Analysis of the Application and Potential of Renewable Energy in Landscape Architecture

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***Abstract*—The field of landscape architecture is constantly evolving to address sustainability and climate change. There is a rising chance to use these technology into landscape design as renewable energy sources become more prevalent. An effective technique for evaluating the possibility of incorporating renewable energy management into landscape architecture is currently required. As a result, decision-making procedures are now manual and subjective, requiring greater precision and consistency. Deep learning algorithms can be used to examine the possibilities for renewable energy management in landscape architecture, which would help to solve this problem. Deep learning is a branch of artificial intelligence that automatically extracts complicated relationships and patterns from data using multi-layer neural networks. With inputs like topography, solar radiation, and climate, the algorithm can determine where in a particular landscape renewable energy installations would be most effective.**

***Keywords*—Landscape architecture; sustainability; renewable energy; decision-making; deep learning; artificial intelligence**

I. Introduction

The term "renewable energy management" in landscape architecture describes the process of integrating sustainable energy systems and sources into outdoor area management and design [1]. The objective of this method is to mitigate the adverse effects of human activities on the environment and simultaneously meet user energy needs, so fostering a harmonious balance between the built and natural environments [2]. Concerns about climate change and the depletion of non-renewable resources have made it more and more necessary to incorporate renewable energy sources into landscape architecture [3]. Landscape architects have a crucial role to play in managing energy resources as they possess the skills and knowledge to create and maintain outdoor spaces that are both functional and environmentally friendly [4]. One of the critical aspects of renewable energy management in landscape architecture is incorporating design elements that utilize natural resources such as sunlight, wind, and water [5]. It can include the placement of buildings and structures to maximize solar gain for heating and lighting, the installation of wind turbines to generate electricity, and the use of hydroelectric systems to power water features. , landscape architects are also responsible for managing the energy consumption of outdoor spaces through the use of efficient systems and technologies [6]. It can include the implementation of energy-efficient lighting, irrigation systems, and other technologies that reduce energy consumption and promote sustainability [7]. In order to encourage the adoption of sustainable energy sources and methods, landscape architects must also engage in stakeholder education and engagement as part of renewable energy management [8]. Incorporating renewable energy into outdoor spaces with customers, educating the public about the advantages of renewable energy, and pushing for laws and policies that encourage its usage in landscape design are a few examples of what it might include [9]. Landscape architecture can create stunning and useful outdoor areas that benefit people and the environment while simultaneously reducing the negative effects of human activity on the environment by putting into practice an integrated approach to renewable energy management [10]. Because of its ability to lessen the effects of climate change, lessen reliance on non-renewable resources, and advance sustainable development, renewable energy has drawn more attention recently [11]. Consequently, many landscape architects now consider it a top priority to include renewable energy sources into their designs. However, there are a number of obstacles to overcome and a number of technical considerations that must be carefully taken into account when implementing renewable energy management in landscape architecture [12]. The planning and selection of sites is one of the main problems with renewable energy management in landscape architecture [13]. Renewable energy systems require access to wind and sunshine, thus landscape architects must carefully evaluate the site's constraints in order to select the best renewable energy technology [14]. It can be a challenging undertaking, particularly in metropolitan areas where there are limited space and potential shadows from nearby buildings. Integrating renewable energy technologies with the overall landscape design presents another difficulty [15]. Infrastructure for renewable energy, such wind turbines and solar panels, can detract from the landscape's natural beauty and be aesthetically unsettling. The aesthetic impact of these structures must be taken into account, and landscape architects must make sure they blend in seamlessly with the overall design. The following constitutes the paper's primary contribution:

1) Integration of renewable energy systems: The integration of renewable energy systems, such solar panels, wind turbines, and geothermal systems, into the planning and development of the built environment is known as renewable energy management in landscape architecture.

2) Enhancement of landscape performance: Incorporating renewable energy systems into landscape design can also contribute to the improvement of landscape performance. For example, using solar panels to power outdoor lighting or irrigation systems can reduce energy consumption and decrease the carbon footprint of the site.

3) Promoting sustainability: One of the primary goals of landscape architecture is to create sustainable and resilient environments. By incorporating renewable energy management into design, landscape architects can contribute to the reduction of carbon emissions and promote sustainable practices for the built environment.

The next chapters make up the remainder of the research. The most current research-related efforts are described in Section II. The suggested model is explained in Section III, and the comparative analysis is covered in Section IV. Ultimately, Section V presents the findings, and Section VI discusses the study's conclusion and future directions.

