An Intelligent Web-based Energy Management System for Distributed Energy Resources Integration and Optimization

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Abstract

The integration of renewable energy sources into power distribution systems frequently presents challenges for conventional energy management systems (EMS) due to the unpredictable and unstable characteristics of such energy sources. As a result, novel and cutting-edge solutions are required. This paper presents an intelligent web-based energy management system (iW-EMS) specifically designed to address the integration and optimization of distributed energy resources, as outlined in the proposed approach. The system incorporates a hybrid novel optimization approach that integrates simulated annealing and cone programming to effectively manage the distribution of energy resources and attain optimal outcomes from the proposed EMS. Additionally, it leverages generative AI services to create optimal scenarios based on historical data and real-time information, ensuring adaptability to the dynamic nature of renewable energy generation, providing a user-friendly

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and flexible web environment for scenario planning. The proposed framework facilitates seamless communication and collaboration among stakeholders involved in renewable energy integration, while also enabling the incorporation of real-world data sources such as weather forecasts and energy consumption patterns into the planning process.

Keywords: Energy management systems, web engineering, generative AI, active distribution networks, soft open points, dynamic scenario generation.

1 Introduction

Energy systems have key components known as renewable energy parts. These parts possess various characteristics, including widespread resource distribution, significant potential for advancements, minimal impact on the environment, and sustainability for nature. They promote the development of a balance between humanity and natural energy resources, aligning with China's efforts to address the growing energy and environmental challenges. Additionally, renewable energy plays a crucial role in establishing a smart grid. Currently, access to renewable energy involves centralized and distributed approaches. In the future, we can expect more widespread and dense utilization of renewable energy at the distribution system level, connecting it to the distribution grid through distributed access, thereby increasing its significance [1].

The presence of distributed generations (DGs) within the distribution network offers several benefits, such as reducing system losses, enhancing power supply reliability, and mitigating environmental pollution [2, 3]. However, when integrating distributed power, especially intermittent sources, into the distribution network, its operation is influenced by the environment, resulting in noticeable randomness and fluctuation. Consequently, the distribution network faces challenges such as unstable voltage and network congestion [4, 5]. The conventional distribution system's limited regulation mechanisms are insufficient to handle multiple intermittent distributed power sources. For example, renewable energy sources like wind and solar power are inherently intermittent and variable. This means that their energy output can fluctuate rapidly due to weather conditions and time of day, making it difficult for conventional EMSs to maintain a stable power supply. EMSs designed for conventional power generation may struggle to adapt to these rapid changes. Accurate forecasting of renewable energy generation is essential for grid stability. Conventional EMS relies on historical load data and predictable generation from fossil fuel power plants. However, renewable generation forecasting can be challenging due to uncertainties in weather patterns. Accurate prediction of renewable energy output is critical for balancing supply and demand effectively.

Also, the integration of renewable energy sources requires changes in grid management practices. Conventional EMS systems may lack the necessary tools to control and optimize renewable energy generation, storage, and distribution. Grid operators need to adapt their control strategies to incorporate new parameters, such as ramping rates and response times, which differ from conventional power plants. Maintaining grid stability becomes more complex as the share of renewable energy sources increases. Conventional EMS systems are not inherently designed to handle the rapid changes in power supply and demand that renewable sources can be introduced. Grid stability becomes a more significant concern, and EMSs must incorporate advanced control algorithms to address these issues.

Moreover, many renewable energy sources, such as wind and solar, can benefit significantly from energy storage solutions. Integrating energy storage systems into the grid adds an extra layer of complexity. Conventional EMSs may lack the ability to manage and optimize energy storage effectively, which is crucial for storing excess renewable energy when it's abundant and delivering it when needed. With distributed generation from renewables like rooftop solar panels, power can flow in two directions – both from the grid to the consumers and from consumers back to the grid. Conventional EMSs may not be equipped to manage this bidirectional power flow efficiently.

On the other hand, the integration of renewables also introduces new regulatory and market challenges. Conventional EMSs may not be designed to participate in energy markets, where renewables can offer surplus energy or provide ancillary services. These systems need to adapt to new market structures and regulations to accommodate renewable energy integration. Integrating renewable energy sources requires more extensive data collection and communication infrastructure. Conventional EMS may not be equipped to handle the increased data demands and may require upgrades in data management and communication systems to ensure real-time monitoring and control of renewable assets.

The evolving energy landscape, characterized by renewable energy integration, grid decentralization, digitalization, and changing market dynamics, demands innovative EMS solutions. These solutions are essential for ensuring grid reliability, efficiency, and sustainability while meeting the challenges and opportunities of the modern energy sector.

To address these challenges, a groundbreaking intelligent power distribution instrument called the “soft open point” (SOP) has been introduced to replace traditional contact switches [6–8]. SOP planning is a crucial aspect of power distribution systems that aims to enhance the flexibility, reliability, and efficiency of electricity distribution. In essence, it refers to the strategic deployment of intelligent switching devices and control mechanisms within the distribution network, enabling the seamless rerouting of electrical power when needed. This concept is particularly pertinent in the context of modernizing power distribution systems to accommodate renewable energy sources, demand response, and evolving grid architectures.

The primary goal of SOP planning is to facilitate dynamic and automated changes in the configuration of the distribution grid to optimize energy flow, mitigate disruptions, and accommodate the integration of distributed energy resources (DERs). This adaptive approach is becoming increasingly important as power distribution systems transition from conventional centralized generation to a more decentralized, diversified, and resilient model.

By strategically implementing SOPs and advanced automation, utilities and grid operators can efficiently manage the distribution of electricity, respond to outages, and integrate renewable energy sources into the grid, all while ensuring grid stability and the reliable delivery of electricity to consumers. As renewable energy and distributed generation continue to play a central role in our energy landscape, SOP planning becomes a critical tool in achieving a sustainable and resilient power distribution system.

Compared to traditional contact switches, SOP offers safer power control, increased reliability, and continuous real-time control, effectively managing the new issues associated with distributed power access. The SOP is typically implemented using fully controlled power electronics, resulting in high costs related to investment, operation, and maintenance. Therefore, strategic planning for SOP deployment becomes crucial. Although existing literature has explored the fundamental principles and model of SOP [6], and simulated its steady-state and transient operation [7, 8], the specific issue of SOP planning has yet to be addressed.

A generalized constraint equation for an SOP in a distribution system represented as follows:

$$I_{SOP} = I_{in} - I_{out}$$

where I_{SOP} represents the current flowing through the SOP, I_{in} represents the total current entering the SOP from various sources or feeders, and I_{out} represents the total current leaving the SOP to downstream feeders or loads.

The equation ensures that the current at the SOP remains balanced, reflecting the conservation of electrical current. Depending on the specifics of the distribution network and the SOP's purpose, additional constraints related to voltage, power flow, and other operational parameters may also be included in the constraint equations to ensure the safe and efficient operation of the system.

