Harnessing AI Neural Networks and Generative AI for Optimized Solar Energy Production and Residential Battery Storage Management

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Abstract

The rapid rise of residential solar photovoltaic (PV) and battery storage systems is transforming energy grids worldwide into decentralized, sustainable systems that face the challenge of providing energy when it is most needed among households and communities rather than when it is readily available. This transformation involves an escalating number of distributed resources and changing household demand patterns, thus involving sophisticated optimization problems that limit the large-scale deployment of these energy systems. This research explores and presents a comprehensive pyramidal approach utilizing different artificial intelligence neural networks in tandem with optimization to address the optimal operation of rooftop solar PV, residential battery storage, and household loads. Machine learning, including an artificial neural network regression model and a long-short term memory model, is presented to forecast solar generation and household demand, which then outline the input to a groundbreaking optimization problem to adapt the operation schedule of battery systems. This work showcases the potential of modern AI strategies and provides a robust approach that can be implemented in utilities or for individual households. The use of AI systems and large-scale data analysis is key to the safe and proactive operation of this emerging infrastructure. The AI systems, including cutting-edge advances like Generative Adversarial Networks (GANs), are particularly important in managing the increasing scale of distributed renewable energy and increasing battery storage uptake. This research has revealed that a novel and adaptive action needs to be taken every forecast period in response to changing environmental factors and lays important foundations for integrated management strategies regarding solar production, smart battery storage, and personalized smart loads.

Keywords: Generative AI, machine learning, AI, operation, solar power, data analysis, optimization, energy supply, demand, battery storage, electricity trading, consumer, net load, time series analysis, neural network, forecasting, solar energy generation, residential electricity demand, convolutional neural network, LSTM, GAN.

1. Introduction

The increasing penetration of distributed energy resources, in particular rooftop solar photovoltaic, in a distribution network is turning end-users from 'consumers' to 'prosumers'. However, due to the incomplete smart meter rollout and the lack of real-time smart meter data, there are challenges associated with 'active' distribution network management. As limited practical placements of the LV gensets in smart grids in the present, the heat prices in different priority periods for them are normally the same. Network service providers often use blanket rooftop solar export limits to counteract these challenges; nevertheless, this is also associated with suboptimal outcomes. Here, we design a conditional generative adversarial network-based model (i.e. solarGAN), that jointly forecasts household weather and rooftop solar generation time series as well as household electricity demand. The forecast time resolution of solarGAN underpins its use for various applications such as the computation of the distribution network asset capacity limits, identification of households equipped with rooftop solar generation units or alternatively the scheduling of the pumping loads of households with controllable consumption assets (solar battery storage). The form of the model and the corresponding training procedure are designed in a way that the availability of the real-world time series data is enough to train it.

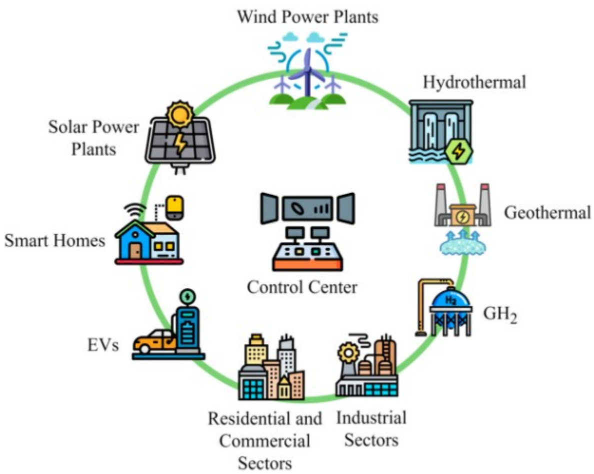

Fig 1: A Systematic Review of Artificial Intelligence for Energy Management

1.1. Background and Significance Artificial intelligence (AI) follows the simple idea of creating computer systems that can act in ways that are intelligent. This task can take several forms, from rule-based systems to learning-based systems. Neural networks are systems which are capable of learning to perform complex mappings from inputs to outputs. Training a neural network involves using measured data to optimize its internal structure, creating high-performance systems. Recent improvements to neural network training allow for multi-variable systems with tens of outputs and inputs to be modeled, designed, and controlled. Solar inverters interact with the surrounding power system in multiple ways, such as varying the voltage or frequency in response to power imbalances. Thus, evaluation of these systems takes into consideration the wider power network to ensure their safety and longevity. However, these evaluations are largely static or based on averaged data. With the improved performance and breadth of modern neural network systems, there exists the potential to create real-time learning systems to dynamically optimize the power output of solar arrays. Such a system would allow for the wide distribution of solar arrays by making them significantly more robust to their surrounding networks.