II. Related Works

The smart framework, a revolutionary method for constructing green roofs in buildings that take into account both energy conservation and thermal comfort, has been explored by Mousavi, S., et al. [16]. It incorporates a number of variables, including building attributes, plant preferences, and temperature conditions, to maximize design efficiency and yield the highest possible gains in thermal comfort and energy efficiency. The intelligent landscaping framework, as described by Jiao, Y., et al. [17], suggests incorporating green infrastructure into the design of net-zero-energy smart cities. This entails combining natural systems like rain gardens, green roofs, and urban forests with renewable energy technologies and sustainable building materials. This strategy seeks to lessen energy use while fostering a resilient and sustainable urban environment. M. Zekić-Sušac et al. [18] have talked about A data-driven strategy called machine learning is used to manage energy efficiency in the public sector. It leverages models and algorithms to examine patterns in energy consumption and optimize energy use in infrastructure and public buildings. It is a useful instrument in the creation of smart cities since it can result in large cost and energy savings. In an integrated energy-water optimization model for buildings, data mining with 12 machine learning algorithms has been discussed by Javanmard, M. E., et al. [19] as a way to help anticipate expenses and carbon dioxide emissions. Large datasets can be analyzed by algorithms like decision trees and neural networks to find patterns and trends. This allows for the optimization of water and energy use in buildings, which lowers expenses and lowers carbon emissions. An IoT-enabled integrated system for green energy in smart cities, which combines sophisticated technologies like automation, data analytics, and sensors with renewable energy sources, has been covered by Zhang, X., et al. [20]. By making cities more efficient and habitable, I contribute to the optimization of energy production and consumption, the reduction of carbon emissions, and the promotion of sustainable growth. How machine learning algorithms can predict the effects of changes in land use and land cover on seasonal urban thermal features has been covered by Kafy, A. A., et al. [21]. These algorithms predict changes in urban thermal patterns by analyzing data on changes in land use and cover as well as environmental factors. This helps to influence urban planning and lessen the effects of climate change. The topic of smart city landscape design for reaching net-zero emissions has been covered by Liu, M., et al. [22]. In order to replicate and assess energy consumption, carbon emissions, and other environmental aspects, a digital twin model of the city must be created. In order to achieve the city's objective of net-zero emissions, it enables effective planning and the implementation of sustainable solutions. Jia, Y., et al.'s discussion of machine learning's revolutionary impact on nanomaterial design and discovery may be found in [23]. We are able to forecast and enhance the characteristics and behavior of these materials by utilizing algorithms and data analysis. It significantly cuts down on the time and expense needed for experimentation, which speeds up advancements in the field of nanotechnology. According to Mazzeo, D., et al. [24], data on energy production and consumption patterns can be utilized to monitor and forecast a clean energy community's performance through the application of artificial intelligence (AI). Artificial intelligence (AI) algorithms can analyze this data and find trends and patterns, which may be used to optimize the community's use of clean energy and make more accurate projections about future energy requirements. Zhong, T., and others [25] have talked about In order to evaluate the viability of mounting solar panels on noise barriers in urban areas, satellite photos are analyzed as part of the street-view imaging assessment process for solar photovoltaic potentials on urban noise barriers. This approach can be used to support sustainable urban development and find appropriate sites for the production of renewable energy. IoT-based smart and intelligent smart city energy optimization, which uses networked devices and sensors to intelligently and effectively control energy usage in a city, has been covered by Chen, Z., et al. [26]. In order to reduce energy waste and increase sustainability, it entails gathering and evaluating data in order to make well-informed decisions and modifications. In a smart city, it enables more economical and ecological energy consumption. Engine combustion system optimization, which uses machine learning and computational fluid dynamics to study and enhance an engine's combustion process, has been covered by Badra, J. A., et al. [27]. With this method, engine components can be efficiently designed and tuned, leading to increased fuel efficiency, emissions, and performance. The topic of sustainable power management in light-electric cars has been covered by Punyavathi, R., et al. [28]. This entails optimizing energy use and extending the life of the batteries in the cars by combining machine learning control with hybrid energy storage systems. This strategy lowers operating and maintenance expenses while ensuring effective and environmentally responsible transportation. G. Palma et al. [29] have talked about Reinforcement learning is a subfield of machine learning that centers on optimizing rewards within a particular context. It can be applied to energy community management to optimize energy use and cost by drawing lessons from the past and modifying plans as necessary. This approach has been applied in a large-scale study across Europe to improve energy efficiency and management in communities. Wang, H., et al.[30] have discussed Smart Cities Net Zero Planning in Digital Twin involves creating a virtual model of a city to simulate different renewable energy scenarios and optimize its design for maximum energy efficiency. It helps in planning for a sustainable, low-carbon future and ensures that the city's energy needs are met through renewable sources (Table I).

1) Insufficient technological knowledge: Many landscape architects need more technical knowledge and expertise in renewable energy technologies. It can lead to inefficient and ineffective implementation of renewable energy systems in landscape projects.

2) Site-specific challenges: Renewable energy technologies are sensitive to site-specific conditions such as landscape topography, wind patterns, and solar orientation. Landscape architects need to have a deep understanding of these site-