This article presents iW-EMS, a system designed to handle the optimization of distributed energy resources using cutting-edge technologies in a user-friendly web interface. It utilizes advanced technologies, including simulated annealing and cone programming, along with generative AI algorithms. The system offers a user-friendly web interface for scenario planning, facilitates communication and collaboration among stakeholders, and incorporates real-world data sources like weather forecasts and energy consumption patterns to support informed decision-making in the dynamic field of renewable energy integration.

It must be noted that the increasing complexity of distribution system scenarios, particularly when incorporating timing characteristics, poses significant challenges in solving the nonlinear large-scale mixed integer optimization problem. In light of this, the suggested system, which employs a rational planning approach, plays a vital role in enhancing the efficiency of the power distribution system. This aspect is of utmost importance in the energy management process. The system's adaptable control mode is achieved through a hybrid optimization algorithm proposed in this study. Its successful application in the entire EMS highlights its considerable implementation potential. It is a comprehensive solution to the challenges of integrating and optimizing distributed energy resources, with a focus on adaptability, user-friendliness, collaboration, and data-driven decision-making.

2 Related Work

For traditional research on optimizing the dispatching of distribution networks, the most common approach is optimization-based [10, 11]. These methods provide stable and interpretable results. However, they require an explicit mathematical model of the system, which makes it difficult to obtain accurate line parameters and system topology for large-scale networks. Additionally, these methods often rely on assumptions and simplifications during the modelling process to ensure solvability. Excessive assumptions and simplifications can lead to a deviation from real-world scenarios. There are also challenges in efficiently solving optimization problems. For example, when optimizing a distribution network with discrete control devices, the nonlinearity of the system constraints and the discrete nature of control attributes create a nonconvex problem. Generally, mixed integer programming is used to model such problems, but current solvers are relatively inefficient in solving mixed-integer nonlinear programming within a reasonable timeframe.

To address these challenges, researchers have proposed heuristic algorithm-based optimal dispatching strategies for distribution networks [12, 13]. Heuristic algorithms are favored for their simplicity and ease of implementation. Various heuristic methods, including particle swarm, ant colony, genetic algorithms, and simulated annealing, have been applied to optimize distribution network operation. However, these heuristic algorithms cannot guarantee optimal solutions, and, as the complexity of the optimization problems grows in relation to the number of variables and constraints, the computational effort required also increases exponentially. Consequently, solving complex optimization problems for large-scale distribution networks can be time-consuming using heuristic algorithms.

Distribution networks with distributed renewable energy sources face unique challenges. If a centralized control approach is employed, it presents difficulties related to communication and processing of massive information, maintenance of the control center model, agility of control strategies, reliability of the control system, and information privacy [14]. On the other hand, adopting a distributed control approach enables efficient, orderly, safe, and cost-effective integration of renewable energy into the grid through clustering control of distributed renewable energy generation. The consistency algorithm, a classic distributed control method in distribution networks [15], requires controllers to synchronize updates, thereby increasing communication complexity and execution difficulty. This makes it challenging to ensure real-time control and handle voltage fluctuations caused by rapid changes in renewable energy output. The alternating direction multiplier method achieves an efficient solution to the distributed control problem by iteratively addressing the proximity interval and solving in parallel [16]. However, it only exhibits first-order convergence and is inadequate for meeting online control requirements when dealing with large-scale renewable energy sources.

Compared to traditional methods used the intelligent method like the proposed have several advantages [17, 18]. For instance, the complex process of dealing with inaccurate physical models. Obtaining accurate physical models of distribution networks is challenging in practical settings, unlike the main network. Determining line impedance and network topology typically requires a substantial amount of data recorded by phasor measurement devices or a large quantity of recorded data based on time scales. The limited observability of the distribution network makes it difficult for operators to acquire precise line parameters and topology. Traditional optimization methods heavily rely on accurate physical models, and deviations in model parameters can impact control. In contrast, deep reinforcement learning methods achieve control without depending on physical models, mitigating the impact of inaccurate models on control performance through rational design.

On the other hand, exploiting historical data offers a notable advantage. As measurement devices and intelligent terminals are increasingly employed, the distribution network continuously generates large volumes of data with complex structures and correlations. These data contain valuable information that can be effectively utilized to support system operation and optimization. While optimization-based methods and heuristic algorithms do not capitalize on the value of historical data, deep reinforcement learning extracts empirical dispatch knowledge from historical records during offline training, effectively leveraging the valuable information contained within historical data.

From this point of view, the use of generative AI algorithms is an advantage that allows the system to create optimal scenarios based on historical data and real-time information. This adaptability is crucial when dealing with the unpredictable and dynamic nature of renewable energy generation. Generative AI can help generate solutions that respond to changing conditions and variables. Moreover, the application of web engineering technology provides a flexible environment for scenario planning. This technology likely involves web-based interfaces and platforms that enable communication and collaboration among stakeholders involved in renewable energy integration. It can also facilitate the integration of external data sources such as weather forecasts and energy consumption patterns, enhancing the accuracy of energy management decisions.

It must be noted the system's ability to integrate real-world data sources, including weather forecasts and energy consumption patterns, is essential for making informed decisions. Weather forecasts are particularly crucial for renewable energy systems since they help predict energy generation from sources like solar and wind. Integrating these data sources can improve the system's ability to adapt to changing conditions. In addition, the emphasis on seamless communication and collaboration among stakeholders involved in renewable energy integration is crucial. Energy management often requires coordination between various parties, including utility companies, consumers, and renewable energy providers. A web-based system can facilitate this collaboration, making it easier to manage distributed energy resources effectively.

3 Multi-scene Modelling Considering Wind and Light Uncertainties

Multi-scene modelling considering wind and light uncertainties is a crucial tool in the planning and operation of renewable energy systems. By accounting for the inherent variability and uncertainty of wind and solar resources, it enables more informed decision-making, better risk management, and improved energy system reliability.

3.1 Probabilistic Model for Wind Power Generation

Weibull probability distribution composed of two parameters is typically used to model the velocity of the wind defined by:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{1}$$

where *v* denotes the velocity of the wind; *k* and *c* represent parameters of shape and scale, respectively.

The velocity and the power of wind are related and represented by

$$P_{WT} = \begin{cases} 0, & 0 \leq v \leq v_{ci} \quad \text{or} \quad v \geq v_{co} \\ av^3 + b, & v_{ci} < v < v_r \\ P_{WT,N}, & v_r \leq v \leq v_{co} \end{cases} \tag{2}$$

where $P_{WT,N}$ is the rated power of wind power generation; v_{ci}, v_r, and v_{co} is the cut-in wind speed, rated wind speed, and cut-out wind velocity, respectively; *a* and *b* are the fitted parameters found by the power curve, which can be calculated according to Equations (3) and (4):

$$a = \frac{1}{v_r^3 - v_{ci}^3} P_{WT,N} \tag{3}$$

$$b = \frac{v_{ci}^3}{v_r^3 - v_{ci}^3} P_{WT,N}. \tag{4}$$

The probability density function (PDF) of wind power when the Weibull distribution is used for the velocity of the wind is obtained through Equations (1)–(4):

$$f(P_{WT}) = \begin{cases} \left[1 - e^{-\left(\frac{v_{ci}}{c}\right)^k} + e^{-\left(\frac{v_{co}}{c}\right)^k}\right] & P_{WT} = 0 \\ \quad \times\delta(P_{WT} - P_{WT,N}), & \\ \frac{k}{3ac^k}\left(\frac{P_{WT} - b}{a}\right)^{\frac{k-3}{3}} e^{-\frac{(P_{WT}-b)^{\frac{k}{3}}}{a^{\frac{k}{3}}c^k}}, & 0 < P_{WT} < P_{WT,N} \\ \left[e^{-\left(\frac{v_r}{c}\right)^k} - e^{-\left(\frac{v_{co}}{c}\right)^k}\right] & P_{WT} = P_{WT,N} \\ \quad \times\delta(P_{WT} - P_{WT,N}), & \end{cases} \tag{5}$$

where $\delta(\cdot)$ is the impulse function.

