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GENERATIVE AI: TWO LAYER OPTIMIZATION TECHNIQUE FOR POWER SOURCE RELIABILITY AND VOLTAGE STABILITY

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ABSTRACT

Wind and solar power are essential in the fight against climate change and for reaching carbon neutrality targets. Due to their inherent unpredictability, renewable energy sources pose a threat to the power system's transient voltage stability, dependability, and flexibility. These consequences might add complexity to power scheme design. This paper introduces a two-tiered optimization approach for control foundations and network design to discourse the effects of renewable vigor on electrical organization preparation, particularly regarding dependability and transient voltage stability. Constructing designs for generators and energy storage units are determined by upper-layer network planning, which assesses the system dependability index. Transient stability demands and constructing and maintenance expenses are addressed by lower-layer challenges. It is suggested to use a two-layer iterative technique using adaptive particle swarm optimization (PSO) for successful nonlinear problem solution. Implementing the suggested approach on an IEEE 33 system of testing demonstrates its practicality. In addition to improving the network's operational efficiency and reliability, the findings show that the suggested optimization method also fixes the issue with regard to program and group planning. Future plans for the operation and planning of the power scheme may be informed by the outcomes.

Keywords: *Climate Change, Renewable Energy, Two-layer Optimization, Voltage Stability, PSO*

1. INTRODUCTION

Climate change is an urgent problem that impacts every single individual on our planet [1]. The onus for reducing emissions of greenhouse gases is on the power industry in China because to the country's goal of carbon neutrality and emissions peak targets [2]. Significant steps toward reaching carbon neutrality by the year 2060 may be taken by developing renewable energy sources, increasing the share of power in the ingesting of primary energy, and enhancing the degree of electrification in energy ingesting overall [3]. In light of this, the addition of renewable energy sources into power grids is booming. The conventional, fossil fuel-based, high-carbon power system is gradually giving way to the new, renewable power system that relies heavily on wind and solar power, among other renewable energy sources. However, issues with planning and

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operating power systems will arise due to the fact that renewable energy's unpredictability and severe fluctuation will provide a stark contrast with the need to guarantee a steady and uninterrupted power supply [4].

Integrating renewable energy sources and networks in a coordinated and optimum way has been the subject of much study in an effort to make the power system more flexible [5]. Demonstrating the economic benefits of coordinated development, an integrated expansion planning strategy for transmission lines and renewable energy was suggested in. In order to find a balance between costs and environmental implications, a multi-objective optimization model was used to solve the generating expansion issue, which incorporated transmission limitations [6-8]. In, a strategy for static planning was developed. Studies in this area included stochastic optimization and resilient optimization to better handle the difficulties posed by renewable energy's inherent unpredictability [9]. The authors suggested a method for system planning known as stochastic adaptive robust optimization. Battery energy storage systems (BESSs) and transmission expansion were modelled using a stochastic multistage co-planning approach [10].

A robust optimization strategy for transmitting network design specified net injection uncertain as an easy uncertain set instead of a probability distribution [11]. The time required to ramp up energy and the length of construction to increase renewable producing were included in a detailed and accurate planning model [12].

To guarantee safe and cost-effective operation, power system design must emphasize dependability as renewable energy penetration increases. Probabilistic planning methods that include power system reliability are widely studied [13-15]. The growth planning methodology that considered reliability was more cost-effective and trustworthy. An optimization objective included the cost of expected energy not supplied while planning the power set and circuit [16-18]. Stochastic co-optimization planning models incorporated losses of load expectation (LOLE), a measure of long-term stochastic dependability. Based on dependability indicators, the best transmission strategy was determined [19].

Research has examined system transient stability of voltage using a time-domain simulation, direct, and AI. Direct method assesses transient stability using an unstable energy factor [20]. In addition, time domain modeling can examine how renewable energy accessible scale and design affect transient voltage stability. Lack of theoretic support makes it problematic to assess electrical system transient stability using existing methods [21]. Dynamic reactions and power system tolerance to external disturbances may be examined using input-to-state stability (ISS) theory.

Generation and transmission power system scheduling is a multidimensional optimization problem with complex restraints. Heuristic or mathematical optimization methods handle planning problems. Mixed-integer linear programming was planned for multi-objective [22]. A heuristic strategy was future to enhance the financial strategy while bolstering the dependability level. Because it is effective with discrete variables and may now theoretically attain global convergence, the heuristic technique is a promising candidate for this problem's resolution. Particle swarm optimization (PSO) is an excellent method because it is easy to use, converges quickly, and has excellent search efficiency [23]. As a result, several academics both at home and abroad have been interested in it ever since it was suggested. An adaptive-weight multi-objective PSO method was suggested in. A learning factor and inertia weight were fine-tuned. A stable mutations operator was suggested for use with particles that are not in a stable environment, allowing them to undergo mutation operations. Particles' capacity for local exploration is improved by the hybrid approach. In, SPO-based modifications to particle swarm optimization were suggested, including dynamic momentum [24]. To address a three-object operational issue, a PSO-based multi-level optimization approach was offered.