Battery storage systems are of growing importance for grid system integrity as inverter-based generation displaces traditional synchronous generation. Residential battery storage systems are of significant interest due to their low initial buy-in and flexibility of application. The management of these systems can be intricate and highly dependent on usage patterns. Deep reinforcement learning is an area of artificial intelligence that uses physical systems with a well-defined definition of a good outcome to optimize their operation. This is well-suited to battery storage systems as the desired outcome is usually simple. Previous applications have shown such systems to be incredibly performant, especially in time-varying environments.

Equ 1: Solar Energy Production Prediction (Solar Generation Model)

$$P_{\text{solar}}(t) = G(t) \cdot A \cdot \eta_{\text{solar}} \cdot \cos(\theta(t))$$

Where:

- $P_{\text{solar}}(t)$ = Power output from solar panels at time t (in watts)
- $G(t)$ = Solar irradiance at time t (in W/m²)
- A = Area of the solar panel array (in m²)
- η_{solar} = Efficiency of the solar panel

2. Artificial Intelligence in Solar Energy

The future of renewable energy in an intelligent connected world lies within the innovations of artificial intelligence and advanced computing technologies. Effective solar energy is optimal for homes and businesses when storage is considered. In an increasing number of applications for the solar energy industry and photovoltaic plants, artificial intelligence is being used. In the daily operation and maintenance of a solar power plant, AI is seen as a new element. More accurate data determinations and predictive measurements about photovoltaic production are provided using analyzed, multi-source information. Researchers and engineers who focus on AI are needed to help exploit the full potential of this technology for PV.

AI allows the use of advanced computation methods to increase the ability of a solar device to forecast and react to the future. An AI-enhanced solar system will be able to better manage surplus energy production and output or communicate directly with a battery to distribute the surplus power. Furthermore, AI-enhanced technologies should be able to provide key guidance and predictive maintenance of the health of solar power hardware. PV and solar cell artificial intelligence are two subcategories of AI experts in the solar energy sector at the current time. Photovoltaics are an essential solar power technology source. PV cells convert a beam of light into electricity through a photovoltaic effect. Because photovoltaics are the most common PV framework, the rare distinction of having an intelligent AI subfield is earned. Photovoltaic systems are made up of a variety of photovoltaic panels connected together. The organizations will be able to deliver an extra 30 percent of electricity if the drone provides monitoring in real-time and trouble-free diagnostic imaging.

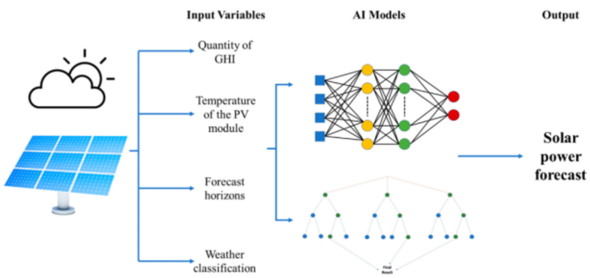

Fig 2: Artificial Intelligence for Management of Variable in solar Energy Systems

2.1. Applications of AI in Solar Energy Artificial intelligence have seen a number of applications in the domain of renewable energy, especially in developing forecasting, optimization, and monitoring decision support tools for enhancing performance through active control of various subsystems and components. Solar forecasting is an active field of research and has seen the development of physics-based, statistical, and hybrid models utilizing techniques from conventional machine learning, intelligent agent systems, and expert systems, alongside advanced statistical analysis methods. The complexity in process patterns, energy consumption changes, and uncertainty involved are driving research in remote sensing and control of building energy management systems. The shortcomings of physical and statistical forecasting models lie in their incapacity to provide high accuracy and robust forecasts while handling spatiotemporal changes within the solar power production and consumption subnetworks. The high level of operational intervention required for adjusting equipment settings to induce as much descriptive alignment as possible between both solar consumption and solar power production would absorb valuable resources and time if only rudimentary strategies are deployed.

