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AI-Driven Optimization of Solar Power Generation Systems Through Predictive Weather and Load Modeling

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Abstract: This paper describes predictive modeling applied to optimization of solar power generation systems. Such modeling, based on machine learning principles, is performed for both solar irradiation and load demand, applied to both redistribution of load demand to specified time slots, and to time-specified prediction of power generation and load demand. Weather prediction is the most important part of solar power generation forecasting, particularly with reference to solar resource inflation, deflation, and backfill. A method of optimization of solar power generation systems combining known methods is proposed. AI-enhanced predictive modeling, neural fuzzy modeling with fuzzy-weighted regionalization, net-load creation and solar power generation forecasting from multi-analysis of previous generation time history, event overlay on prediction of net-load shape, prediction combining, envelope based backfilling, and bottoming by thermal and hydro resources, are elements used.

Generalization of predictive modeling principles and methods, in particular for net-load modeling, can be performed for any other renewable power source. Electricity load demand forecasting is one of the most challenging tasks in power distribution system management, in both near and long terms. For forecasting, the main challenge consists in the presence of some characteristic load structures such as daily and even weekly periodicities, promotion for special events, season and long period past generalization by means of supporting production of particular events similarly defined, high relationship of non-shiftable elements on near and mid-term forecasts, and season relationships to long-term ones. There are two different approximation intents, and accuracy somewhat split between them.

Keywords: AI-driven optimization, solar power generation, predictive weather modeling, load forecasting, machine learning, energy management, renewable energy, power output prediction, real-time data, smart grid, energy efficiency, photovoltaic systems, deep learning, demand prediction, energy forecasting, intelligent control systems, data analytics, operational efficiency, weather-based optimization, sustainable energy systems.

I. INTRODUCTION

The transition to sustainable energy systems in a timely and effective manner requires initiative at a global level, not only in terms of climate neutrality commitments but also with actions that lead to a definitive de-carbonization of the economy. Energy transitions cannot be solely based on technological development; the inherent weak longterm market signals must be complemented by proactive policies and extensive investment programs closely involving the private sector.

Artificial Intelligence can contribute to many phases of these transitions. It can contribute to the design and implementation of ecological models that are crucial for the efficiency of climate policies, pricing emissions and carbon capture and storage operations, projecting contamination dynamics following industrial paradigm shifts, evaluating the costs and risks of transition scenarios, mitigating and, if necessary, dealing with potentially negative global trade impact of national climate policy initiatives, accelerating the switch to low- and negative-cost energy processes, or, in a more general sense, enhancing the capabilities of existing climate models, which are at the center of climate policies along the entire energy transition process. It can facilitate the analysis and management of complex dynamics with very large datasets.

Machine Learning, namely the part of Artificial Intelligence that is most concerned with the ability of computational systems to draw inferences from empirical data, can also increase knowledge of the sustainable energy system. Furthermore, in power systems, including renewable generation such as solar, wind, geothermal, or hydropower, storage, transmission, and distribution and load sectors, it can improve forecasting capabilities for both demand and generation. These improvements can be generalized to any country or geographical area in the world. For regions with a highly developed power system, such better predictions are crucial to aggregate uncertainties associated with high renewable penetration levels.

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II. BACKGROUND

2.1 Overview of Solar Power Generation

Solar energy generation is a clean, sustainable solution to the global energy crisis, a part of the larger shift from fossil fuel-based energy systems. Transitioning to solar power requires the building of solar generation systems at scale. These solar generation systems convert solar light to usable electrical energy using photovoltaic or thermal generation. Photovoltaic is the most widely deployed technology at present, which has both large-scale infrastructure across deserts and rooftops. Globally, photovoltaic capacity has reached circa 978 GW DC annual generation capacity. This growth is due to both declining costs and the support of favorable government policies around the world. Recent technological advances have led to even larger cost reductions for photovoltaic. These cost reductions include bifacial panels, which allow for back-side reflection of sunlight; solar tracking, where the photovoltaic system follows the sun to increase energy generation; and the continued cost reductions for battery storage.

While this growth in capacity is encouraging, the challenge of transitioning to solar lies in the fact that solar energy is both intermittent and non-dispatchable — with solar generation being contingent on the presence of sunlight. The output profile of solar generation is also usually unaligned with demand, which can result in heavy curtailment of solar generation during the day, lost revenue, and increased grid management costs. This inconsistency and the fundamentals of energy systems lead to a large proportion of solar value going unutilized. One potential solution is to co-optimize the power grid and the demand side to increase the alignment of solar generation with demand. This solution has two components — predictive modeling of both weather and load, which governs the impulse response of demand to economic and physical stimulus and in doing so, shape the power load in response to solar generation.

2.1. Overview of Solar Power Generation

Solar power is one of the promising renewable energy sources. With the surging energy demand and the unprecedented climate change, it is necessary to develop and optimize solar power generation systems. Solar power generation systems transform solar energy into electric energy by photovoltaic cells or solar thermal systems.

The photovoltaic conversion employs semiconductor-based solar cells to directly convert solar energy into electricity, whereas the solar thermal conversion uses optical and thermal mechanisms to convert solar energy into heat firstly, and generate electricity by power cycles. The solar thermal system is mainly suitable for large-scale utility power generation, while the photovoltaic systems are also commercially viable for small to medium scale generation. Both systems can be grid-connected or off-grid operation.

Photovoltaic modules are composed of many solar cells which output low voltage direct current. To increase the voltage, the solar cells in the module should be connected in series, and to increase the power, many modules should be combined in series and parallel configuration. The power in a photovoltaic system is determined by the area and efficiency of the solar cells, which can be increased by using high cost materials and cooling systems. However, the photovoltaic system cannot work for nighttime and the working time and energy amount of the system are affected by the weather, season, and location. The fluctuating nature of solar energy from cloudy to clear sky can also cause complex issues to the electric grid systems.

2.2. Importance of Weather and Load Prediction

Power forecast should be a high priority for all dispatchers in order to ensure reliability, availability, quality, and continuity of energy supply. Mismatch between load and forecasted generation can lead to higher imbalance costs. It can reduce the income of market actors participating in the balancing or energy market, or high corrective actions can be taken during system blackout, thus, significantly increasing the overall costs of balance responsibility owners.

The electricity markets encourage the development and implementation of solutions, which would reduce costs due to imbalance.