TABLE I. COMPREHENSIVE ANALYSIS

Authors	Year	Advantage	Limitation
Mousavi, S., et. al [16]	2023	Minimizes energy consumption and promotes thermal comfort while improving building aesthetics and sustainability.	Sensitivity to local climate and building characteristics may limit the applicability of the framework to certain regions or structures.
Jiao, Y., et. al [17]	2024	The ability to reduce energy consumption and promote sustainability by incorporating green spaces and vegetation into city design.	Dependence on implementation of other smart city technologies and cooperation between various government and private entities for efficacy.
Zekić-Sušac, M., et. al	2021	One potential advantage could be the ability to analyze complex data and make accurate predictions for energy consumption and cost savings.	The potential for bias and lack of transparency in decision-making due to the "black box" nature of machine learning algorithms.
Javanmard, M. E.,et. al [19]	2021	An integrated energy-water optimization model for buildings may accurately anticipate expenses and carbon dioxide emissions by utilizing data mining with twelve machine learning algorithms.	One limitation is the reliability of the input data used for training the algorithms, which may affect the accuracy of the predictions.
Zhang, X., et. al [20]	2021	The seamless integration of IoT technology allows for efficient monitoring and management of renewable energy sources, reducing reliance.	High initial investment cost for implementation and maintenance may limit its scalability and accessibility to some cities.
Kafy, A. A., et. al [21]	2022	Because machine learning algorithms are fast and effective at anticipating how changes in land use will affect urban thermal features, they can save time and money.	A limitation is the inability of machine learning algorithms to account for unpredictable or unknown factors that may influence thermal characteristics.
Liu, M., et. al [22]	2024	Improved accuracy in predicting energy use and minimizing waste by simulating building and infrastructure performance in a virtual environment.	One limitation is that digital twin modeling can be expensive and time-consuming to create and maintain for large or complex cities.
Jia, Y., et. al [23]	2021	To help scientists create innovative, effective, and functional nano materials, machine learning can analyze enormous datasets and spot trends.	One limitation is the reliance on training data, which can lead to biased and incomplete representations of nanomaterial properties.
Mazzeo, D., et. al [24]	2021	AI applications can quickly and accurately analyze complex data sets, providing valuable insights for optimizing energy usage and reducing costs in clean energy communities.	The accuracy of AI predictions may be impacted by rapidly changing external factors that are difficult to predict.
Zhong, T., et. al [25]	2021	Cost-effective: Using readily available street-view imagery eliminates the need for expensive on-site surveys, making the assessment more affordable for cities.	Possible limitation: Inability to accurately reflect localized variations in light availability or shading caused by nearby buildings or other obstructions.
Chen, Z., et. al [26]	2022	Improved energy efficiency and reduced costs through real-time data analysis and auto mation of energy usage in buildings and infrastructure.	Limited access to IoT devices or technology may result in unequal energy optimization across the city.
Badra, J. A., et. al [27]	2021	Improved efficiency and performance by accurately predicting and optimizing engine combustion conditions based on data-driven and simulation-based methods.	Inability to account for all variables and uncertainties in the complex and dynamic nature of engine combustion.
Punyavathi, R., et. Al [28]	2024	Optimized energy usage and longer battery life resulting in reduced environmental impact and cost savings for the owner.	Sustainable power management in light-duty electric vehicles with hybrid energy storage and machine learning control may be hampered by the high cost and complexity of integrating numerous energy storage systems.
Palma, G., et. al [29]	2024	One advantage of Reinforcement Learning is its ability to continuously adapt and improve energy community management strategies over time.	Reinforcement Learning heavily relies on accurate and complete data, which can be difficult to obtain in real-world energy community management scenarios.
Wang, H., et. Al [30]	2024	By precise and timely monitoring of the digital twin, Smart Cities Net Zero Planning aids in the reduction of carbon emissions and maximizes the use of renewable energy resources.	Inability to accurately predict the future performance of renewable energy systems due to changing environmental and technological factors.

specific challenges to integrate renewable energy systems into their designs effectively.

3) Integration challenges: Integrating renewable energy systems into landscape designs can be a complex process. Landscape architects need to consider various factors such as aesthetic, social, economic, and environmental impacts while integrating these systems, which can be a significant challenge.

A subset of artificial intelligence called "deep learning" has been more well-known in recent years as a result of its amazing capacity to manage complicated data and jobs with little assistance from humans. Deep learning fundamentally makes use of a multilayered artificial neural network to learn from and forecast large volumes of data. This algorithm's true depth is found in its technological originality. Deep learning algorithms are more precise and efficient than typical machine learning methods because they can automatically extract complicated features from data without the need for human interaction.

III. PROPOSED SYSTEM

A. Construction Diagram

1) Phasor measurements: Phasor measurements involve using a device called a phasor measurement unit (PMU), which can measure the magnitude and phase angle of an electrical signal at a specific point in the power system. These measurements are taken at a very high frequency (typically 30-60 samples per second) and are synchronized with other PMUs connected to the same power grid. This allows for creating a synchronized network of measurements, known as a synchrophasor system. The PMUs use GPS timing to ensure that all measurements are taken simultaneously, regardless of the physical distance between the PMUs.

The quantity of energy produced by a WT energy system can be stated as a

$$F_{zf}(v) = \frac{1}{2} \times S \times I_j \times Z_q^3(v) \tag{1}$$

Both the air density and the turbine blade area are indicated by, respectively.

The total daily energy consumption of all electrical appliances is listed below:

$$G_V^b = \sum_{v=1}^{V} G_d^b(v) \tag{2}$$

The cost of energy can be estimated using a variety of pricing techniques, giving consumers flexibility and options.

They include time-of-use pricing, real-time pricing, critical peak pricing, and critical peak rebates.

This synchronization is crucial for accurate measurements, as it eliminates the time delays in traditional measuring devices, such as SCADA systems. Once the signals are measured, they are converted into phasor values, consisting of a magnitude and phase angle, representing the electrical signal's strength and direction. These phasor values are then transmitted over a communication network to a central data repository, where they are time-stamped and aggregated with measurements from other PMUs.

2) Topology processor: The Topology Processor is a central component of modern computer systems that is responsible for managing the connections and relationships between different system elements. It plays a critical role in maintaining the system's structural integrity and ensuring efficient communication between components. At its core, the Topology Processor is a software layer that sits on top of the system's hardware components. It uses information from the hardware and other software layers to construct a hierarchical map of the system's components and their interconnections. This map is referred to as the system's topology. One of the main functions of the Topology Processor is to keep track of changes in the system's topology. As components are added or removed or connections between components are established or broken, the Topology Processor updates the topology map accordingly.

In this sense, linear equations (LTI) can be used to model the system that needs to be regulated as a discretetime state space. These equations are as follows:

$$H(y+1) = J_b h(y) + I_b o(y) \tag{3}$$

$$k(y) = D_b h(y) + C_b o(y) \tag{4}$$

where it the symbols u represent vector values for multiple inputs, x stand for state vectors for the RES, y for output vectors, B for input matrix, A for state matrix, C for output matrix, and D for feedforward matrix.

This is crucial for maintaining the accuracy of the map and ensuring that all system components are correctly identified and connected. Another critical aspect of the Topology Processor's operations is its ability to optimize the communication between components. It does this by analyzing the topology map and identifying the shortest and most efficient paths for data to travel between components. This is particularly important in large and complex systems, where data may need to pass through multiple layers of components before reaching its destination.

3) Pseudo measurements: Pseudo-measurements are a standard tool used in data analysis to account for uncertainties and improve the accuracy of results. They involve incorporating additional measurements into the data analysis process that are not actual physical measurements but simulated values based on statistical analysis and assumptions. These pseudo-measurements can offer insightful information and enhance data comprehension, making them an effective tool in physics, engineering, and data science, among other disciplines. Fig. 1 displays the construction diagram.

