily load and discharge characteristics of the batteries (storage), solar power production (Psolar), family usage (Pons), electricity tariffs, plus usage of energy from the power company (Pgrid). It is essential to highlight that the solar energy data utilized was derived from actual measurements, including measurement ambiguities and inaccuracies. This fact demonstrates the efficacy and resilience of the suggested approach.

The MDMS manages the battery's capacity and discharge based on the time-of-use electricity tariff, aiming to minimize costs for the consumer. In light of residential usage and solar generation, this administration significantly modifies the load curve observed from the utility (Pgrid), as depicted in the figures. The decline in demand during peak periods is evident in all instances, and similar to taxes, the least costly period aligns with the time of maximum strain on the SG (peak), contributing to the alleviation of grid overload for the company. Significant shifts in the load profile observed by utilities occur during periods of solar output, as solar energy, following the charging of the batteries and, if required, to support the battery, contributes power to the network.

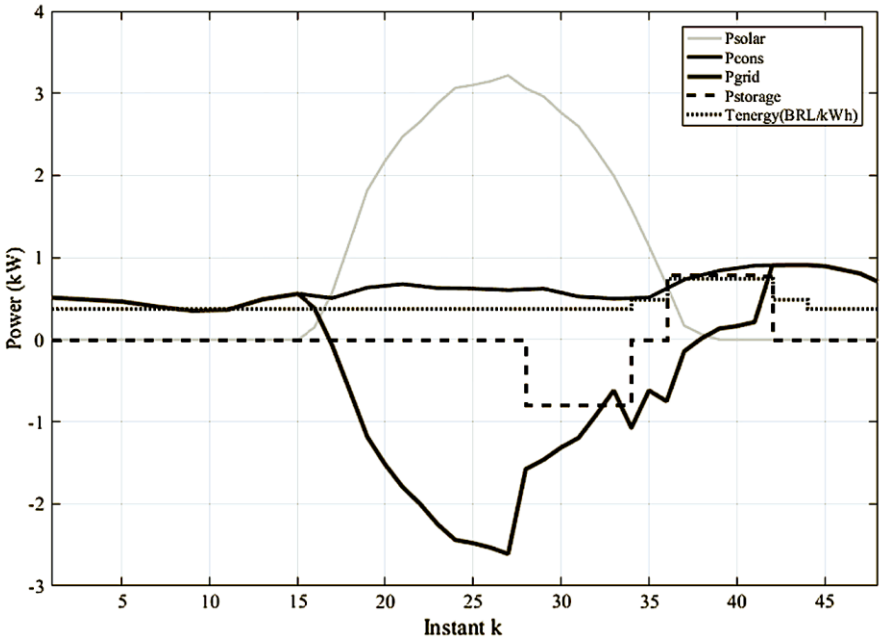


Fig. 3: Power Curve Analysis

Conclusion

The study suggested an active supply-side management approach utilizing optimization and ML to manage energy storage in residential consumers, which is equipped with distributed energy production to reduce electricity costs for the customer. This approach was assessed for residential consumers utilizing rates. However, it possesses the potential for application to families with alternative tariff structures, such as hourly rates or even other client categories. The MDMS setup illustrated how to optimize ANN training procedures for a particular case study. The findings for the battery charging and discharging curves resembled the optimum ones. The preconfigured MDMS had three distinct solar generation characteristics corresponding to a varied consumer description. The results indicate that MDMS can effectively control battery operations to minimize consumer power bills, and it is evident that increased solar energy supply correlates with reduced energy expenses for users.

References

Chen, Z., Wu, J., Xia, Y., & Zhang, X. (2017). Robustness of interdependent power grids and communication networks: A complex network perspective. *IEEE Transactions on Circuits and Systems II: Express Briefs*, *65*(1), 115-119.

IqtiyaniIlham, N., Hasanuzzaman, M., & Hosenuzzaman, M. (2017). European smart grid prospects, policies, and challenges. *Renewable and Sustainable Energy Reviews*, *67*, 776-790.

Mohammad, N., & Mishra, Y. (2018). Demand-side management and demand response for smart grid. In *Smart grids and their communication systems*, 197-231. Singapore: Springer Singapore.

Cui, L., Qu, Y., Gao, L., Xie, G., & Yu, S. (2020). Detecting false data attacks using machine learning techniques in smart grid: A survey. *Journal of Network and Computer Applications*, *170*, 102808. https://doi.org/10.1016/j.jnca.2020.102808

Belila, A., Benbouzid, M., Berkouk, E. M., & Amirat, Y. (2018). On energy management control of a PV-Diesel-ESS based microgrid in a stand-alone context. *Energies*, *11*(8), 2164. https://doi.org/10.3390/en11082164

Wu, Y. C., & Feng, J. W. (2018). Development and application of artificial neural network. *Wireless Personal Communications*, *102*, 1645-1656.

Wu, X., Freese, D., Cabrera, A., & Kitch, W. A. (2015). Electric vehicles' energy consumption measurement and estimation. *Transportation Research Part D: Transport and Environment*, *34*, 52-67.

Said, O., Al-Makhadmeh, Z., & Tolba, A. M. R. (2020). EMS: An energy management scheme for green IoT environments. *IEEE access*, *8*, 44983-44998.