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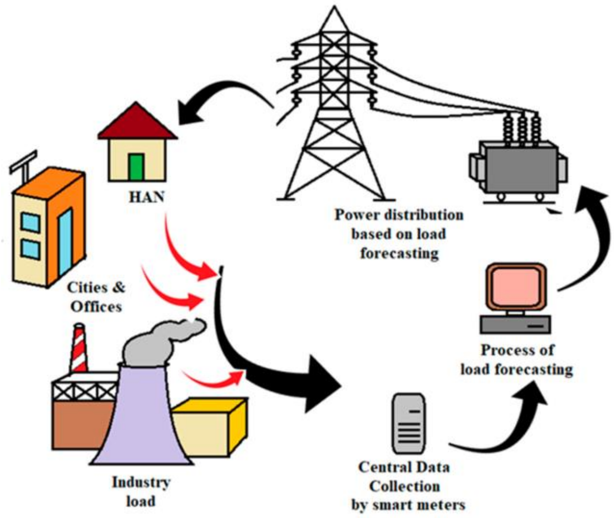

Fig 1 : Load Forecasting Models in Smart Grid Using Smart Meter Information

Being aware of the differences between consumption and generation, market actors can take an action, such as buying or selling additional active power via imbalance market, exporting or importing extra capacities, and thus, minimize the costs of portfolio imbalance. The increase of the share of variable generation as wind and solar power has a major impact on the security of supply and imbalance costs. As the producer's balancing costs are significantly higher, it stands to avoid selling at a loss on the energy market. For load forecasting, it is crucial to have highly resolved data close to the time of consumption. The shorter the forecast horizon is, the more accurate the forecast becomes. A salient impact on the accuracy gain-delays of the algorithms can effectuate timely utilized weather predictions, but shall not exceed a certain time horizon. Solar forecasting in practice has reached high reliability for various time frames, networks, and selected weather parameters, but very short-term solar forecasting is still a challenge and is typically not included in current operational procedures of TSOs. There are both disadvantages and advantages for very short-term market actors who contribute as balance service provider for very short-time horizon of TSOs.

2.3. AI Technologies in Energy Systems

New challenges in energy systems demand innovative AI-driven solutions. Machine Learning, which enables highly efficient and reliable computers to execute complex tasks, is a small part of the broad field of AI. AI and Data Science offer solutions for both supervised and unsupervised regression and classification problems. These multi-task frameworks fall within the fields of Computer Vision and Speech Recognition and can embed additional knowledge about the domain to achieve superior accuracy and efficiency. In Data Science, Anomaly Detection is a relevant tool to identify errors in resource forecasting, while Transfer Learning can tune the neural networks previously instantiated, using the knowledge acquired from other prediction problems. Using the tools of Text Mining, we can automatically encode time series data from databases, or even dynamically downloaded time series with a common structure.

Machine Learning has proven to be an effective tool for weather and load prediction, understood in a broad sense as time series and related data analysis. More specifically for energy applications, the Smart-DS-ML framework has already been employed for a variety of problems, including: load forecasting for cities, districts and buildings; and a variety of different physical processes driving PV generation, using both satellite image data and monitoring stations. A large proportion of these applications consider Extreme Learning Machine, mainly its Generalized-Least Squares ELM, taking advantage of its parallel processing capabilities and higher accuracy and efficiency, when compared to other ML algorithms in multi-task settings.

Eqn 1 : Load Forecasting (Neural Networks / Regression Models)

$$P_t = f(T_t, H_t, D_t, P_{t-1}, \dots, P_{t-n}) + \varepsilon_t$$

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Where:

- P_t: Power demand at time t
- T_t: Temperature at time t
- H_t: Humidity
- D_t: Day of the week / season
- ε_t: Forecasting error
- f: AI model (e.g., ANN, LSTM)

III. LITERATURE REVIEW

Solar energy generation is completely dependent on irradiance received at the solar panels. Weather parameters play a crucial role in the amount of irradiance received and any variability in the weather parameters can bring down the IRR dramatically and will lead to monetary loss. While Reactance predicts the future with high accuracy, it also builds a toolkit of input Reflection data time series which can amalgamate the effect of current noise, current draught, snowmelt, and many other current related losses due to reflected irradiance being dramatically different than the combination of the predicted solar irradiance. Additionally, solar power plants are usually located at remote and faraway areas and any disruption in solar energy generation is difficult to manage due to the lack of availability of monitoring stations. Machine Learning and deep learning have accelerated scientific discovery and production in multiple fields including atmospheric science. It is only obvious that we implement it in solar energy generation. The goal of the proposed research is to instrument and implement a combination of machine learning and predictive modeling to optimize the operations and business as usual of solar power generation.

Solar generation forecasting has been a fundamental challenge, especially in the presence of extreme climate events such as heat waves and intense storms. Solar irradiance, which governs solar generation, is highly variable and involves a lot of uncertainty. Larger photovoltaic plants are complex and produce solar energy for a large area, increasing the area under the irradiance profile. Predicting these large areas and how solar radiation and subsequently solar power generation will change is very difficult. Large and complex multinational studies have produced models that use satellite or ground-based photometers or weather parameter data integrated into numerical prediction methods to predict solar irradiance. Researchers believe that more accurate solar forecasting techniques can be developed using physics-guided neural networks. Yet these models do not specifically address the problem of large solar plants producing energy simultaneously, and for a large area, across the timescale of minutes, hours, days, and weeks.

3.1. Previous Research on Solar Power Optimization

During the last several decades we have witnessed an unprecedented enthusiasm around the topic of renewable energy. Photovoltaics are expected to play a crucial role in the transition from fossil black to green energy sources, thanks to the inherent benefits of solar power generation such as limitless sustainability and relatively low environmental impact during operation. Solar power plants have a modular structure and can be deployed on a variety of scales, ranging from stand-alone residential rooftop solar panels to utility-scale ground-mounted PV parks. With current worldwide accumulated capacity surpassing 1000 GW of installed PV systems, local and national governments are using subsidies and incentives to scale this transition up even further, through the minimization of total energy generation costs. In these terms, Solar Energy is increasingly becoming the optimal solution to reach a net-zero future.