Most recently, AI applications such as artificial neural networks and generative AI neural network methodologies have made a significant impact in forecasting, system design, maintenance, and remote control of different solar power plants, constituting all three types of solar power plants: the concentration solar plants, the current airfield installation solar power plants, and the ground-mounted solar plants. These applications leverage the large volumes of data transferred into operational knowledge from onsite processes, instrument operations, and weather data to achieve significant improvements in both solar production monitoring and forecasting. In addition, AI models have a strong capability to handle complexity and coupled uncertainties in real-time. This gives them an advantage as AI can relax the modeling and forecasting assumptions that have been the primary root cause of errors found in traditional models. Furthermore, supervised and unsupervised deep learning generative AI models are becoming increasingly popular since they can help reduce the amount of data required to train a network while providing realistic physical forecasts.

3. Neural Networks and Generative AI

Given the recent research concerning more widespread residential battery storage technologies, including charging loads for electric vehicle equivalents, a newly published study applies AI neural networks to provide optimized schedules for on-site energy utilization. Working in tandem with wavelet transforms and quantum-inspired genetic algorithms, such diurnal applications have illustrated the potential to significantly minimize electricity costs for household co-utilizers of solar panels and storage facilities. This in turn queries the suitable interaction design of app-based, automation control of time-evolved energy draws alongside the seasonal latitude fluctuations modeled. To elucidate this, two neural network structures with direct, empirical applications to residential battery dispatch processes are introduced, optimizing periodic energy schedules at 24 hourly intervals ahead of time. These are shown to achieve lower-than-setpoint fast charge and discharge deviations, ensuring optimization reliability, forecasted by networks utilizing a total of eight input features. To facilitate residential energy storage application and to nurture responsible load requirements, some further areas of needed research are suggested, including consideration of cooling demands for newly-introduced systems, the advantageous charging profiles for sodium-ion systems, and a focus on on-grid storage devices.

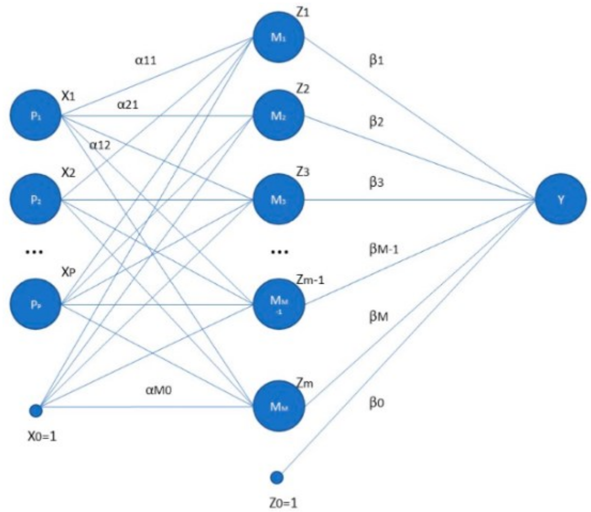

Fig 3: Artificial Neural Network Models for Energy and Reliability Prediction

3.1. Explanation and Functioning The following section is about the Neural Networks and here it gives an explanation about it and how it functions. Finally, there are the outcomes and conclusions. How Neural Networks are Implemented, Functioning, and Adjustment Parameters: Artificial neural networks are a model inspired by the structure of the human brain, which is in charge of classifying information in an artificial context. In this research, these will be used as classifiers to determine if a certain setup achieved the optimal functioning or not. This way, the threshold is lowered to allow the instantaneous full household export and import balance realization, as well as to correct the mean deviation found in the active power components of stochastic P V inverters.