3.2 Probabilistic Model of Photovoltaic Power Generation

A beta probability distribution is typically used to describe the intensity of the light:

$$f(I) = \frac{1}{I_{max}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\frac{I}{{I_{max}}^{\alpha-1}\frac{I}{{I_{max}}^{\beta-1}}}} \tag{6}$$

where *I* denote the intensity of the light; I_{max} denotes the highest score of *I*; α and β represent the Beta probability distribution's two parameters; $\Gamma(\cdot)$ denotes the gamma function.

Since the PV power P_{PV} is roughly proportionate to the intensity of the light *I*, the PDF of the PV power obeying Beta distribution is obtained as follows:

$$f(P_{PV}) = \frac{1}{P_{PV,N}}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left(\frac{P_{PV}}{P_{PV,N}}\right)^{\alpha-1}\left(1 - \frac{P_{PV}}{P_{PV,N}}\right)^{\beta-1} \tag{7}$$

where $P_{PV,N}$ is the rated power of PV power generation.

3.3 Optimal Scene Generation Based on Wasserstein Distance

The uncertainty of the power output of distributed power sources such as wind and light is generally denoted by continuous PDFs. In contrast, in planning models, discrete distributions are generally used instead of continuous distributions for simplification. Replacing continuous PDFs with discrete ones and the probability values corresponding to the scenarios is called scenario simulation, also called scenario generation. Based on continuous PDFs regarding wind power and PV power output already obtained, the discrete scenarios can be obtained by using the method called scenario generations to minimize the errors of the discrete scenarios and the original distributions, and by discretizing the continuous PDFs regarding wind power and PV power output. Considering the strong nonlinearity and high dimensionality of the tidal optimization problem itself, how real PDFs are approximated based on a few discrete ones poses a modeling difficulty. In scene generation, a method called optimal scene generation using the Wasserstein distance has been widely implemented.

Assumed that x is a random variable denoted by a PDF $f(x)$ and it is desired to approximate $f(x)$ by a discrete scene with S discrete points, the method called optimal scene generations using the Wasserstein distance to obtain the optimal points can be obtained by Equation (8):

$$\int_{-\infty}^{z_s} f(x)^{\frac{1}{r+1}} dx = \frac{2s-1}{2S} \int_{-\infty}^{+\infty} f(x)^{\frac{1}{r+1}} dx. \tag{8}$$

The p_s denotes the probability corresponding to z_s and is calculated according to Equation (9):

$$p_s = \int_{\frac{z_{s-1}+z_s}{2}}^{\frac{z_s+z_{s+1}}{2}} f(x)dx. \tag{9}$$

z_0, z_{S+1} denote the lower and upper bounds of the variable x, respectively, which will be $-\infty$ and $+\infty$, respectively, if not otherwise specified; r is the order; Wasserstein distance represents an integral of the gap between two PDFs at an exponent of order r (taken as $r = 1$).

Thus, the power points and the corresponding probabilities of wind power and photovoltaic power generation could be attained separately, and the optimal scenario of the combined scenery based on Wasserstein distance can be obtained jointly.

4 Two-layer Planning Model for SOP Siting and Capacity Setting

The two-layer planning model for SOP (solar power) siting and capacity setting is a strategic approach used in the renewable energy industry, specifically

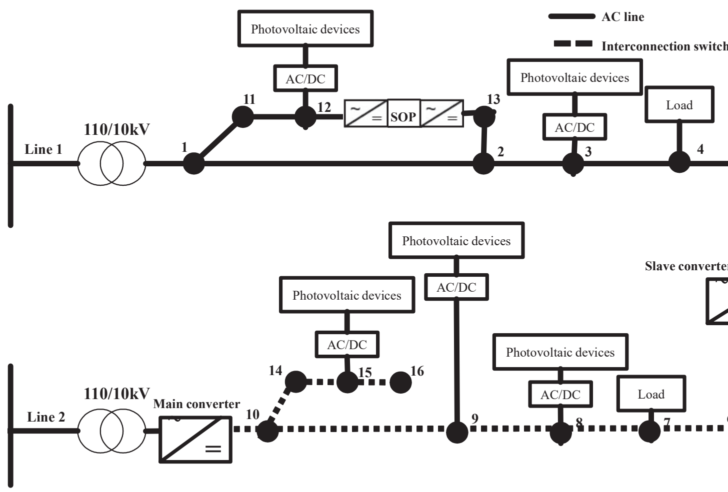

Figure 1 SOP installation.

for determining the optimal locations and capacities for solar power generation facilities. This model consists of two distinct layers or stages that work together to guide decision-making in the deployment of solar energy projects.

4.1 The Main Functions and Mathematical Model of SOP

SOPs are mainly installed at conventional contact switches, as shown in Figure 1, and could adaptively control the transmitted active power between two feeders and give certain reactive power support. The application is primarily dependent upon completely controlled power electronics, and three main types of implementations exist: back-to-back voltage source converter (B2B VSC), static synchronous series compensator (SSSC), and unified power flow controller (UPFC).

In the manuscript, SOP planning in the power distribution system is exemplified by taking back-to-back voltage source converters, and the controllable attributes of the SOP include four: active power and reactive power output of two converters. Though the back-to-back voltage source converters present high efficiency, when there is an uneven distribution of distributed power sources and loads, and the active tide needs to be transferred in a wide range, certain power losses will be generated, and a certain loss factor is considered in the modeling process of this paper. It is supposed that the SOP injects power into the grid in a positive direction. The reactive power output of the two converters does not affect each other due to the isolation of the DC link, and only the capacity constraints of the respective converters need to be satisfied. Here, the PQ-V_{dc}Q control was chosen as the SOP's control mode, and the following SOP constraint equation is obtained. PQ-VdcQ control is a comprehensive strategy that combines active and reactive power control with DC voltage control to effectively manage the power flow and voltage quality in the system, particularly when voltage source converters are utilized.