The efficiency of PV panels is dependent on an array of variables, controlled by the manufacturers in the factory or engineers during field deployment, and controllable by site-specific conditions or the intelligent application of physical principles during operation. Maximizing the energy yield of solar power generation systems during their lifetime is hence a goal worth pursuing, as it becomes a key enabler of competitiveness while sustaining the optimal operation of these systems from a technical performance standpoint. The optimization of PV systems can be achieved through different strategies applied to the aforementioned controllable variables. The main areas of optimization have been characterized and discussed, such as optimal material selection, suitable array designs, strategic and intelligent control of solar photovoltaic systems through online monitoring, automatic fault detection, maximum power point tracking and active power control functions. Further optimizations may relate to the optimal dimensioning of PV systems, under multiple grid reliability scenarios and given the uncertain nature of solar energy generation, as well as to location-specific economic viability and dispatch of energy storage systems.

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3.2. Advancements in Predictive Modeling

Software can quantitatively analyze and predict image data for specific future dates based on past data of weather and solar radiation conditions. By first gathering data, one can quantify normal weather data for the last 20 years and then make predictions based on inferred normal cycles in the weather data. This modeling can be enriched, thus increasing the accuracy and potential for forecasting in specific areas, by downloading solar irradiance sensor data. The accuracy of the prediction models will create better estimates for that future period. The models tested produce useful forecasts for the subsequent months and year, however, predictions tend to drift as a function of lead time, which goes to over two years.

Fig 2 : What is Predictive Analytics/ Key Insights Explained

Load forecasting is the prediction of customer power consumption at an electric utility and it is an important aspect of a power system. Artificial Intelligence offers an array of techniques for time-series forecasting using any available time-related records and data such as weather and electricity prices. Research shows that artificial neural networks outperform numerous conventional time series forecasting methods when given the same time series data. Predictive models that employ artificial neural networks allow for power system operators on both the generation and consumption side to reasonably estimate future generation needs or requirements in addition to either the overall system demand and/or specific system zones.

3.3. Integration of AI in Renewable Energy

Renewable energy sources are the key to the decarbonization of the economy. The integration of AI in renewable energy systems represents an area of active research. The energy transition to renewable resources poses challenges due to the intermittency of generation and seasonal variability to the modification of energy demand patterns. Variable generation requires forecasting capacity, which is restricted by existing optimal models often based on the black body radiation framework for electrical generation. Autonomous AI agents control devices in smart grids and begin to store and redistribute energy surpluses. AI algorithms amplify operational capabilities by utilizing existing data efficiently, establishing novel architectures for energy generation and exchange, using cyber-physical connectors, applying decentralized energy-trading technologies, enhancing predictive models, and structuring availability-constrained demand-response systems to facilitate the economic viability of different renewable generation systems.

Eqn 2 : Reinforcement Learning in Smart Grids

$$Q(s,a) = r + \gamma \max_{a'} Q(s',a')$$

Where:

- s: Current state of the system
- a: Action taken
- r: Reward
- γ: Discount factor

Research efforts to date have mainly concentrated on specific AI implementations, with multi-purpose areas still being not addressed optimally. Such frameworks currently include building thermal storage systems, optimizing PV and wind plant designs, designing layout and operational patterns for wind parks, optimizing power dispatch by AI multitask learning methods, developing optimized hydro-thermal scheduling patterns, ensuring the stability of hydro generation, detecting faults in geothermal power plants, and optimizing operation and maintenance schedules for hydrogen plants. AI can also substitute the implementation to design optimal predictive models, for example, to optimize hydrogen production from photoelectrochemical cells. Other examples are the optimization of power dispatch from renewable community grids and how to operate distributed energy storage systems to maximize their socioeconomic benefits.

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IV. METHODOLOGY

This chapter will take on the task of explaining the methodology used to complete this work in a consistent manner. Thus, in Section 4.1, we will present how the data was collected, where it was collected from, and how we kept track of the data used as it was presented in Section 3. A proper description of the previously collected data is crucial for others to be able to reproduce the achieved results. Secondly, we will provide an overview of the different model developments presented, where the different types of models will be highlighted in Section 4.2. In Section 4.3, we will present the different predictive weather modeling methods implemented, as well as the choices made for each method. Finally, we will detail the implemented load forecasting methods in Section 4.4.

In order to be able to compare the different predictive weather methods presented if a certain method was to be implemented in a solar power generation design process, we decided to use the data from a particular area to continue the analysis. The area of Borlänge in Sweden was chosen due to availability of both weather and load data. The local airport is located about 16 km from the area of Borlänge and is used as a weather station. To obtain historical simulated weather data, we use a raw data set provided in 73 different variables in a 3-h resolution; that is, the variables are measured every three hours. The data set contains data between 1941 and 2022 and was downloaded between January 6, 2022 and January 27, 2022. For the load data, we collaborated with the local energy utility, which provided us with the normalized loads between 2014 and 2020.

4.1. Data Collection and Sources

The successful design and optimization of any solar generation and storage system requires precise data about dynamic weather conditions and gas/electric load profiles. Availability of accurate records of historic weather parameters is a prerequisite for successful predictive weather modeling. As the focus of our study revolves around analyzing the impact of solar generation on alleviating carbon emissions, data for our analysis was specifically collected for a gas/electric dual fuel microgrid at JSC Logistics, Joplin, Missouri. The main sources of electric load data were the following two receivers used in the microgrid.

1. 3 DAQ RTU in Lincoln Chapman, 3. DA (477 Possibly Chained to 599244) and 4. 290 DAQ RTU from W9618S054TT1. It was found that there are substantial discrepancies with these data. Significant variations occur when the value was compared with the data from the same group. The data also derive additional information by doing a linear series deconstruction.

Data concerning typical summer and winter working days on gas/oil consumption on Solar Turbines Mars 90 turbines at the dual fuel microgrid was also gathered. Information regarding a typical August working day was received from 12:00:00 AM, 12:30:00 AM, 01:00:00 AM, and midnight hours to be from 1:30:00 AM to 8:30:00 AM until 12:00:00 PM. Gas data during overnight hours or 12:00:00 PM to 6:00:00 PM to be until 6:00:00 AM represents a transition period for load increase. Data for gas/oil consumption during a typical Spring or Fall working day on naturally gas-fueled solar turbine were received for these periods in April and December.