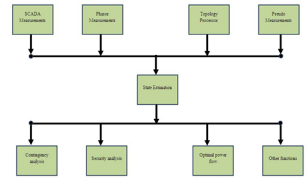

Fig. 1. Construction diagram.

The basic principle of pseudo-measures is to add artificial data points to the existing dataset to improve the final result's accuracy. This is done using statistical models or algorithms to generate simulated values that closely resemble the data. These simulated values are then included in the overall data analysis process, giving a more comprehensive and refined understanding of the data. One of the main advantages of using pseudo-measurements is that they can account for uncertainties in the data. Real-world measurements are only partially accurate, and there is always a degree of uncertainty associated with them. To calculate how much money is spent daily on the cost of energy to run household equipment, use the following equation:

$$D_V^{fg} = G_V^{fE} \times \varphi(v) \tag{5}$$

where, Cpe T is a symbol that shows the price of power for each time slot as well as the total cost of electricity for home appliances.

The limiting factor that was applied is identified by the equation. The constraint applied is this equation.

$$h_{b,y} = O\left(1_y, of_y\right) \tag{6}$$

The notation (np(ex)) represents the neighbors in the explosion process for verification purposes. This may be located in the cited work.

$$mf(ex) = mf \times gi \times gd \tag{7}$$

In this sense, the variables for represent the explosion counter, eb is the explosive base, and np stands for points of.

A more accurate outcome can be obtained by taking this uncertainty into account and lowering it with the use of pseudo data produced by statistical techniques.

4) Contingency analysis: Contingency analysis is a critical operation in power system analysis, used to evaluate the security and reliability of the power grid under various abnormal or unforeseen conditions. It involves simulating the system behavior by considering multiple contingencies such as equipment failures, unexpected outages, and load or generation pattern changes. The primary purpose of contingency analysis is to assess the impact of these contingencies on the power system, identify potential vulnerabilities, and recommend preventive or corrective measures to maintain grid stability.

An illustration of how to phrase our optimal problem is as follows:

$$Obj = \min\left(\sum_{v=1}^{v} G_{bill}(v) - (\varphi_e(v) + BSS(v))\right) \quad (8)$$

The electricity consumed by each of the following appliances-both schedule-able and not-is added up to produce its E-bill:

$$G_{bill}(v) = \left(A_1^{sch}(v) + J_1^{nsch}(v)\right) \times EP(v) \quad (9)$$

The first step in contingency analysis is establishing a baseline power system model. This model includes all the grid components, such as generators, transmission lines, transformers, loads, and their physical and electrical characteristics. After that a steady-state power flow analysis is performed on the baseline model to ascertain the system's basic operating parameters, such as voltage levels, active and reactive power flows, and system losses. Several contingencies are added to the baseline model after it has been created in order to replicate the effects of various disturbances on the grid. These contingencies can be categorized into two types: single and multiple contingencies. A single contingency refers to the failure of one component in the system, while various contingencies involve the simultaneous failure of multiple components.

5) Security analysis: A security analysis assesses the prospective worth and dangers of a variety of financial products, including derivatives, equities, and bonds. To make well-informed investment selections, it carefully looks at market trends, company-specific data, and economic and financial statistics. Gathering pertinent information is the initial stage in the security analysis process. The financial statements of the business, the management team, market trends, and economic indicators are all included in this. Gaining a thorough understanding of the company's financial situation and market standing is the goal. The next step after gathering data is to evaluate it using a variety of methods and resources. In security analysis, market, technical, and fundamental analysis are the approaches that are most frequently employed.

What is meant by PAR, or maximum usage in relation to total load consumption during a time slot t during the allotted period, is the proportion of peak load.

which Eq. (1) illustrates, "yi" represents both the true value and the expected value for the sample.

$$MSE = \frac{1}{n}\sum_{b=1}^{m}\left(\hat{k}_b - k_b\right)^2 \quad (10)$$

To make the model simpler, more pruning or modification can be applied. As the name implies, pruning is the act of cutting off branches that do not considerably lower the cost function.

In this instance, bootstrapping is used, when samples are taken from the same population or set of data repeatedly. This method is known as "bagging".

$$F_{bag} = \frac{1}{i}\sum_{b=1}^{i} f_b \quad (11)$$

The fact that every decision tree trained for the prediction may have a high correlation is one of the disadvantages of bagging.

To ascertain the profitability, revenue growth, and financial stability of the organization, fundamental analysis entails looking over the financial statements. It also entails assessing the management group, competitive edge, and potential for future expansion of the business. This assists investors in determining if a stock is overvalued or undervalued and in making wise investment choices. In contrast, technical analysis employs historical market trends and patterns as a means of forecasting future price changes. Technical indicators, trend lines, and charts are used to find buying and selling opportunities.

6) Optimal power flow: A crucial optimization method for power networks, optimal power flow (OPF) establishes the most affordable and efficient way to dispatch power generation and transmission. It ensures the power system operates safely and dependably while assisting in reducing the overall cost of electricity generation. We will go into great detail on OPF's operations in this paragraph. OPF's primary goal is to reduce the overall cost of power generation while meeting a variety of requirements, including equipment limitations, load demand, voltage and frequency limits, and restrictions.

Bayesian techniques adjust the probability distribution to effectively identify potential concepts without over-fitting.

$$F(J \mid I) = f(I \mid J)\frac{F(J)}{F(I)} \quad (12)$$

Naive Bayes, multinomial Naive Bayes, Gaussian naive Bayes, Bayesian network, a mixture of Gaussians, and Bayesian belief network are a few of the most widely used algorithms.