(1) The active power constraint of the SOP is:

$$P_{i,SOP}(s) + P_{j,SOP}(s) + P_{ij,SOP}(s) = 0 \tag{10}$$

$$P_{ij,SOP}(s) = A_{i,SOP}|P_{i,SOP}(s)| + A_{j,SOP}|P_{j,SOP}(s)|. \tag{11}$$

(2) The reactive power constraint of the SOP is:

$$-S_{ij,SOP} \leq Q_{i,SOP}(s) \leq S_{ij,SOP} \tag{12}$$

$$-S_{ij,SOP} \leq Q_{j,SOP}(s) \leq S_{ij,SOP}. \tag{13}$$

(3) The capacity constraint of the SOP is:

$$\sqrt{P_{i,SOP}(s)^2 + Q_{i,SOP}(s)^2} \leq S_{ij,SOP} \tag{14}$$

$$\sqrt{P_{j,SOP}(s)^2 + Q_{j,SOP}(s)^2} \leq S_{ij,SOP} \tag{15}$$

where s is the operation optimization scenario; *i* and *j* denote the node numbers of the SOP linked to the distribution system; $P_{i,SOP}(s)$, $P_{j,SOP}(s)$, $Q_{i,SOP}(s)$, and $Q_{j,SOP}(s)$ denote the injected active and reactive power by the two converters of the SOP in the sth scenario, respectively; $A_{i,SOP}$ and $A_{j,SOP}$ denote the loss coefficients of the converter; $P_{ij,SOP}(s)$ denotes the transmission loss of the SOP; μ denotes the absolute value of the power factor angle sine; $S_{ij,SOP}$ denotes the capacity of the SOP linked between *i* and *j* nodes.

The SOP siting and capacity planning problem involves both determining the location and capacity of the SOP installation location and capacity, but also calculating the optimal operating phase of the entire distribution system under each scenario. This is a typical two-level planning problem.

4.2 Upper Layer Optimization Model

The objective function of the upper layer planning model was to minimize the yearly integrated cost *C*. The mathematical expression is:

$$\min C = C_I + C_O + C_L. \tag{16}$$

The meaning and calculation of each component cost are as follows.

(1) Converted to annual SOP fixed investment costs:

$$C_I = \frac{d(1+d)^y}{(1+d)^y - 1} \sum_{k=1}^{N_{SOP}} c_{k,SOP} S_{k,SOP} \tag{17}$$

where *d* represents the discount ratio; *y* denotes the SOP's economical service life; N_{SOP} denotes the SOP numbers to be selected for installation; $S_{k,SOP}$ and $c_{k,SOP}$ are the capacity of *k* SOPs to be installed and the corresponding investment cost per unit capacity, respectively.

(2) SOP's yearly operation and maintenance costs:

$$C_O = \eta \sum_{k=1}^{N_{SOP}} c_{k,SOP} S_{k,SOP} \tag{18}$$

where η is the yearly operation and maintenance cost factor.

(3) Yearly power supply loss cost of the distribution network:

$$C_L = ct \sum_{s=1}^{S} \left\{ \sum_{i=1}^{N} [P_i(s) + A_{i,SOP} |P_{i,SOP}(s)|] \cdot p(s) \right\} \tag{19}$$

where *c* is the tariff; *t* is the supply time; *S* is the number of scenarios; *N* represents the system node numbers; $P_i(s)$ denotes the total of the injected active power at the *s*th scenario node *i*; $p(s)$ shows the probability that corresponds to the *s*th scenario, where $P_i(s)$ could be stated by the active current constraint equation shown in Equation (21).

The constraint is:

$$0 \leq S_{k,SOP} \leq S_{k,SOP}^{max} \tag{20}$$

$$S_{k,SOP} = m_k s_{SOP} \tag{21}$$

where s_{SOP} is the unit SOP installed capacity, i.e., the minimum optimizable capacity of the installed converter, such as 10 kVA, 100 kVA, etc.; m_k is a non-negative integer; $S_{k,SOP}$ indicates the SOP capacity installed at the selected location; $S_{k,SOP}^{max}$ is the SOP's highest capacity allowed to be installed at the selected location.

In the manuscript, the SOP's location and capacity are considered uniformly through an integer variable. If the capacity of SOP to be installed is planned to be 0, it is considered that the location does not need to install SOP, and then the capacity is determined along with the installation location.

4.3 Lower Layer Optimization Model

The lower layer planning model is to minimize the sum of network loss and SOP loss for each scenario while satisfying various constraints of the distribution network. The model's objective function is given by:

$$\min\left[\sum_{\mathrm{s}=1}^{\mathrm{S}}\sum_{\mathrm{i}=1}^{\mathrm{N}}\mathrm{P_i(s)}+\sum_{\mathrm{s}=1}^{\mathrm{S}}\sum_{\mathrm{i}=1}^{\mathrm{N}}\mathrm{A}_{\mathrm{i},SOP}|\mathrm{P}_{\mathrm{i},SOP}(\mathrm{s})|\right]. \tag{22}$$

In addition to considering the operational constraints of SOP Equations (10)–(15), the constraints to be considered include:

$$\begin{aligned} P_i(s) = \sum_{j\in N(i)} & U_i(s)U_j(s)[G_{ij}\cos\theta_{ij}(s)+B_{ij}\sin\theta_{ij}(s)] \\ & + G_{ii}U_i(s)^2 = P_{i,DG}(s)+P_{i,SOP}(s)-P_{i,LD}(s) \end{aligned} \tag{23}$$

$$\begin{aligned} Q_i(s) = -\sum_{j\in N(i)} & U_i(s)U_j(s)[B_{ij}\cos\theta_{ij}(s)-G_{ij}\sin\theta_{ij}(s)] \\ & - B_{ii}U_i(s)^2 = Q_{i,DG}(s)+Q_{i,SOP}(s)-Q_{i,LD}(s) \end{aligned} \tag{24}$$

$$U_i^{min_i{}^{max}_i} \tag{25}$$

$$\begin{aligned} I_{ij}(s)^2 = {} & (G_{ij}^2+B_{ij}^2)[U_i(s)^2+U_j(s)^2-2U_i(s)U_j(s)\cos\theta_{ij}(s)] \\ & \leq I_{ij}^{max^2} \end{aligned} \tag{26}$$

where $N(i)$ represents the set of nodes linked to node i; $U_i(s)$, $U_j(s)$, and $\theta_{ij}(s)$ represent the voltage magnitude and phase angle difference of the sth scene node i and j, respectively; G_{ii}, B_{ii}, G_{ij}, B_{ij} represent the self-conductance, self-conductance, mutual-conductance, and mutual-conductance of the node conduction matrix, respectively; $P_{i,LD}(s)$, $Q_{i,LD}(s)$ represent the active and reactive powers injected by the load at node i of the sth scenario, respectively; $P_{i,DG}(s)$ and $Q_{i,DG}(s)$ represent the active and reactive powers injected by the distributed power source at node i of the sth scenario, respectively; U_i^{max} and U_i^{min} represent the upper and lower limits of the voltage magnitude at node i, respectively; $I_{ij}(s)$ is the current magnitude at the sth scenario of branch ij; I_{ij} max is the upper limit of the current amplitude of branch ij.