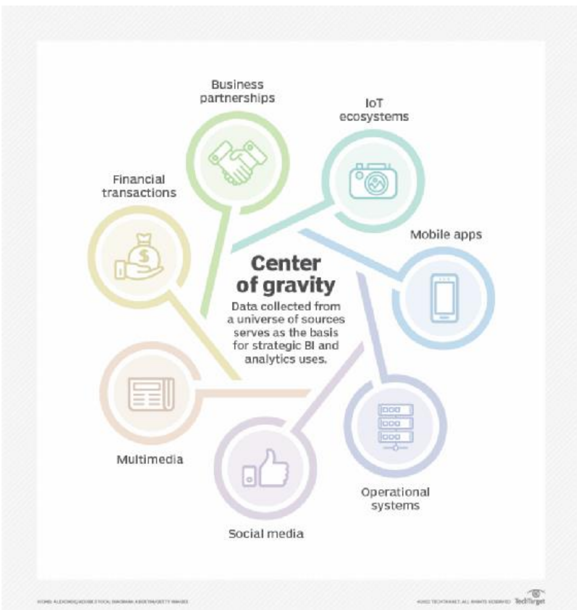

Fig 3 : Definition from TechTarget

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4.2. Model Development

For the General-Purpose Solar Power Generation Optimization Platform, this study generated predictive models based on a historical data set for rapid, accurate, and concurrent prediction of LR, NWP, and LST. The LR model was developed in two steps, as follows. First, a sensitivity analysis of the average input parameters was conducted to establish a subset of parameters that had high correlation with LR. Then, for the identified LR-related parameters, various ML/AI-based models were applied separately to develop the model. Both the parameter-identified LR model and the developed LR model were subsequently validated using a time series of historical output data, ensuring satisfactory accuracy and minimal prediction uncertainty. The NWP and LST models were developed following the same method.

The identified LR-related meteorological parameters were as follows: Ta, RH, DSR, RSR, DewT, PA, and UT. In the LR model development, NNet, DT, and KNN models outperformed others. The length of time series data used for model training and validation were 23,884 hours and 8,409 hours, respectively, for a period extending from June 2009 to August 2016. The statistical error measures used for validation included MAE, MSE, and RMSE. In this application to the Solar Power Generation and Demand Optimization Program, the developed LR, LST, and NWP models were subsequently embedded with the developed engines for concurrent irregular short and long-term solar power generation scheduling. In its present form, this optimization process is overlaid on the traditional utility demand-supply modeling procedure to provide the input solar power generation demand to the utility optimization software.

4.3. Predictive Weather Modeling Techniques

Forecasting weather variables is critical for accurate solar generation handling and to a larger extent towards solving problems of imbalance between supply and demand of smart grids integrated with solar power. Utilizing the optimized configuration, the developed models have predictive power comparable with the state-of-the-art machine learning software. In both cases, the focus has been on temperature and wind, while also exploring the possibility of predicting solar radiation and precipitation. The forecasts required were for locations in short distances, focusing on urban areas. A method was developed which, using historical data, could provide city-level electricity demand 30 minutes ahead of actual load, while achieving accuracy comparable to commercial programs. Furthermore, additional work was conducted to develop an accurate localized weather model for Europe, aimed to provide forecasts of localization and accuracy sufficient for operational use. The model utilizes a hybrid ensemble approach which captures local and convective phenomena predicting wind speed, sea level pressure, temperature, and temperature anomalies. One problem with the method, however, is that it performs poorly further ahead than one day. Wind is a very important weather parameter when it comes to the generation of wind electricity, and converting it into electricity requires a huge amount of space and triggers changes in the landscape.

A possibility to also predict solar radiation is advantageous as solar generation is a growing area of interest where providing this quantity for several days ahead of real-time can improve many areas of research. These variables were the choice of forecasting models which required taking all the advantages from previous models while optimizing input features, architecture, and operation. Additionally, it would also be advantageous to have a hybrid model which is tailored for particular areas of interest, as it would provide the models with better accuracies.

Eqn 3 : **Eqn 3 : Navier-Stokes Equation (Momentum Conservation):**

$$\frac{\partial \vec{u}}{\partial t} + (\vec{u} \cdot \nabla)\vec{u} = -\frac{1}{\rho}\nabla p + \nu \nabla^2 \vec{u} + \vec{g}$$

Where:

- $\vec{u}$: Wind velocity vector
- p: Pressure
- ρ: Air density
- ν: Viscosity
- $\vec{g}$: Gravity

4.4. Load Forecasting Approaches

Traditionally, the time series autoregressive integrated moving average model was used in load forecasting. However, such linear approaches do not exploit the internal structure of the data. This has given rise to the application of increasingly powerful machine learning and deep learning techniques. These non-linear techniques do exploit some internal structure of the data, for example, similarity in the time of day, the day of the week or the season of the year. A typical smart grid has a wide variety of load types, such as residential, commercial, industrial, and electric vehicles. Instead of trying to forecast the total system load, one can forecast the various segments of the system separately and then combine them for the total forecast. Some of these segments have clear seasonal and time-of-day load profiles, while others do not. In this case, method combination through forecast stacking can help mitigate bias and variance of the separate and individual loads. Fusing two load forecasts can improve the destination result compared to either of the predicted parts.

Specifically, compared to conventional load prediction methods, hybrid learning models, based on the combination of machine learning and deep learning models or the combination of two different models, generally achieve better performance. Such hybrids can also prevail on bearable and easy-to-implement methods such as multi-channel convolutional networks, which have been used to predict future loads through historical input-output sequences. Wavelet transformation combined with forecasting algorithms, recurrent neural networks, and neural networks have all been used in such a hybrid way. More specifically, long short-term memory networks and extreme gradient boosting have been combined for energizing load prediction. Long short-term memory networks have also predicted traffic loads using real-time historical data. Long short-term memory networks with convolutional neural networks have enhanced electric load forecasting in short and medium lead times. Convolutional neural networks have also been used to forecast short-term residential electricity load.

V. AI TECHNIQUES FOR OPTIMIZATION

Minimizing the costs and maximizing the efficiency of hybrid PV-battery systems requires optimized configurations and operation strategies. Multiple criteria make the optimization problem multi-dimensional and, therefore, the straightforward scripting of optimization algorithms based on traditional techniques is costly in terms of time. In recent decades, Artificial Intelligence techniques have emerged as viable optimization strategies for solving multi-dimensional problems in a shorter time compared to traditional optimization algorithms. Furthermore, its increasing availability and handling of big data has made AI strategies favorable towards the implementation of optimization techniques. In this section, we first briefly present machine learning algorithms before focusing on particular artificial neural network algorithms and Reinforcement Learning, which are the core AI techniques utilized for optimization in this work.