It is a nonlinear optimization problem that takes into account the various power system components' operational characteristics, including transformers, transmission lines, and generators. Finding the best power generation schedules for each of the system's generators is the first stage in the OPF process. The power flow equations, which are nonlinear equations that depict the link between power generation, load demand, and network factors (such as impedance and admittance), are solved in order to do this. For every bus in the system, the ideal generator output is found by solving the power flow equations. The best way to dispatch power across the transmission network is to figure out the generator schedules that operate best.

B. Functional Working Model

1) Energy Management Centre: The Energy Management Centre (EMC) is a critical component of the modern electric power system and ensures a reliable and efficient supply of electrical energy to end users. It is a centralized facility that uses advanced technologies and sophisticated algorithms to monitor, control, and optimize the utilization of energy resources. EMC's first and foremost task is to monitor the energy demand and supply in the system. This is achieved by collecting real-time data from various sources, such as power plants, transmission lines, and end-user consumption. The data is transmitted to the EMC through high-speed communication networks and is continuously analyzed to identify the energy demand patterns and potential issues.

The radial basis function, 54 perception methods, back-propagation, and feedforward propagation are examples of frequently used ANN learning algorithms.

$$x_b^n = \sum_{a=1}^{M_x^{n-1}} Z_{ba}^n \cdot k_a^{n-1} + i_a^n, \tag{13}$$

$$k_b^n = J\left(x_b^n\right). \tag{14}$$

Eq. (4) and (5) are utilized to compute the ANN's output, which is displayed in Fig. 4. Let M be the number of layers and Nm h be the number of nodes in each layer. In this case, common features can be determined by resolving the following optimization problem:

$$\min_{z} \text{mizize} \sum_{b=1}^{m} R_b(Z) + \lambda \|Z\|_p^2 \tag{15}$$

where W is the feature matrix, or shared low-dimensional representation. is the task's loss function, which uses the shared representation to gauge how well the model performed on that particular job.

Based on the analysis, EMC predicts the future demand for electrical energy and establishes a plan to meet that demand. This involves coordinating with power plants and strategically dispatching power to different regions to ensure a stable and reliable electricity supply. Furthermore, EMC also ensures that the energy production is within the system's capacity and avoids overloading of transmission lines. As part of its operations, EMC also utilizes sophisticated control systems to regulate the frequency and voltage levels of the grid. This is crucial for the proper functioning of electrical equipment and prevents damage to the grid.

2) Main grid: The Main Grid, also known as the virtual or global grid, is a fundamental infrastructure component of modern power systems. It aims to facilitate efficient and reliable electricity transmission from power generation sources to consumers. The grid is made up of a system of transformers, high-voltage power lines, and other devices that link power plants to distribution networks and, eventually, to final consumers. Power generation is the initial stage of the primary grid's operation. Power plants generate electricity that is fed into the system using fuels like coal, natural gas, nuclear, and renewable energy. The functional block diagram is displayed in Fig. 2.

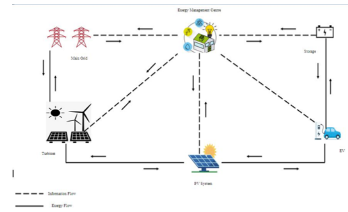

Fig. 2. Functional block diagram.

The amount of electricity produced must closely match the demand from consumers, as any imbalance can result in blackouts or damage to equipment. Once the electricity is generated, it is transmitted through the primary grid at high voltages to reduce energy loss over long distances. The primary grid is divided into different regions, each with its transmission operator responsible for managing the flow of electricity within its boundaries. The viscous Burgers' equation, which may be expressed as follows, can be utilized to solve forward problems using the PINN model, demonstrating the model's effectiveness:

$$\frac{\partial o}{\partial v} + \eta \frac{\partial o}{\partial x} = t \frac{\partial^2 o}{\partial h^2} \tag{16}$$

where u is the unknown function that we are trying to identify given x and t The variable, m , is a constant that is positive. The spatial variable is x.

One model's parameters are optimized during this procedure, while the others remain unchanged. For a fixed generator, a unique optimal discriminator can be identified, which is defined as

$$C^*(h) = F_{\text{data}}(h) / \left(f_{\text{data}}(h) + f_e(h)\right) \tag{17}$$

They also showed that when the generated data distribution, matches the original data distribution, pdata, the generator G operates at its best.

In order to preserve the stability and dependability of the system, these operators continuously monitor the grid and modify the flow of electricity. A network of communication centers and control centers is used by the primary grid to effectively regulate the flow of electricity.

3) Turbines: Devices called turbines are used to transform a fluid's energy into mechanical energy. They are extensively utilized in numerous industrial operations, aircraft propulsion, and power generation systems. A turbine's main function is to convert the kinetic energy of the fluid that passes through it into rotational motion. Energy conservation is the foundation for how turbines operate. This principle states that although energy cannot be generated or destroyed, it can change forms. The energy of a fluid (such as steam, water, or gas) is transformed into rotational motion in turbines.

The weighting coefficient is applied in the following equation in the same way as the preceding weighting coefficients to penalize these deviations in the cost function.

$$A_b^{slaxk} = \sum_n \gamma_n \epsilon_{n,b}^2 \tag{18}$$

These set-points could be biased, for instance, with the intention of penalizing deviations exclusively below the set-point rather than beyond it (this is especially pertinent in applications involving heating systems).

Below are the stages involved in calculating a FR and a class of the spring-affecting factor.

$$PL = \frac{J \mid I}{D \mid C} \tag{19}$$

In a typical turbine, the fluid enters through an inlet and passes through a set of stationary blades called stators. These blades direct the fluid towards the rotating blades, also known as rotors. The rotors are attached to a shaft, and as the fluid passes through them, it imparts its kinetic energy to the blades, causing them to rotate. The shape and design of the blades play a crucial role in the efficiency of a turbine. They are designed to extract the maximum energy from the fluid without causing excessive turbulence.