Equations (23)–(24) in the above model is the system current constraint, Equation (25) is the nodal voltage constraint, and Equation (26) is the branch current constraint. Equation (25) is the node voltage constraint, and Equation (26) is the branch circuit current constraint.

The variables to be solved contain the SOP's installation location and capacity, the voltage magnitude and phase angle at each scene node, and the active and reactive power transmitted by the SOP the active power, and the emitted reactive power. Therefore, Equations (10)–(26) constitute a two-layer planning model to configure optimally the SOPs.

5 Solving the Two-layer Programming Model of SOP

For the above SOP siting and capacity setting two-layer planning model, it can be seen that the upper-layer planning passes the SOP's installation location and capacity to the lower layer, and the lower-layer planning optimizes the operation phase of the distribution system concerning each scenario on this basis and returns the optimization results to the upper-layer, which then uses the results passed up from the lower-layer planning to compute the score of the objective function of the current SOP planning scheme. This planning problem poses a nonlinear large-scale mixed integer programming. Thus, a single method is not enough to resolve the problem. Moreover, a method employing hybrid optimization composed of simulated annealing and cone programming was proposed in the article.

The method of hybrid optimization basically uses simulated annealing as the framework of the whole hybrid optimization algorithm to find the SOP's installation location and capacity. During each iteration of the simulated annealing algorithm, the cone programming algorithm was employed to resolve the optimal operation of the distribution system in each scenario, and after obtaining the optimal operation of each scenario, the adaptation degree of the individuals in the simulated annealing algorithm is further calculated.

5.1 Simulated Annealing Algorithm

The simulated annealing method, a heuristic stochastic search method using the iterative solution scheme of the Monte Carlo method, begins initially with a certain high temperature and uses the Metropolis sampling criterion with probabilistic jump characteristics to search in the solution space randomly, and reiterates the process of the sampling to decrease the temperature to obtain a solution that is the near-optimal solution of the problem.

Applying the simulated annealing to the SOP siting and capacity problem, the solution idea is considered to combine the installation location and capacity of a group of SOPs as the state in which the particle is located, and the score of the objective function under the combination, i.e., the annual comprehensive cost, as the energy of the state in which the particle is located, and the problem's optimal solution is regarded to have been obtained when the score of the objective function could no longer be reduced after changing the location and capacity of SOPs for several times as the temperature decreases continuously.

5.2 Cone Programming Algorithm

The cone programming problem could be characterized as the problem that solves the minimization of a linear objective function subject to the non-empty pointed convex cone import bias order, linear equation, and linear inequality constraints, and its feasible domain is the intersection of the Cartesian product of the convex cone and the affine subspace [19, 20].

The system current constraint and the branch current constraint in the model described in Section 4.3 are nonlinear functions concerning the node voltage magnitude and phase angle difference. Thus, the cone programming's rigid conditions for a linear objective function and the feasible domain are not met. Therefore, when applying the cone programming algorithm for the solution, the model needs to be transformed accordingly [9, 21].

First, the linearization of some constraints is achieved by variable substitution.

$$\begin{cases} X_i(s) = \dfrac{U_i(s)^2}{\sqrt{2}} \\ Y_{ij}(s) = U_i(s)U_j(s)\cos\theta_{ij}(s) \\ Z_{ij}(s) = U_i(s)U_j(s)\sin\theta_{ij}(s) \end{cases}. \tag{27}$$

Second, the nonlinear constraints Equations (14) and (15) are transformed into the following rotational cone constraints by transforming the equations as follows:

$$P_{i,SOP}(s)^2 + Q_{i,SOP}(s)^2 \le 2\frac{S_{ij,SOP}}{\sqrt{2}}\frac{S_{ij,SOP}}{\sqrt{2}} \tag{28}$$

$$P_{j,SOP}(s)^2 + Q_{j,SOP}(s)^2 \le 2\frac{S_{ij,SOP}}{\sqrt{2}}\frac{S_{ij,SOP}}{\sqrt{2}}. \tag{29}$$

The following constraints are added:

$$M_{i,SOP}(s) \ge 0 \tag{30}$$

$$M_{i,SOP}(s) \geq P_{i,SOP}(s) \tag{31}$$

$$M_{i,SOP}(s) \geq -P_{i,SOP}(s). \tag{32}$$

Finally, the nonlinear second-order rotating cone constraint is introduced so that the optimized model is within the constraints of the pointed convex cone [22, 23].

$$2X_i(s)X_j(t) \geq Y_{ij}(s)^2 + Z_{ij}(s)^2. \tag{33}$$

This constraint holds naturally in the above model and therefore does not cause a change in the solution to the original problem.

After the cone transformation process, Equations (10)–(13), (16)–(22) and (27)–(33) constitute the cone planning model for SOP siting and capacity setting.

5.3 SOP Two-layer Planning Model Solving Process

With the SOP's location and capacity to be installed as the control variables, the upper-level planning uses a simulated annealing algorithm to generate a planning scheme and perform a cone closing planning algorithm to run optimization calculations for each scenario under the scheme and pass the optimization results to the upper-layer planning; Figure 2 depicts the algorithm flow.

6 Simulation and Analysis of Algorithms

The overall design of a data center can be classified in four categories: Tiers I–IV.

In the article, an IEEE 33-node test feeder was employed to analyze and validate the proposed two-layer programming approach and hybrid optimization method. Figure 3 depicts the structure of the IEEE 33-node test feeder, and the voltage class is 12.66 kV.

To completely see the influence provided by the access of distributed power, five typhoon power units and three groups of photovoltaic systems are connected respectively in the calculation example. Table 1 summarizes the fundamental configurations of the parameters. Figure 4 depicts the annual variation curve of wind velocity and the intensity of the light in the region where the distribution network is set. The SOP adopts a back-to-back voltage source converter and relevant parameters of the SOP. Table 2 shows the fans. According to wind velocity and the intensity of the light, Weibull distribution