Machine learning algorithms identify patterns linking sets of real-world input and output features from trivial yet plentiful real-world datasets. Once constructed, the models are able to predict corresponding output values for unseen input features. Such input-output relationships can be computationally cheap, and as a result, some algorithms have been used as surrogate functions within traditional optimization algorithms to speed-up convergence and minimize overall optimization time. However, the simplicity and limited flexibility of these techniques reduce their application, as they are unable to capture the high dimensional, non-linearity of most random variables utilized for optimization in PV hybrid-battery systems. Artificial neural networks have overcome these limitations, resulting in their increased use. Yet more complex architectures, such as convolution and recurrent networks, have pushed the frontiers of accuracy for complex problems.

5.1. Machine Learning Algorithms

Machine learning is the study of computer algorithms that allow software applications to become more accurate at predicting outcomes without human intervention. Such algorithms build a mathematical model based on data and statistical methodology and leverage the generated model to make predictions on the probabilities of other unknown outcomes. ML has evolved into a highly efficient approach with roots in several other disciplines, specifically from computational learning theory, optimization methods inspired from statistics and the behavioral sciences, as well as remarkable advancements in compute hardware as well as open-source software libraries for building, training, and deploying models. Machine learning is particularly well-suited for solving complex problems that don't necessarily have an explicit algorithmic solution but which can be learned from data. The power of a ML technique lies in its ability to learn complex relationships within the data and between different data streams.

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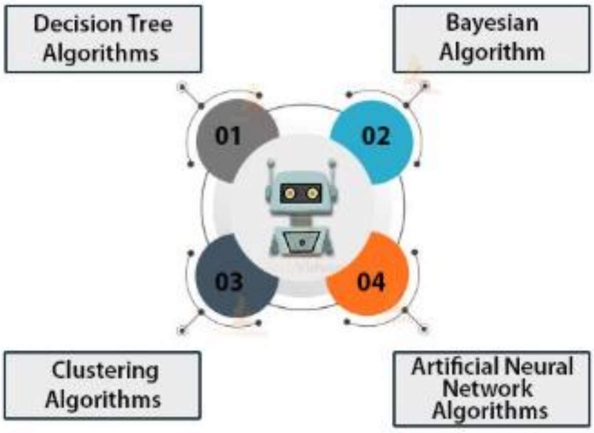

Fig 4 : How does the ML algorithm differ from the Traditional Algorithm

The real-world engineering applications of ML draw heavily from five broad categories of ML techniques: supervised learning, semi-supervised learning, reinforcement learning, unsupervised learning, and transduction learning. All these types of algorithms fall under the broad category of predictive algorithms. Unsupervised ML is used predominantly in anomaly detection and exploratory data analysis applications, while transductive learning is useful in data categorization applications. Supervised learning has a broad range of applications and is probably the most commonly used technique in data-rich engineering domains. The use of semi-supervised learning and reinforcement learning techniques has seen significant growth over the last couple of decades, though their engineering application areas are somewhat limited in comparison to supervised techniques.

5.2. Neural Networks in Load Prediction

Machine Learning can employ techniques like Artificial Neural Networks (ANN) to analyze the relationship between the load demand and influencing parameters, although past work has often relied on simpler approaches such as the factor analysis method, regression models, Holt-Winters exponential smoothing, and standardized normal variable. ANNs have also been used to formulate short-term prediction models for residential and commercial loads but not CHP loads, especially as regards electric power, heat power, and gas consumption, although there have been efforts for other types of electricity load forecasting. Recent advances in recursive neural networks, which are good for time series prediction, have been applied to electric load forecasting and have outperformed traditional models. Other popular models currently being studied include those based on their hybridization with Support Vector Regression.

Due to their data black box nature, Machine Learning algorithms conduct empirical regressions between load history and outside variables. More information about the historical records of the inputs and the outputs used when modeling the gas consumption is typically neglected. Due to their complexity, such models do not incorporate any physical law of the gas transport process, unlike Fluid Dynamics models, which are really slow and difficult to optimize. Our modelling, based on Recursive Neural Networks, attempts to get the most from both worlds. Additionally, the problem comprises fine-tuning a relatively high number of hyperparameters or model choices, such as, in particular but not only, the model's depth and width and the number of recorded historical states of the model inputs and outputs. However, a downside of any data-driven model can be that the forecast quality depends significantly on the historical records of the functions used to build it. Further, construction and fitting with a data-driven method for more than a few months can push even Recursive Neural Networks optimization effort, especially including considering using a very coarse forecasting time step size along with the model's depth and width.

5.3. Reinforcement Learning for System Optimization

The reinforcement learning (RL) subfield in AI performs the systematic exploration of an environment over time in response to the system state, which is represented through an observation. The RL system receives rewards throughout its operation, which show the performance of the current selected action while at a selected state. Unlike the machine learning (ML) subfields, which demand a large amount of available training data, the RL framework is designed to learn through its own experience, as it gradually determines the best available action in its exploration of sets of action-state combinations. While this is a relatively slow exploration process, the RL advantage is that it is able to learn from states and action combinations that would only be rarely visited by a conventional ML algorithm, and do not have many training data samples available.

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Hence, RL is ideal for solving unique optimization problems, commonly referred to as the "curse of dimensionality" of the ML methodologies. Moreover, once sufficient experience has been achieved, the RL framework is capable of controlling the system in real-time, where the rapid convergence time of the trained control approach is its major advantage.