4) PV System: An energy conversion device that turns sunshine into electricity is a photovoltaic (PV) system. It is made up of multiple essential parts that cooperate to produce useful energy. The solar panels are the first part of a photovoltaic system. Individual solar cells, which are usually composed of silicon, make up these panels. An electric field is produced when sunlight strikes the solar cells, causing a reaction in the silicon atoms. Direct current (DC) electricity is produced by the flow of electrons caused by this electric field.

At the output layer, the desired output will be obtained. The signal will be delayed if the total output exceeds the threshold value. A synapse that is stronger has a higher weight than one that is weaker.

$$I = z_1 h_1 + z_2 h_2 + \ldots + z_m h_m \tag{20}$$

$$B = \sum_{b=1}^{m} z_b h_b \tag{21}$$

The inverter comes next, and it's what transforms the DC electricity from the solar panels into AC , or alternating current, which is the typical electricity used in buildings and homes. Electronics and home appliances require AC electricity to function. A meter, which gauges the quantity of electricity the PV system generates, is used to connect the AC electricity to the main grid.

The Newton-like update provides this approximation for the Hessian matrix in the LM algorithm:

$$H_{y+1-} H_y - \left[A^V A + \eta B\right]^{-1} A^V g \tag{22}$$

The Bayes theorem can be used to compute distribution.

$$F(z/C) = \frac{f(C/z) f(z)}{f(C)} \tag{23}$$

where $\mathrm{D} = \{\mathrm{t}\}\mathrm{n}$ is the collection of target vectors and w is the weight vector. This enables the owner of a business or residence to monitor the amount of energy they produce and use. Excess energy from the PV system can be stored in batteries for later use if it generates more electricity than is required. This maximizes the utilization of solar energy and is referred to as battery storage. It is growing in popularity.

C. Operating Principles

1) Initialization of search agents and of grey wolf: Search agents are optimization algorithms inspired by the behavior of animals or insects in nature. This algorithm finds the optimal solution or the best possible outcome for a given problem. To initialize search agents, the first step is defining the issue and its variables. This includes identifying the objective function, a mathematical function that calculates the value to be minimized or maximized, and the constraints, which are the conditions that must be met for the solution to be considered valid.

We must move in the direction of descent in order to calculate the step size. The weight and t-th gradient descent iteration are used to determine the step size.

$$z_b^{(v)} = z_b^{(v-1)} - \mu_b^{(v-1)^*} \operatorname{sgn}\left(\frac{\partial G^{(v-1)}}{\partial z_b^{(v-1)}}\right) \tag{24}$$

By using CGP updates, this function modifies the weights and bias values. The constant βk in the PolakRibiére update can be found via

$$\beta_y = \frac{e_{y-1}^V e_y}{e_{y-1}^V e_y - 1} \tag{25}$$

The ratio of the norm squared of the present gradient to the norm squared of the prior gradient is known as βk, and it is a positive scalar. The new gradient, gradients from the previous iteration, and the variation in the weights provided in equation determine the search direction in the subsequent iterations.

$$cN = -eN + Jd\left(N_{step}\right) + BC(dgm) \tag{26}$$

where Ac and scalar products are the gradient, dgM is the gradient change from the previous iteration, and Mstep is the change in the weights from the previous iteration.

The search agent algorithm employs a population of agents to search the search space and identify the best answer once the problem has been described. Each agent in the initial population of agents represents a collection of potential solutions to the problem, and they are formed at random. Subsequently, the algorithm determines each agent's fitness value, a measure of how successfully it solves the task. The search agents are directed toward the best answer by this fitness value, which is determined using the objective function. After creating and assessing the initial population, the algorithm starts its search. In order to do this, the agents must navigate the search space, iteratively modify their solutions, and evaluate their fitness values along the way.

2) Search agents findings: Search agents or search bots are computer programs designed to automatically search and retrieve information from the internet based on specific instructions or queries. These search agents are responsible for the functioning of search engines and play a crucial role in providing quick and accurate results to users. The operations of search agents can be broadly divided into three main phases: crawling, indexing, and ranking. The operational flow diagram has shown in the following Fig. 3.

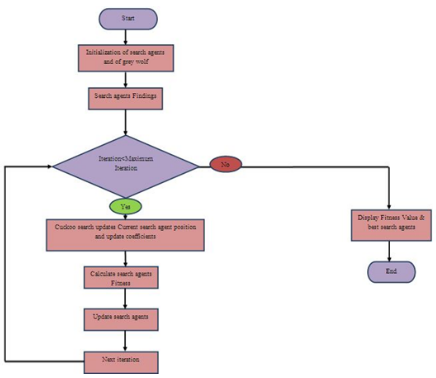

Fig. 3. Operational flow diagram.

Crawling is the process by which search agents scan the web and gather information about available web pages. This is done by following links from one web page to another and indexing their content. Initially, the search agent starts with a list of known URLs, usually provided by the search engine, and then explores the links on these pages to discover new URLs. This process is repeated continuously to ensure the search engine database remains up-to-date.

In this study, we examine general form parametrized and nonlinear partial differential equations:

$$o_v + M[o; \lambda] = 0, h \in \Omega, v \in [0, V] \tag{27}$$

where Ω is a subset of R D 86, $\mathrm{N}[\bullet; \lambda]$ is a nonlinear operator parametrized by λ, and $u(t, x)$ represents the latent (hidden) solution.

Starting with the first challenge mentioned above, let's focus on the problem of calculating data-driven to partial differential equations.

$$o_v + M[o] = 0, h \in \Omega \in [0, V], \tag{28}$$

where $\mathrm{N}[\bullet]$ is a nonlinear differential operator, $\mathrm{o(v,x)}$ represents the latent (hidden) solution, and $^{\mathrm{SM}}$ is a subset of R.