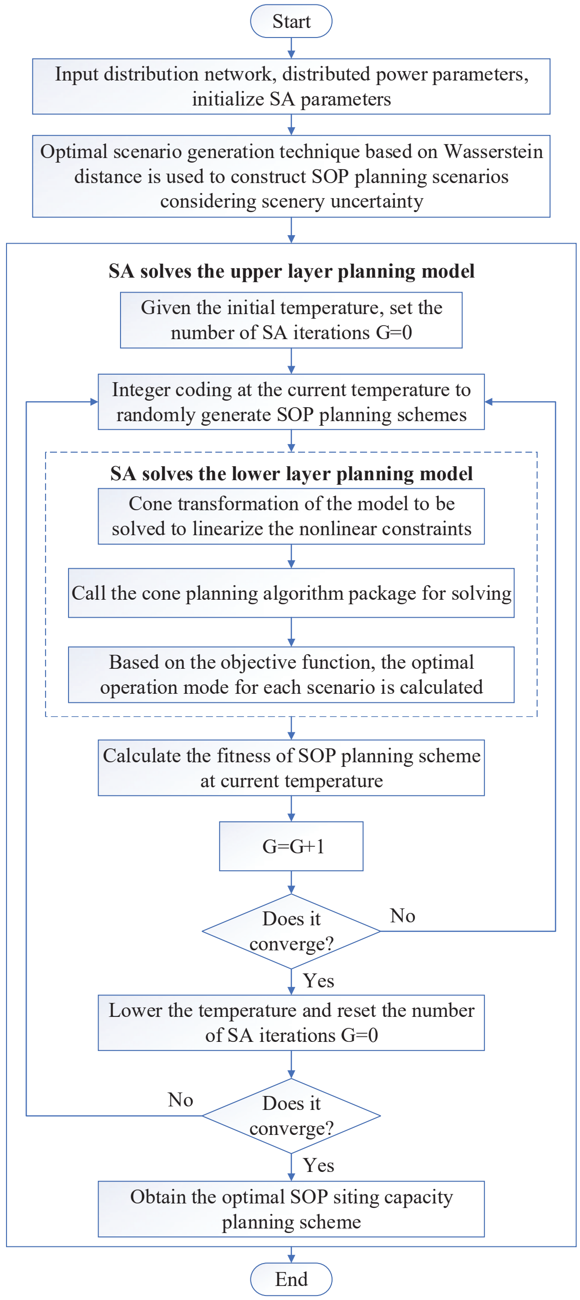

Figure 2 Flowchart showing the SOP's optimal siting and sizing.

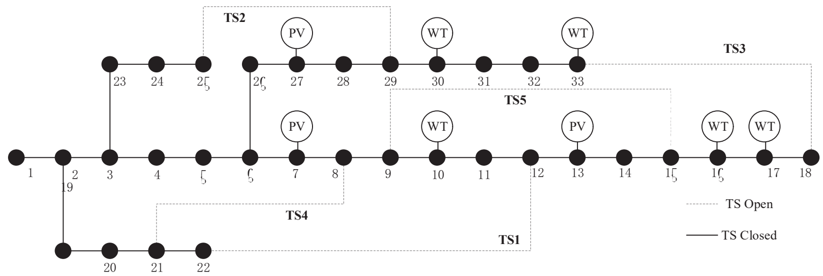

Figure 3 Structure of the IEEE 33-node test feeder.

Table 1 Parameters of DGs

Parameters	Wind Turbine					Photovoltaic Systems		
Location	10	16	17	30	33	7	13	27
Capacity/kW	500.0	300.0	200.0	200.0	300.0	500.0	300.0	400.0

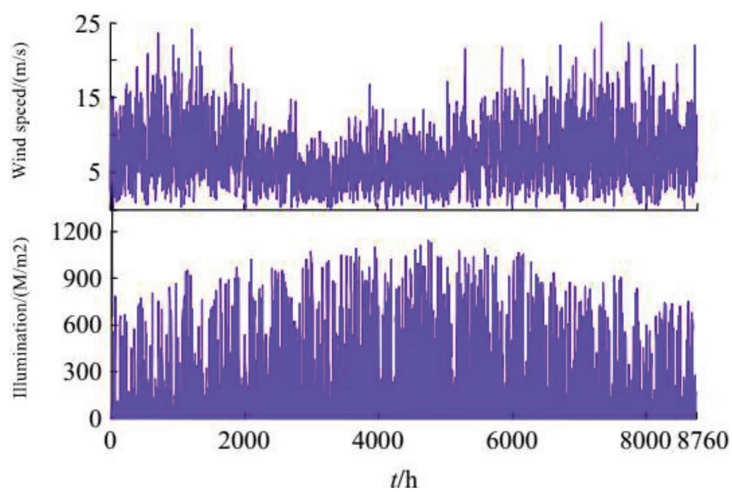

Figure 4 Yearly curves of the wind velocity and the intensity of the light.

scale parameter $c = 2$, shape parameter $k = 10$, and Beta distribution parameter $\alpha = \beta = 0.95$ were calculated.

Considering the scenery output uncertainty, the PDF is obtained, and the technique generating an optimal scenario using the Wasserstein distance was employed to construct a planning model with two layers concerning the determination of both the SOP siting and capacity. Considering the limitation of geographical location, the SOP to be selected is located at the contact switch, and the location and capacity to be installed are optimally

Table 2 Parameters of the studied case

Parameters	Value
Discount ratio	0.08
SOP economic useful life/year	20
SOP unit capacity investment cost/(yuan/kVA)	1000
SOP unit optimized capacity/kVA	100
SOP loss coefficient	0.02
SOP operation and maintenance cost coefficient	0.01
Fan cut-in wind velocity/(m/s)	3
Fan-rated wind velocity/(m/s)	15
Fan cut-out wind velocity/(m/s)	25
Electricity price/(yuan/(kW·h))	0.5

selected. Among them, the simulated annealing algorithm is implemented by a Matlab scripting program, and the cone planning algorithm toolkit Mosek 6.0 is called. Intel Xeon CPU E5-1620 with 3.70 GHz, 32 GB of memory, Win7 64-bit operating system, and Matlab R2014a are employed to conduct calculations.

6.1 Planning Results

Utilizing the parameters of the obtained Weibull PDF, the wind turbine's relevant parameters, and the rated output power $P_{WT,N} = 1.0$ pu, Equation (34) gives the wind turbine's probability mapping according to Equation (5):

$$f(P_{WT}) = \begin{cases} 0.088 \cdot \delta(P_{WT} - 1), & P_{WT} = 0 \\ 1.5P_{WT}^{-0.333} \cdot e^{-2.25P_{WT}^{0.667}}, & 0 < P_{WT} < 1. \\ 0.103 \cdot \delta(P_{WT} - 1), & P_{WT} = 1 \end{cases} \tag{34}$$

Based on the obtained Beta distribution parameters and relevant parameters of the PV system with rated output power $P_{PV,N} = 1.0$, the probability mapping of the PV power was obtained using Equation (7):

$$f(P_{PV}) = 0.904P_{PV}^{-0.05}(1 - P_{PV})^{-0.05}. \tag{35}$$

When the Wasserstein distance index *r* is set to 1 and the scene numbers S are set to 5 to get the optimal scene power points and probabilities of wind power and PV power respectively, we finally get the joint optimal scene power and its corresponding probabilities, as shown in Table 3.

After considering the wind power and PV power output uncertainty scenarios, the proposed hybrid optimization algorithm is used to solve the SOP

Table 3 Wind and photovoltaics' probability distribution

	P_{PV}				
P_{WT}	0.0966	0.2971	0.5000	0.7029	0.9034
0.0000	0.0180	0.0174	0.0173	0.0174	0.0180
0.0795	0.0916	0.0885	0.0882	0.0885	0.0915
0.3163	0.0468	0.0452	0.0451	0.0452	0.0468
0.7094	0.0268	0.0259	0.0258	0.0259	0.0268
1.0000	0.0210	0.0203	0.0203	0.0203	0.0210

Table 4 Locations and capacities of the SOP

Location	TS1	TS2	TS3	TS4	TS5
Results	1	2	3	0	0
Scheme	100 kVA	200 kVA	300 kVA	–	–

Table 5 Economic analysis of SOP installation

Item/10,000 yuan	C_I	C_O	C_S	C
Before	–	–	46.95	46.95
After	7.27	1.24	35.48	43.99

site-selected capacity planning model. Tables 4 and 5 present the obtained planning scheme and the planning outcomes below.