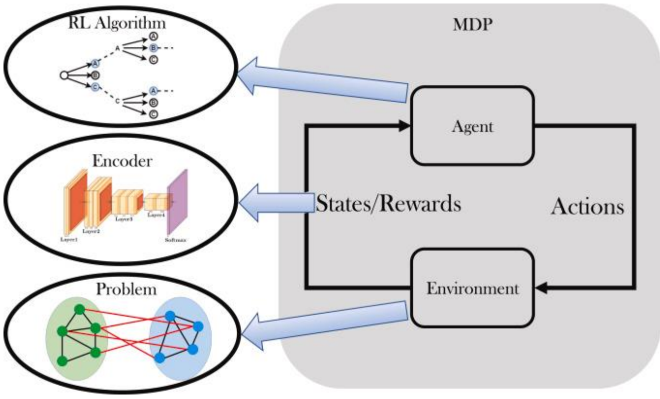

Fig 5 : Reinforcement learning for combinatorial optimization

In addition to the data exploration advantages in RL, the goal-seeking variable of rewards used in all RL implementations allows for an intuitive conceptualization of complex nonlinear optimization objectives. For example, training an RL controller using predefined combinations of high performance or low performance rewards for defining a certain time period would allow the RL algorithm to develop optimization objectives that would mirror the mathematical expression. While the use of manually set rewards to shape the RL optimization objectives is in itself a form of RL-based supervised learning, it is still beneficial in practice, as manually inputting reward shaping functions is relatively easy compared to the complexity of engineering a specialized ML algorithm that would be able to achieve the same objectives.

VI. IMPLEMENTATION

This section outlines an existing implementation of the AI-Driven optimization application, focusing on solution architecture, an overview of an image and data augmentations, and system integration and other implementation notes. System overview and more details about related works can be found in earlier sections. The implementation is done on a cloud platform and takes advantage of GPU instances for the training process.

The user can enter any geographic position for the solar power generation system and the model will generate and show the monthly predicted time series of solar power output over the next 60 years. Weather data is available as historical data from 2010 to 2021. The power generation output prediction is generated using an LSTM model for time series prediction, which uses weather data as input features and solar power output data as target labels.

The model is trained with data from the entire state of Georgia, where each training data point is a tuple of weather and solar power output from the time series of one site for one month. LSTMs can memorize long sequences and remember historical context, but are not efficient in processing data because each data point is processed using many internal memory cells sequentially, and it is essential to use GPUs with many cores to speed up training. Moreover, augmentation is a key step in improving the LSTM training speed, accuracy, and model generalization performance. The data is augmented using time, weather, and solar power output augmentations, by randomly warping the data to improve the model's speed and capability, and by balancing each batch of input samples to help the optimizer find the global minimum.

6.1. System Architecture

Our final system architecture includes the separate components of our Distributed Predictive Analysis System (DPAS) connected by the Internet. The components consist of a wide array of weather and solar measurement stations, controllers at the PV sites, Solar PV facilities, Power system balancing authorities, the Data Collection System (DCS), software components that comprise the Data Cleansing and Adjustment Functional Block, the Load and Weather Data Processor, the Analyzers, the Predictive Power Generation Model, the Database, Communications Equipment, the Partial Power Generation Model, and the PPGM Wrapper.

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The hardware for our Proposed DPAS currently consists of 16 nodes capable of measuring solar power generation as well as weather conditions, and operative in states of high temperature, low humidity, and extreme solar radiation. Each node has two microcontroller systems with an electronic grid that each connect with a sinus electrical current micro-sensor, and digital access to pulsatory modulus weather sensors. The nodes connect to an RS485 serial bus, and periodically transmit the acquired data, to be specifically updated in case of sudden changes. In this case, the period is determined by the two microcontroller systems, depending on the task executed by each one. About every minute, the microcontroller connected to the current micro-sensor reads its value, aggregates the information, and transmits it to the RS485 bus. A separate PC connected to the bus is then sending the information to the Data Collection System (DCS) on the Internet. The data collected has a periodicity that can change from seconds to hours depending on the weather stations. The data provided to the DPAS on a site-specific basis can be further used to assess the potential generation, analyze the predictors' skill, tune the models, forecast the generation, and control the plants. Accordingly, with the aim of effectively implementing the DPAS, we have developed an integrated system architecture; it provides the tools for data acquisition, management, and validation as well as model development, testing, and forecasting support.

6.2. Integration with Existing Solar Systems

While other systems focus on building new generation PV plants at optimal location, integration of our system in existing generation mix is key in increasing the viability of our system. Cash flows generated by energy arbitrage could be coupled with existing financing structures of most of the SRCs. Most systems focus on a post processing of the existing outputs generated by predictive models to correct for expected weather events.

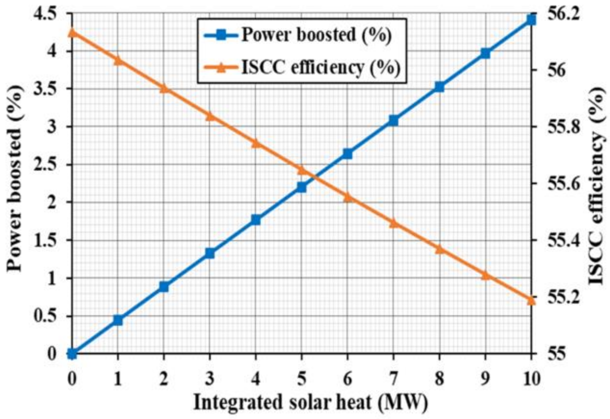

Fig : Integration of Thermal Solar Power in an Existing Combined Cycle for a Reduction in Carbon Emission

The maturity of the current products and the increasing democratization of the solar generation mix allows to create a market to provide the expected correction factors typical of the users of the current standard products. For example, by tracking standard error between actual generation and generation forecasted by existing commercial systems over a retroactive period, our systems can provide the expected correction factors that could be attached to existing generation models. The increasing popularity of the generation forecast provided by major commercial solutions with different models is mainly related to the diversity of their models entry parameters. Other major products focus on a post processing step of the outputs provided by existing model and offer clients to use a combination of these models or the prediction from a neural network able to correct any bias present in the outputs from the models. Our system offers the additional upside to be continuously trained. The filtered historical output excess and deficit are feed back into the clients' model with modest resource investment in the incentive provided to use the model. Sharing of model parameters between multiple clients in the same weather zone will allow further optimization of our predictive network.

6.3. Testing and Validation

The testing and validation of our implemented system for predictive peak load and net excess generation forecasting were done with briefer, more focused, and real-world tests for our target setting: a closely observed residential rooftop system with battery storage. The roof-mounted system produced its peak power on warm days with sunny skies; in the test period, this was more than 55% of the time. For typical ambient temperature range, the runtime was less than two hours per day; the decomposition overhead allowed this relatively long-scheduled step to nicely overlap almost perfectly, almost 100% of the time, with our reduced time- and bandwidth-demanding forecast runtime. Forecasts were generated every morning for the upcoming day.