We define $\mathrm{p(v,h)}$ to be provided by equation's left side.

$$p := o_v + M[o] \tag{29}$$

Proceed by using a deep neural network to approximate $u(t, x)$. This plus Eq. (3) yield a neural net 115 work $f(t, x)$ that is influenced by physics.

The set 382 of divergence-free functions is searched for solutions to the Navier-Stokes equations:

$$o_h + t_k = 0. \tag{30}$$

The continuity equation for incompressible fluids, which 384 explains the conservation of, is this additional equation.

Indexing provides an organized method for quickly and effectively retrieving the data that was collected during the crawling phase. Finding and removing pertinent keywords and phrases from web pages, then saving them in a database, is the process of indexing. The terms and phrases function as pointers to the content of the web pages and aid in delivering pertinent search results to the user.

3) Calculate search agents fitness: Calculate search agents. Fitness is a function used to measure the effectiveness and performance of different search agents in optimization algorithms. This function receives as input the search agents, which are essentially a set of solutions to an optimization problem and evaluates their fitness or quality based on a fitness function. The first step of this operation is to define a fitness function, which represents the objective or goal an optimization algorithm is trying to achieve. This function takes in a solution or a set of solutions and returns a numerical value indicating how close the solution is to the optimal solution. The string governing equation in the continuum limit of the Fermi-Pasta issue. The formula is as follows:

$$o_v + \lambda_1 O o_h + \lambda_2 o_{hhh} = 0, \tag{31}$$

Where the unknown parameters are $(\lambda 1, \lambda 2)$. Normal and diffuse solar radiation, which varies according to the sun's location in the sky and the season, serves as the PV system's energy source. To determine the total radiation on the solar cell, apply Eq. (4).

$$B_V = B_i L_i + B_c L_c + (B_i + B_c) L_i \tag{32}$$

Where Rd is the tilt diffuse factor, Rr is the tilt factor for reflected solar radiation, and Ib is normal radiation and Id is diffuse solar radiation.

The fitness function can vary depending on the problem, but it should always be carefully designed to accurately evaluate a potential solution's quality. Once the fitness function is defined, the search agents are randomly generated and evaluated using the fitness function. A search agent's fitness is assessed by plugging its solution into the fitness function and obtaining a fitness value. This value is then compared to the fitness values of other search agents and used to rank their performance. The ranking of the search agents based on their fitness values is essential in determining which agents are the most promising and should be used to generate new solutions in the next iteration.

4) Next iteration: The next iteration is a programming concept that allows repeating a particular set of instructions or operations in a loop. It is a powerful tool that enables the execution of a specific block of code multiple times, with each iteration potentially producing a different outcome. The process of the Next iteration begins with the initialization of a loop, which defines the number of times the code will be repeated. Depending on the programming language used, this can be achieved through a for loop, while loop, or do-while loop. Once the loop is initialized, the program will start the first iteration and execute the instructions within the loop. The battery bank is in the charging state when the total HRES output exceeds the energy requirement; otherwise, it is in the discharging state. Eq. (19) can be used to determine the battery bank's charge quantity at time t.

$$G_I(v) = G_I(v-1)(1-\sigma) + \left(\frac{G_{EJ}(v) - G_R(v)}{\mu_{ivv}}\right)\mu_{\text{bat}} \quad (33)$$

where $\mathrm{EGA}(t)$ is the total energy produced by renewable energy sources after energy loss in the controller, and $\mathrm{EB(t)}$ and $\mathrm{EB(t-1)}$ are the charge quantities of the battery bank at the times t and $(\mathrm{t}-1)$.

The first step in each iteration is to check the loop's conditional statement. This statement determines whether the code / will continue to run or if the loop should terminate. If the condition is met, the next step is to execute the code within the loop. This can include mathematical calculations, string manipulations, or any other operations necessary for the program. After completing the instructions within the loop, the program will reach the end of the iteration and return to the beginning of the loop. Here, the conditional statement will be re-evaluated, and if the condition is still valid, the next iteration will commence.

5) Display fitness value and best search agents: The operation of Display Fitness Value is an essential step in any search algorithm. This function evaluates a particular or candidate solution's performance in the search space. It is often used to guide the search process and make decisions on the next best possible solution. The fitness value of a solution is determined by comparing it to a predefined objective or fitness function. This function rates each answer according to how well it meets the specified requirements. The answer is deemed to be better the greater its fitness value.

The total amount of charge and the health of the battery. The limitations indicated in equation apply to the battery bank's charge quantity.

$$G_{I_{\min}} \leq G_I(v) \leq G_{I_{\max}} \quad (34)$$

where the battery bank's maximum and minimum charge quantities are located.

The cost of energy is also influenced by capital costs, operating and maintenance expenses, the amount of energy produced annually, the depreciation period, the possibility of an equipment cost decline with increasing volume, etc. Eq. (27) provides a basic relation for cost calculation.

$$D_G = D_{\text{cap}} \times \frac{L}{G_{\text{Tot}}} + D_{o\&kN} \quad (35)$$

Where G Tot is the total amount of energy produced, CE is the energy cost, D Cap is the capital cost for the HRES generator and storage device, R is the yearly discount rate for capital expenses, and CO&M is the annual cost of operation and maintenance.

The search algorithm needs to iterate through each candidate solution and apply the fitness function to calculate the fitness value. This is typically done in a loop until a stopping criterion is met. Several search agents can be used to find the best solution in a search space. These include local search, global search, evolutionary algorithms, and artificial intelligence techniques such as genetic algorithms and neural networks. Local search agents focus on improving a single candidate solution by making small changes and evaluating its fitness value. This approach is suitable for solving problems where the search space is small, and the solution is close to its optimal value.