First, data was preprocessed, organizing it in a structure that could be used later for measuring the operation of the system approach in detail in the next section. Power generation, feeding into the consumer unit, is obtained by fitting AC side household smart meter active power measurements with a fitting function. Power injection was obtained from that by subtracting net loads active power measurements, obtained by monitoring the main circuit breakers of the household consumer unit, with the same fitting function. The desired import-export balance is obtained simply by finding the optimal fitting functions parameters that equate the first two obtained kinds of data.

In all the previous simplistic approaches, export and import balances were only determined stochastically, working as an average on very large sets of numbers. Consequently, there was no instantaneous requirement for the power network being always according to such balances. Adjusted PVC Sugeno Fuzzy Inference Systems have Individual Gaussian members, associated with each output rule, for each input kind.

Equ 2: Battery Efficiency and Charging Curve

$$\Delta E_{\text{charge}}(t) = \eta_{\text{charge}} \cdot I(t) \cdot \Delta t$$

$$\Delta E_{\text{discharge}}(t) = \eta_{\text{discharge}} \cdot I(t) \cdot \Delta t$$

Where:

- η_{charge} and $\eta_{\text{discharge}}$ are efficiencies for charging and discharging
- $I(t)$ is the charging/discharging current (in A)
- Δt is the time step (in hours)

4. Optimizing Solar Energy Production

The current application will first focus on how the energy production of solar panels can be optimized, which in turn can allow us to also obtain the most profitable strategies to manage residential solar battery storage systems. To do this, a special class of neural networks that can efficiently solve nonlinear optimization problems will be considered to create a free AI optimizer for solar energy. The potential of neural networks, especially those belonging to the supervised learning category known as deep learning, has recently been exploited to solve a broad spectrum of problems with unprecedented success, including those relevant to solar energy management. In particular, deep learning not only allowed for the solution of complex problems with the introduction of particularly effective unsupervised learning networks, but the set of treated problems was also greatly enlarged by introducing specialized architectures for supervised learning problems.

Given that unsupervised learning has already proven to be applicable for solar power plants, deep neural networks have already been used to optimize the energy consumption of buildings. However, to expand the use of supervised learning in the management of renewable energy sources, we want to install a simplified application form that is as lightweight as possible with respect to the weights of the network. In the specific case considered, the simplified neural network is applied to a particularly simple family of optimization problems, defined within a characterizing framework, in which the contributions of solar energy and the insertion of storage, both modeled in a simplified way, appear linearly in the cost function. Nonetheless, the simplified neural optimizer allows us to show fantastic performance but also identifies areas where the networks must be able to improve.