The annual comprehensive cost after planning is reduced by 29,600,000 yuan compared with that before planning, among which, the yearly loss cost of the distribution system was decreased by 114,700,000 yuan, greatly enhancing the operation economy of the whole distribution system. Considering the future development of converter technology and further reduction of production costs, the comprehensive benefit of SOP will be further improved. In addition, SOP has flexible and diverse control modes, which can provide voltage support when faults occur, reactive power compensation as the voltage surpasses the limit, and improve the ability of distributed power sources to consume, and regarding the above-mentioned contributions regarding economic and environment, the SOP's empirical contribution would be more enhanced.

6.2 Algorithm Validation

To validate the rapidity and convergence of the hybrid optimization method proposed in this paper to resolve the problem of SOP planning, and to experiment with the transformation of the cone approach's correctness and the method to generate optimal scenarios using the Wasserstein distance,

Table 6 Comparison of the performance with the hybrid optimization algorithm and BONMIN

Number of Discrete Scenes	Algorithms	Time/s
Based on Wasserstein's	Hybrid optimization algorithm	138.89
discrete 25 scenarios	GAMS BONMIN	719.53
Equidistant discrete	Hybrid optimization algorithm	2954.36
100 scenes	GAMS BONMIN	No convergence

the obtained scenery output PDF is discretized to 10 scenes at equal distances respectively, constituting a scenery of 100 scenes, based on which the hybrid optimization algorithm is used for SOP planning. For comparison, the SOP planning model is solved using the BONMIN module of the GAMS software package which provides an optimization algorithm employing the interior point approach, and is capable of solving mixed integer nonlinear programming problems. The SOP planning model based on Wasserstein distance discretization for 25 scenarios (decision variable dimension: 195*25) converges for each algorithm, but the BONMIN module solves the SOP planning model based on equal distance discretization for 100 scenarios (decision variable dimension: 195*100) is no longer reliably convergent. The algorithms converge to obtain the same SOP planning scheme, as shown in Table 4, and Table 6 presents the solution times of each algorithm for different scenarios.

The method used for generating optimal scenarios using the Wasserstein distance remarkably decreases the scenario numbers and significantly enhances the computational efficacy while assuring the rationality of the planned scenarios. When the number of scenarios is small, each algorithm can converge and obtain optimal results, and the hybrid optimization algorithm suggested in the manuscript could be solved swiftly; when the scenario numbers increase, the dimensionality of decision variables increases dramatically, and the BONMIN solution algorithm appears to be non-convergent, and the hybrid optimization algorithm, due to decoupling the integer variables from the continuous variables, uses the intelligent optimization algorithm and mathematical planning method to solve the problem, respectively, and shows good convergence with the hybrid optimization algorithm because it decouples the integer variables from the continuous variables and solves them using the intelligent optimization algorithm and mathematical programming method, respectively. Therefore, the hybrid optimization method suggested in the article outperforms the commercial software algorithms in terms of speed and convergence.

7 Cutting-edge Technologies

The paper uses generative AI algorithms to generate the best scenarios using historical and real-time data. This ensures that the planning process can adapt to the changing nature of renewable energy generation. Web engineering technology is also used to create a flexible environment for scenario planning. These technologies allow for easy communication and collaboration among stakeholders involved in renewable energy integration, and they facilitate the inclusion of real-world data sources in the planning process.

7.1 Utilizing Generative AI Algorithms for Scenario Creation

Generative AI algorithms are powerful tools in the field of artificial intelligence. They have the ability to create data that imitates patterns observed in the training data. This paper used a generative adversarial network (GAN). GAN is a type of machine learning model used for unsupervised learning. It consists of two neural networks called the generator and the discriminator, which are trained together in a competitive way. The main purpose of GAN is to create realistic data samples, which are impossible to tell apart from real data.

The generator's objective is to take random noise (usually from a normal distribution) as input and produce data that looks like real data samples. Its aim is to generate high-quality fake data. During training, the generator generates fake data samples, which are then passed to the discriminator. The generator's loss is determined by how well the discriminator is fooled by these fake samples. Its goal is to minimize this loss. As training progresses, the generator gets better at generating realistic data.

The discriminator acts as a binary classifier. It takes both real data samples from the training set and fake data samples from the generator and tries to distinguish between them. Its objective is to correctly classify real and fake data. During training, the discriminator is given both real and fake data samples. Its training aims to maximize its ability to differentiate between them by minimizing a loss function. The discriminator becomes better at distinguishing real from fake data as training progresses.

GANs work in an adversarial training loop. The generator and discriminator are trained iteratively, each trying to outperform the other. The generator and discriminator have opposing loss functions. The generator aims to minimize its loss (by fooling the discriminator), while the discriminator aims to minimize its loss (by correctly classifying real and fake data). The

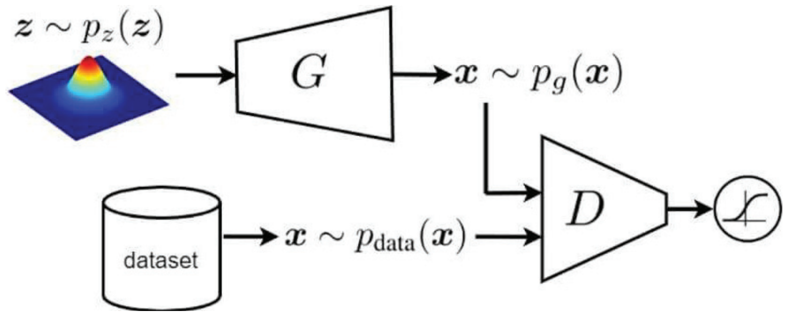

Figure 5 GAN architecture.

training process reaches a Nash equilibrium when the generator produces data that is indistinguishable from real data, and the discriminator cannot reliably classify between the two. Figure 5 shows a depiction of the GAN architecture.

In the context of renewable energy integration, these algorithms can be particularly useful as they can generate synthetic scenarios that closely resemble real-world conditions. GANs heavily rely on historical data for generating accurate scenarios. This historical data encompasses various information related to past weather patterns, energy generation, energy consumption, and other relevant factors. For instance, historical weather data would include details such as the number of sunlight hours, wind speeds, and cloud cover in a particular region over a specific period.

To make the generated scenarios adaptable and current, generative AI algorithms can also incorporate real-time data. For example, these algorithms can access real-time weather conditions, solar panel efficiency, and power grid load. By considering such up-to-the-minute information, the generated scenarios can accurately reflect the dynamic conditions prevailing at any given moment.