IV. Result and Discussion

The performance of proposed method Trust Region Policy Optimization (TRPO) have compared with Generative Adversarial Transformer Network (GATN), Restricted Boltzmann Machine (RBM) and Convolutional Deep Belief Network (CDBN).

A. Accuracy

In a landscape architecture project, this refers to the deep learning algorithm's capacity to precisely assess and forecast possible renewable energy sources. It is assessed by contrasting the predictions made by the algorithm with the real data. The accuracy comparison of the suggested and current models is displayed in Table II.

TABLE II. Comparison of Accuracy (in %)

No. of Images	GATN	RBM	CDBN	TRPO
100	77.13	72.79	83.92	88.16
200	71.27	70.63	77.95	88.25
300	72.41	68.92	76.46	88.33
400	71.27	66.06	73.22	88.38
500	70.39	64.49	73.94	88.42

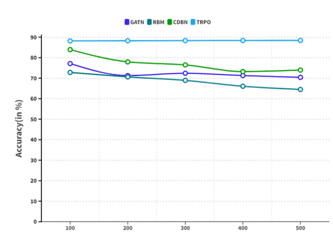

Fig. 4. Comparison of accuracy.

Fig. 4 shows the comparison of Accuracy. In a computation cycle, the existing GATN obtained 70.39 %, RBM obtained 64.49 %, CDBN reached 73.94 % Accuracy. The proposed TRPO obtained 88.42 % Accuracy.

B. Speed

The processing speed of the algorithm is another important technical performance parameter. It determines how quickly the algorithm can analyze and identify potential renewable energy sources, which is crucial in time-sensitive projects. Table III shows the comparison of Speed between existing and proposed models.

TABLE III. COMPARISON OF SPEED (IN %)

No. of Images	GATN	RBM	CDBN	TRPO
100	75.13	81.79	78.92	86.16
200	69.27	79.63	72.95	86.25
300	70.41	77.92	71.46	86.33
400	69.27	75.06	68.22	86.38
500	68.39	73.49	68.94	86.42

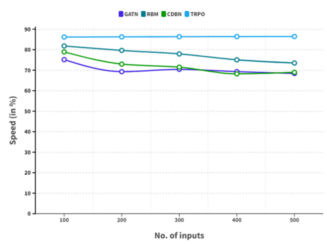

Fig. 5. Comparison of speed.

Fig. 5 shows the comparison of Speed. In a computation cycle, the existing GATN obtained 68.39 %, RBM obtained 73.49 %, CDBN reached 68.94 % Speed. The proposed TRPO obtained 86.42

C. Scalability

As landscape architecture projects can vary in size and complexity, the deep learning algorithm used for potential analysis of renewable energy management should be able to handle large and diverse datasets. This parameter refers to the algorithm's ability to scale and efficiently handle increasing data. Table IV shows the comparison of Scalability between existing and proposed models.

TABLE IV. COMPARISON OF SCALABILITY (IN %)

No. of Images	GATN	RBM	CDBN	TRPO
100	71.13	83.79	81.92	90.16
200	65.27	81.63	75.95	90.25
300	66.41	79.92	74.46	90.33
400	65.27	77.06	71.22	90.38
500	64.39	75.49	71.94	90.42

Fig. 6 shows the comparison of Scalability. In a computation cycle, the existing GATN obtained 64.39%, RBM obtained 75.49%, CDBN reached 71.94% Scalability. The proposed TRPO obtained 90.42 % Scalability.

D. Robustness

The algorithm's ability to handle unexpected or noisy data is essential for accurate and reliable predictions. It should withstand variations in data inputs and still produce consistent results. This parameter is crucial for the algorithm's overall performance and reliability in real-world applications. Table V shows the comparison of Robustness between existing and proposed models.

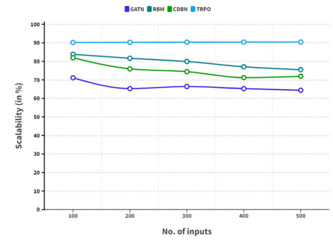

Fig. 6. Comparison of scalability.

TABLE V. COMPARISON OF ROBUSTNESS (IN %)

No. of Images	GATN	RBM	CDBN	TRPO
100	81.13	73.79	75.92	82.16
200	75.27	71.63	69.95	82.25
300	76.41	69.92	68.46	82.33
400	75.27	67.06	65.22	82.38
500	74.39	65.49	65.94	82.42

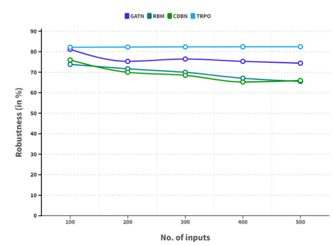

Fig. 7. Comparison of robustness.

Fig. 7 shows the comparison of Robustness. In a computation cycle, the existing GATN obtained 74.39%, RBM obtained 65.49%, CDBN reached 65.94% Robustness. The proposed TRPO obtained 82.42 % Robustness.

V. CONCLUSION

In conclusion, the potential of renewable energy management in landscape architecture can be greatly enhanced through the use of deep learning algorithms. These algorithms have the ability to accurately predict and optimize renewable energy generation in a given landscape, leading to more efficient and sustainable use of resources. Additionally, by incorporating renewable energy management into landscape architecture, we can create environmentally conscious and aesthetically pleasing designs that contribute to the larger goal of transitioning to a renewable energy future. Further research and implementation of deep learning algorithms in landscape architecture is necessary in order to fully utilize the potential of renewable energy in our built environment.

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Conflicts of Interests

Authors do not have any conflicts.

Data Availability Statement

No datasets were generated or analyzed during the current study.

Code Availability

Not applicable.

Authors' Contributions

YaWei Wu, is responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Xiang Meng, is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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