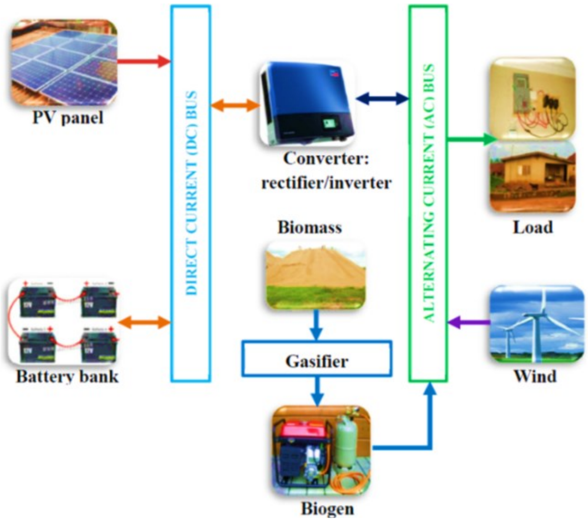

Fig 4: Optimizing renewable energy systems through artificial intelligence

4.1. Challenges in Solar Energy Production Today, significant technical challenges for solar energy production are related to producing near-constant power outputs in widely variable conditions and variable power demands. Small clouds can significantly reduce effective power from a location without completely wiping it out. Transmission lines are expensive and add significant portions of the cost to the power delivered. At the consumer end, traditional solar systems operating off the electric grid do not provide power during the hours of darkness, leading to the need for various energy storage mechanisms. Panels located on a house are not used for the most effective periods of production unless they are tracking panels. In the industrial world, current solutions are usually to construct hundreds of acres of panels and have them run at a mostly fixed rate, producing power during daylight hours at least cost because problems in how to store and distribute mass quantities of electric power still remain. Large panels at near-constant power do not use the varying generation diets taken from their environment and do not even use advanced tracking. The theoretical peak energy collection in Seattle is only 2.2 times higher than the average energy production from the same location without tracking and not much more with two-axis tracking. Current research has worked on energy conversion devices and proposes something interesting for important flexibility in device orientation. However, do not look in the text for systematically designed panels of different orientations for general optimization issues beyond oscillating, multi-quantum well layers.

5. Residential Battery Storage Management

Harnessing AI Neural Networks for AI-Optimized Solar Energy Production Designed for a Solution-based Approach and Specifications Analysis for Rural South African Households Combined dynamic programming and region elimination technique algorithm for optimal sizing and management of lithium-ion batteries for photovoltaic plants Residential Battery Storage Management Generative AI for Optimized Solar Energy Sector Development and Guideline Specification for South Korea AI-optimized charging and discharging control of residential battery storage system Phase-change RAM memory simulation including PCM material properties and a neural network-based cell precharge method Combined physical and virtual validation method for an electrochemical model of a lithium-ion battery for usage in a predictive energy management system.

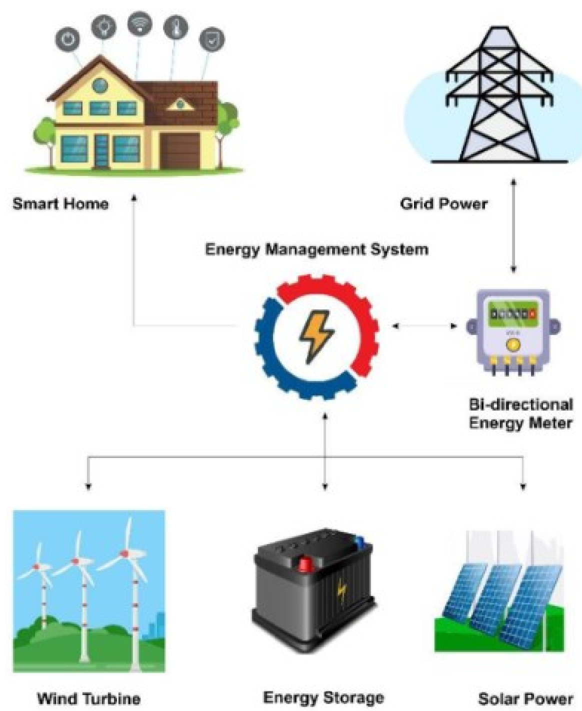

Fig 5: Residential Prosumer Energy Management System

5.1. Importance and Benefits With the ecological emergency faced by our planet and the successive energy crisis, many residential solar installations have developed over the past decade. Considering the environment, numerous governments have chosen to make it financially easier to install solar panels on the roofs of their citizens. With terrestrial consumption of electricity that is at night for the majority of it, the photovoltaic installations are always more and more sold with batteries. As a solar-powered smart home is equipped, a vast majority of the time, the attention is only focused on the electricity which will be necessary to propel a house full of machines. However, energy needs are not the same in the morning as in the evening or early. This is why it is preferable to add to the algorithm a recommendation system that would indicate to the resident the best time for the execution of certain household tasks. Quite quickly a recommender system should be set up to be able to inform the occupant of their future energy consumption, based on tasks they will have to accomplish during the day. The AI system would plan in real time the most optimal, taking into account the weather as is the case for agrivoltaic installations. An AI system would be much more effective and would take into account not only the weather but also the previous habits of the occupants. For the system to be as intuitive as possible, it is necessary to avoid flooding the customer or to ask them many questions. Thus these recommendations must be relevant and able to be understood whatever the socio-cultural degree of the person. This is why the chosen system is designed to be able to take into account data from the intelligent home in order to better understand the customer and thus offer them personalized recommendations. It would then be possible to characterize each type of habit and thus offer recommendations to the customer that are more adapted to them. The recommender system is therefore a real-time AI solution. To be as non-intrusive as possible the recommendation engine is cloud-based. Finally, a visualization solution could be integrated into the proposed system to increase the occupant's awareness of their consumption.