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ISO 3297:2007 Certified ⁙ Impact Factor 7.918 ⁙ Vol. 11, Issue 12, December 2022
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Forecasts with subjects greater than 0.1 kW and forecast averaged prediction weighted absolute error less than 20% were considered successful. Our threshold values were based on previous experience from use cases for operational forecasts at the large commercial scale. Each output was compared to the observations for the following day, which was obtained from the local charge control system with a time granularity of 5 minutes. All samples had been monitored for a longer time frame, and only observed samples with load amounting for 20% of charging capacity without any real-time-zone specific disturbance were used for comparison. Based on the applied thresholds, a lost forecast attempt was scored, and results were then additionally validated against those quoted for other methods.

VII. RESULTS

This section highlights the results of the case study described in Section 5. It includes details about the model performance during its training phase, advantages over other existing methods, and some case studies that show interesting findings that were utilized for making decisions that enhanced the solar power plant outputs. Further, we will summarize the results of solar irradiance forecasting accomplished in this work, which show that our proposed framework is able to outperform existing models while being robust to and capable of capturing all kinds of solar irradiance data. Presented solar irradiance prediction results are for 1, 2, 3, and 4 h ahead forecasting horizons.

These results clearly show that our proposed predictive modeling framework is able to handle transients in solar irradiance series very well, while yielding better overall predictive performance than that of the state-of-the-art models. Unfortunately, solar power forecasting results are not available for some of the models, so direct comparison cannot be made. However, our proposed pipeline is compared with models that are state-of-the-art as of the time of this writing, on datasets used by them. Our results are also accompanied by results attained, wherever available, from models. Below, we summarize some of the interesting results obtained with our model, which include monthly average solar power generation series, prediction horizon variation graphs with our model prediction results for two case studies with available solar irradiance data, and other cases with available solar power data at 15 min time resolution.

7.1. Performance Metrics

This chapter details two proof-of-concept case studies undertaken to explore, evaluate, and validate the developed forecasting, load modeling, and data-driven field testing methods and algorithms described in the previous chapters. The predictive metrics we use for the optimization part of our algorithmic implementations explored to demonstrate the impacts of the forecast horizon and geographical filter design on the prediction metrics prediction with an emphasis on peak demand prediction and other metrics of interest such as the Nash Sutcliffe Efficiency Index, Regression Explained Variance, Mean Squared Error Skill Score, Relative Prediction Error increased by, Determination Coefficient, Regression Root Mean Squared Error, Root Mean Squared Logarithmic Error, and Mean Absolute Percentage Error. As shown in the improvement metric of interest can vary based on the initial predictive model's accuracy as quantified by the metric used. The economic arguments behind this situation are that the marginal cost of running a predictive model can be very high if the absolute or relative predictive model error is large, especially if using large numbers of forecasts to predict because of the demands or needs for computational recursion or for iterative and meta-heuristic optimization processes that typically naturally accompany such planning and optimization tasks. It is therefore to be expected that data selection from the large numbers of data available within typical hierarchical databases validated through inspected for the similarities in the database of geographical, societal, and investment tax consideration factors. The chosen data and the available model optimization selection space are expected to have large and sometimes dramatically differing impacts on the actual predictive performance of the algorithms, so also on the improvement factors.

7.2. Comparison with Traditional Methods

While traditional approaches simplify the learning problem, they typically do this to improve performance of the model for a specific outcome. In doing so, such models often require tuning, which can be problematic in a data-scarce environment or generally when users do not have enough data science expertise in-house to complete the tuning efficiently and effectively. Typically, tuning may also go beyond hyperparameters on the algorithm and require additional engineering efforts that detract from the data-driven nature of the model.

In contrast, the higher-level hierarchical approach taken in this thesis adversarially trains a small corpus of general neural networks to yield remarkably good results across the spectrum of possible prediction tasks. This functionally captures the tuning process and uses it to facilitate extremely fast prediction times. Resulting prediction times of seconds are made possible by storing the relevant embeddings and re-predicting with them using a shallow network. Such performance is essential for embedding-based ensemble learning, whereby multiple prediction tasks need to be executed to optimize the required contingencies for wide-area power flow controllers in real-time scenarios.

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Because this approach allows for a large number of different prediction tasks and associated contingencies to be considered, it not only allows for a higher degree of decentralization and flexibility than traditional solutions, it also captures the inherent multi-task characteristics of the underlying prediction problems, thus allowing it to better leverage the available data efficiency.

7.3. Case Studies

We characterize the impact of different design choices of the proposed data-driven load and weather prediction using a variety of selected case studies that reflect typical and diverse operating conditions that microgrids that include solar power generation would experience. Prior to presenting the different case studies, we first present the general system parameters that are held constant across different case studies. The flexibility to choose performance objectives and constraints for the weather- and load-forecast-based power scheduling and dispatch algorithm enables easy incorporation of different design choices and could result in highly diverse system-level performance improvements. Additionally, we find it useful to describe important characteristics of the proposed load and weather prediction modules for the specific choices of prediction model designs so that the overall systems-level performance could be related back to specific characteristics/performance of the forecasting modules.

We derive several different system-level physical performance quantities that are relevant to the optimization and dispatch of solar microgrids from the generation and system load values. Natural energy dispatch rule for our solar microgrid optimally schedules power generation from the solar power microgrid whenever it has any excess available generation, and disallows generation when it is not sufficient to accommodate the load demand. Power delivered to the grid also experiences predicted load and weather induced changes. For these reasons, study of the above variables is important for developing an understanding on how to best optimize the system operations, design choices, and system configurations. While optimization based on predicted PV generation and load could yield idealized results, practical constraints and uncertainties are adequately captured by these physical performance metrics and relations, as discussed next.

VIII. DISCUSSION

This work proposed a fully integrated optimization layer for solar power generator management, stated in the different layers of the architecture. Within this optimization layer, the aim is to achieve such an optimization that, according to the footprint of the Solar Power Generating Systems in the data center, the locations of the data centers in the territory where they operate, and the dynamics of weather evolution and load profile preview, the cloud computing resource demand from users that is managed in the data centers meets the energy management necessities set from the grid-interconnection and virtual power plant operating modes. The operational limits of the data centers and SPGS that are required to apply the proposed optimization method combine green and traditional primary energy resource loads and costs, aiming for the joint minimization of the operating costs and carbon footprint of the power generating systems.