One of the notable strengths of generative AI algorithms lies in their ability to continuously update scenarios with real-time data. This adaptability factor ensures that the algorithms can keep pace with the ever-changing nature of renewable energy generation. As an illustration, if clouds suddenly appear and obscure the sun, the generative AI algorithm can promptly adjust the scenario to reflect the reduced potential for solar power generation in real time.

Consider the following practical scenario. There exists a solar power project located in a region characterized by regular and unforeseeable cloud cover. In such a circumstance, the application of a generative AI algorithm proves exceedingly advantageous. This algorithm is trained utilizing historical weather data and is linked to real-time weather feeds. It possesses the ability to produce simulated scenarios that depict diverse levels of cloud cover, enabling accurate predictions regarding their influence on solar energy generation. Employing this adaptive approach, project planners can enhance their comprehension of potential energy production fluctuations and consequently make more informed preparations.

7.2 Employing Web Engineering Technology for Collaboration and Data Integration

Web engineering technology encompasses the use of online tools, frameworks, and platforms to develop and maintain applications. When it comes to integrating renewable energy, this technology can be employed to establish an internet-based environment that fosters collaboration and data sharing. This virtual space acts as a central hub, bringing together various stakeholders like energy companies, grid operators, and government agencies to collaborate on projects related to renewable energy integration. The platform provides a range of features, including shared project dashboards, repositories for storing documents, and communication tools.

Through this platform, stakeholders can easily communicate and exchange information with one another. They can efficiently share project updates, real-time data feeds, and reports regarding energy generation and consumption among team members. This facilitates seamless collaboration and enables stakeholders to stay connected and well-informed. Moreover, web engineering technology allows the integration of real-world data sources. For example, it can connect with weather forecasting application programming interfaces (APIs) to provide accurate and up-to-date weather predictions. These forecasts are essential for effectively planning renewable energy initiatives. Additionally, the technology can integrate with energy monitoring systems to gather data on actual energy consumption patterns. By leveraging web engineering technology, stakeholders in the renewable energy sector can enhance their collaboration efforts, improve information exchange, and make informed decisions based on reliable data.

Consider, for instance, a hypothetical renewable energy project bringing together a consortium of engineers, meteorologists, and grid operators. Leveraging the aforementioned web engineering platform, the meteorologist is equipped to promptly disseminate precise weather forecasts. This information, in turn, is seamlessly integrated into the energy generation models by the engineers. Concurrently, the grid operators supply real-time data pertaining to power demand. The harmonious amalgamation of these data sources ensures that planning decisions are premised upon the most current and accurate information obtainable, thereby fostering an environment of informed decision-making and optimal project outcomes.

In the delineated framework, web engineering technology offers a capability for seamless integration with energy monitoring systems. These systems are instrumental apparatuses or mechanisms designed for the systematic collection and meticulous analysis of data pertaining to energy consumption patterns, operational within a specific domain, such as a singular edifice, an urban agglomeration, or an all-encompassing power distribution network.

The process of integration with these energy monitoring systems entails the web engineering platform establishing an interfacing mechanism with the said systems to procure and assimilate real-world data encompassing the veritable facets of energy consumption. This dataset encompasses details concerning the temporal patterns and modalities of energy utilization, the longitudinal trends in energy consumption over a specified timeframe, and the elucidation of the distribution of energy loads across an assortment of consumers or geographic sectors.

By orchestrating the connectivity with energy monitoring systems, the web engineering platform confers upon stakeholders within the sphere of renewable energy a discernible access route to this invaluable dataset. This dataset can be marshaled for an assortment of objectives, inclusive of but not limited to the following:

1. Demand response: The adept comprehension of real-time energy consumption patterns furnishes grid operators and utility entities with the acumen to adroitly adjust their strategies governing energy generation and allocation in concurrence with the authentic demands. This adaptive responsiveness culminates in the bolstering of grid robustness and the augmentation of operational efficiency.
2. Efficiency analysis: A retrospective analysis of historical data chronicling energy consumption patterns empowers stakeholders to discern potential avenues for the enhancement of energy efficiency. This cognitive insight assumes a pivotal role in formulating resolutions with respect to energy-conservation initiatives and the judicious allocation of resources to elicit maximal impact.
3. Resource planning: The accessibility to authentic data pertaining to energy consumption presumes an indispensable role in the elucidation

of a blueprint for the execution of renewable energy undertakings. This manifests in its utility in dimensioning renewable energy installations, such as photovoltaic arrays or wind turbines, predicated on the observed energy consumption patterns within a particular geographic enclave.

4. Optimizing energy distribution: The compilation and analysis of data sourced from energy monitoring systems empower grid operators to orchestrate a refined allocation of energy resources, ensuring their judicious routing to those regions or sectors of the grid where exigency is most pronounced.

For instance, consider a hypothetical scenario in which a municipality is in the process of devising a solar energy project. The confluence of a web engineering platform with energy monitoring systems within this setting would grant municipal authorities immediate access to a reservoir of historical data encapsulating energy consumption patterns prevalent within the confines of the municipality. Subsequently, this data could be invoked to guide decisions regarding the sizing and spatial localization of solar photovoltaic installations, thereby optimizing the generation and distribution of solar energy resources with the utmost efficiency.

8 Conclusion

This paper introduces the iW-EMS, a specialized framework designed for the seamless integration and optimization of distributed energy resources. This system harnesses a sophisticated approach, combining simulated annealing and cone programming to achieve optimal outcomes. Furthermore, it leverages generative AI services to generate optimal scenarios by synthesizing historical and real-time data, thus allowing it to adapt dynamically to the ever-changing landscape of renewable energy generation.

A hallmark of the iW-EMS is its provision of an intuitive web-based environment tailored for scenario planning. This platform not only streamlines communication but also fosters collaboration among a diverse array of stakeholders actively engaged in the intricate process of renewable energy integration. Moreover, the system offers the capability to incorporate real-world data sources such as weather forecasts and energy consumption patterns, enriching the planning process with accurate and pertinent information.

It is imperative to underline that the application of a rational planning approach for SOP has been empirically validated to significantly enhance the efficiency of power distribution systems, a pivotal facet of the overarching energy management process. The system's adaptable control mode confers numerous advantages upon the entirety of the EMS, underscoring its implementation potential.

In response to the escalating complexity of distribution system scenarios, particularly when temporal characteristics are considered, the resolution of the nonlinear, large-scale mixed integer optimization problem assumes an even more formidable nature. This accentuates the heightened relevance of the merits offered by the hybrid optimization algorithm, rendering it an indispensable component for effective problem-solving within the purview of the proposed web interface.

As the integration of renewable energy sources continues to assume a central role in the inexorable transition toward sustainable energy systems, an expansive realm for prospective research emerges. Notably, the burgeoning avenue for future research resides in the further development and integration of generative AI algorithms and advanced web engineering technology. This trajectory holds the promise of refining the domain of optimal energy management, enhancing its efficiency, reliability, and scalability to meet the burgeoning demands of our energy landscape.

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