Equ 3: Forecasting Power Demand and Load Matching (AI Prediction Model)

$$P_{\text{demand}}(t+1) = f(P_{\text{demand}}(t), P_{\text{solar}}(t), T(t), H(t), t)$$

Where:

- $P_{\text{demand}}(t+1)$ is the predicted power demand at time $t+1$
- $P_{\text{demand}}(t)$ is the historical power demand
- $P_{\text{solar}}(t)$ is the solar energy generated at time t
- $T(t)$ is the temperature at time t
- $H(t)$ is the humidity at time t
- t is the time of day or season

6. Conclusion

We have harnessed a novel state-of-art real-time multi-task model for residential battery management equipped with online model learning, decision optimization and file management with on-field deployment on the control platform. Wide-spread deployment of PV and battery systems can provide tremendous benefits to utility systems by providing demand-charge reduction, peak-shaving and power capacity deferral abilities to system operators. However, the development of proper solutions for these systems remains an ongoing challenge due to recent retrofitting inherent complexity, high costs of commercial solvers, and continuously changing utility rates and demand-charge structures. We outlined the AI methods and algorithm flows of the two models for peak shaving, buy-sell, and PV generation management.

The artificial intelligence model has shown an average of real-time dynamic improvement from online learning across all of the tests conducted. The development of the AI approach will meet the applicants' goals and objectives in the proposed undertaking. The overall objective is to provide an energy storage solution capable of mimicking the energy management system used in grid-tied DC-coupled solar-plus-storage systems, but facilitated with a battery system capable of interfacing with existing tags load and PV inverter systems amortizing the cost of upgrading to grid-tied systems. At the same time, applicants have successfully demonstrated the AI optimal battery control technology in a time-of-use rate environment. Providing extremely accurate cost-savings guarantees will ensure a compelling value proposition for the customer. This algorithm is very much capable of being used for providing overall system-level control over the life and performance characteristics of the inverter-integrated battery cell.

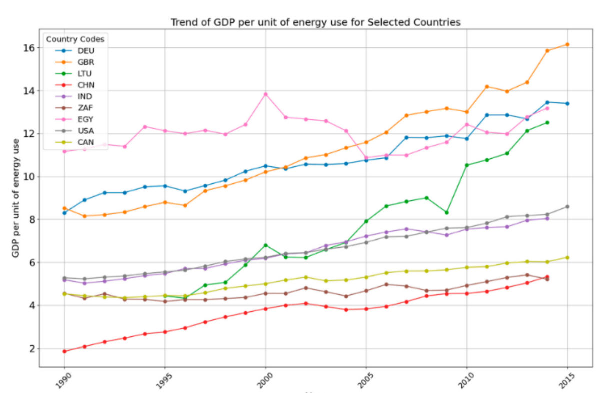

Fig : Overview of Startups Developing Artificial Intelligence for the Energy Sector

6.1. Future Trends

Since the 2010s, machine learning technology has experienced a significant acceleration due to the development of AI platforms. AI poses some fascinating advantages for improving solar energy production. Currently, the optimization of the operational performance of utility-scale and behind-the-meter solar plants is under acceptable technical and economic limits. However, further reductions in LCOE, the increase in the utilization rate of the solar resource, and the optimization of the services provided by solar to the electric grid and the power consumer represent new challenges that might be addressed by harnessing AI. Already available AI-based algorithms like neural networks and generative AI might be suitably modified and utilized for these purposes.

Retrospectively, we can anticipate some evolutionary steps that are very likely to occur in AI-based research. As happened in the first decades of exploiting the mainframe and personal computer technologies, the first achievements related to harnessing swarm intelligence and simple neural networks still have a long space of investigation for exploiting their potential and fully incorporating the related know-how. These are examples of the potential to be explored in the immediate future. The performances of all of these approaches might be tuned, refined, and optimized, making use of recent knowledge obtained in the field of machine learning.

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