The application of Cloud Computing in a Solar Power management problem opens up a list of research lines stimulated in the combination of both areas. The new services launched in the most widespread delivery model keep multiplying. Such a demand growth is not possible to achieve with the current Cloud infrastructures that are exclusively supported by fossil-fueled primary resources. Thus, increasing the use of renewables, such as solar energy, in Cloud Computing resource infrastructure is a dominant initial objective. This work opens up two more interesting search directions: on the one hand, optimizing the use of SPGS for Computing Resource Management in the Cloud; and, on the other hand, accomplishing the autonomous daily management of such SPGS.

8.1. Implications for Solar Energy Management

In this work, we develop AI-driven optimization frameworks and tools for solar power generation systems with embedded Weather and Load Predictive Models, suited to an array of use cases spanning a wide time horizon, from hour- to multi-week ahead. The tactical or operational optimization tools can be used by solar farm asset managers or electric grid operators to optimize real-time solar power management tasks such as generation and balancing demand response schedules. By leveraging the experience and models learned with tactical planning to make probabilistic forecasts about demand or associated uncertainty weeks to months ahead, the strategic optimization framework can be used by solar energy investors to understand the stochastic or reliable generation potential of their investments or the extent to which pairing these assets with battery storages can hedge against uncertain market prices, and develop their operational dispatching methods accordingly. The multiple use cases and AI tunable models of our frameworks provide a flexible and extensible probabilistic and optimization foundation on which to perform optimal solar energy management across multiple temporal hierarchical layers, helping advance operational and market-based solar energy integration into the electric grid, and enabling deployments maximizing the socio-economic benefits for different stakeholders.

International Journal of Advanced Research in Computer and Communication Engineering
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The cost shares structures of trading markets that provide trading incentives for these stakeholders to coordinate their solar energy management and the tuning of the frameworks that would drive stakeholders to contribute towards the coordination and relative scalability of the proposed AI-based solar integration framework are among the many questions in direction of market integration of battery energy storage systems with solar assets that we believe require further investigation before they can be developed and deployed at their true potential within the multi-objective space of solar management systems.

8.2. Challenges and Limitations

Although the research in AI-Driven Optimization of Solar Power Generation Systems Through Predictive Weather and Load Modeling has illustrated the advantages and performance benefits of the introduced AI-driven predictive optimization approach, the contributed systems face a number of challenges and limitations with real-world implementation that are detailed in this section. Although the research in the area of AI-driven solar power generation optimization is still relatively new and unexplored, the focus in such early explorative research works naturally comes with the limitation that it serves only more as a proof of concept. Although it has shown promising results, it is still an early explorative stage system that is not yet ready for fully-fledged real-world deployment and requires testing, refinement, and improvement with real-world data.

Further, the operationalization of such predictive optimizer systems for practical real-world applications in closing the simulation-reality gap imposes several intricate and often complex practical challenges that result from the complex nature and multitude of interdependencies of such real-world problem settings. The proposed predictive optimizer system operates under the assumption that output decision variable profile such as the hourly solar PV panel tilt angle adjustment plans can be determined once at the start of each day in a deterministic manner for the entire day, which can be practically operationalized in a solar energy service provider context that calculates and publishes these solar energy provider configuration plans for all of its service-provisioning clients to use and implement.

8.3. Future Research Directions

The area of predictive modeling for solar generation and load forecasting is broad and multifaceted. Different research directions opening to explore within that area are reviewed in the following subsections. Nevertheless, the research agenda is not exhaustive; we invite the readers to explore further the challenges, open areas of investigations and questions pointed in the different subsections.

There are many areas in research and innovation for solar energy management that require further investigation in terms of predictive modeling for solar generation and load forecasting. Some areas in relation to predictive modeling for forecasting solar energy generation aimed at energy management include: further investigation for regression, hybrid intelligence, and ensemble approaches; domain adaptation and transfer learning specifically aimed to predictive learning and modeling for solar generation forecasting; cloud cover development and anemological predictive modeling studies for dynamic solar generation modeling; discovering physical driven glass ceiling gate models using AI, and solar glass models; semi-transparent solar glass; use of transparent solar concentrator glass; glass cover dust accumulation studies; temporal modeling studies of PV temporal responses due to temperature changes; automation of forecasting operational model selection; self-adaptive operational model selection and switching mechanism; and operational model horizon adjustment studies.

There are also many areas in research and innovation for predictive modeling for electricity demand management that require further investigation, including, but not limited to: demand data geolocation and disaggregation; hybrid intelligence modeling to disaggregate, predict and forecast electricity demand patterns; long-term short-term combined predictive modeling for electricity demand management; automation of predictive modeling and error diagnostics tasks; self-adaptive model switching diagnosis and error correcting methods; self-scaling operational load model selection and prediction horizon adjustments; and root analysis of short-term load changes.

IX. CONCLUSION

Advanced digital technologies are revolutionizing every sector, and the energy sector is no exception. The vast capabilities that exist alongside Artificial Intelligence may optimize traditional resources, such as fossil fuels, natural gas, and nuclear sources, or advance the deployment, operation, and maintenance of renewable energy sources. The great goal for the next years is to eliminate the carbon footprint that is mainly produced by the fossil fuels. In that path, the solar power generation is essential and allows to produce energy in every corner of the earth. With the current advancements of photovoltaic technology, it is possible to reach an acceptable efficiency in a variety of situations, but the question is at which cost. Not only the manufacturing costs are important, but also the investment costs regarding space occupation, maintenance, and operation.

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This paper examined current research efforts regarding the optimization of solar power generation systems through advanced technologies and proposed a system-oriented approach that applies these new opportunities presented by neuroscience artificial intelligence and Internet of Things technologies. The presented simulation framework is proposing predictive probabilistic modeling tools for boundary condition and load modeling for the development of controllable spatial-temporal optimal management planning and advanced exploration of solar power generation. Through the advanced implementation of the proposed system, the current optimization problem may evolve from a deterministic approach into a deterministic chaotic one. The appeal of the proposed modeling is that it is open-ended, i.e., it is possible to include any challenging predictive modeling or exploration procedure, from classical heuristic searching procedures that do not guarantee a solution to dynamic search-based advanced parallel implemented equilibrium meta-symbolic control for an arbitrary convergence to an optimal solution.

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