The design of transmission systems and power production with a big share of renewable energy sources has been the subject of much study. Nevertheless, more research into a planning strategy that takes transient voltage stability and system regulation capacity adequacy into account is still necessary. This work proposes a technique for designing a transmission and generating system that incorporates stability of transient voltage and dependability [25]. The transmission and generation planning models are set up with two layers. An objective-multiplier function is built by taking into account the building cost, the transient stability list, and the reliability criteria EENS. While limiting the impact of energy from renewable sources on system stability, the lower layer optimizes energy resource locations, capacities, and operating costs founded on the optimized form of network design in the top layer. To resolve the two-layer optimization issue, an iterative technique based on heuristics is used. The results demonstrate that system planning achieves its overall optimization goal.

This paper continues as follows: The mathematical simulation of the two-layer power generation is presented in Section 2. Section 3 proposes a solution. Section 4 presents case examples to show the efficiency of the suggested strategy. This article concludes at Section 5

2. FORMULATION IN MATHEMATICS

Designing and optimizing power systems is now possible with the use of a two-layer planning model. Improving the system's efficiency and dependability via optimization of the transmission's planning scheme is the primary goal of the model's top layer. The model's bottom layer uses the optimal transmission design from the top layer to find the best position and capacity for conventional generators, sources of clean energy, and storage devices for energy. This two-tiered approach is an attempt to find a happy medium in the design and operation of power systems, balancing transient stability, system cost-effectiveness, and dependability. The two-layer planning approach may improve the power system's reliability and sustainability by improving transmission planning, power production, and storage allocation.

2.1 Grid Scheduling

2.1.1 Function of the Objectives

It takes into account the building cost of the lines for transmission and the reliability of the system to make sure the planning outcomes are economical and dependable.

$$minF_1 = C_{linv} + C_r \quad (1)$$

Where C_r stands for the expense of the EENS and C_{linv} for the investment cost of the network. Here is one possible way to express the formulation:

$$C_{linv} = \sum_{t\in\Omega^T} \sum_{l\in\Omega^{L+}} \kappa_t x_{lt} L_l C_l^{inv} \quad (2)$$

$$K_t = \frac{1}{(1+r)^{t+1}} \quad (3)$$

This stands for the present-worth value coefficient, κ_t. The rate of discount is denoted as r. As a binary variable, x_{lt} represents the investment status of line l at time t; it is set to 1 if line l is constructed and 0 otherwise. In this context, L_l stands for the line's length. In terms of transmission line investment cost per unit length, C_l^{inv} is the symbol to use.

The following is an expression of the dependability optimization goal in terms of the EENS cost:

$$C_r = \gamma \times \sum_{t\in\Omega^T} \sum_z \sum_j P_z \Gamma_{zjt} dt \quad (4)$$

The lost load cost coefficient is represented by γ. The probability of the event z is represented by P_z. The electronic load shedding of time t is represented as Γ_{zjt}. dt is the length of the time period denoted by t.

2.1.2 Limitations

1. Limited scope of the building plan:

There are several criteria that the building scheme's decision variables must satisfy.

$$X \le X_{lt} \forall l \in \Omega^{L+} \quad (5)$$

The total number of lines that need to be constructed is denoted by Ω^{L+}, and $X \in \{0.1\}$ stands for investing status of line l.

2. Transmission line capacity limitations:

Make that the trans-mission lines have enough capacity to meet the upper limit requirement.

$$s_l \le s_{max} \quad (6)$$

Where the ability to produce line l is represented by s_l. The maximum allowable transmission capacity is represented by s_{max}.

3. Limitations on network connection and open-loop operation:

In order to prevent the formation of an annular electrical supply structure, power systems must provide electricity to all load locations. These limitations are stated in the following way:

$$\underset{E\text{â^Î©}_{LL}\text{Î©}_{EL}}{\text{â}} x_E + \underset{K\text{â^Î©}_{LL}\text{Î©}_{NL}}{\text{â}} x_K \text{â‰¤} N_{LL} - 1 \text{ â^€Î©}_{LL} \qquad (7)$$

The set of branches included in the annular design is denoted as ΩLL, while existing lines and prospective lines are represented as ΩEL and ΩNL, respectively. In the set ΩLL, NLL represents the sum of all branches. The building state of line e and k are represented by xe and xk, respectively.

3. METHOD OF SOLUTION

Grid planning, energy storage preparation, and power group are the two levels that make up the model that is described in Section 2. Traditional optimization techniques face an enormous obstacle in finding a workable solution to the non-convex optimization issue caused by its nonlinear complicated constraints. Optimal planning schemes design is thus suggested by a two-layer iterative method that employs the adaptive PSO approach.

3.1 Algorithm for Weight-Adaptive PSO

Optimal planning issues are often solved in the present study using heuristic algorithms. The algorithm known as PSO is one of the most popular choices for system planners. Furthermore, dependability is considered in this work.

The idea behind the algorithm known as PSO is to mimic the way animals act in groups. Nonlinear optimization problems may be effectively solved using iterations that mimic natural selection and genetic processes, leading to rapid convergence and high accuracy. A collection of solution points in a solution space is first selected at random before the algorithm is started. The optimal locations discovered by the swarming and each point are used to update the point set throughout each iteration. Once the iterations are finished, the best solution may be obtained. The optimal locations discovered by the swarming and each point are used to update the point set throughout each iteration. Once the iterations are finished, the best solution may be obtained.

A solution space is defined with a certain dimension of N. To begin, the initialization of the particle coordinates (z) and velocities (v) is done at random. v is for modifications to the planning configuration, and z is for the optimization model's decision variables. Each particle's current location, z_j, is considered its ideal position q_j the most desirable position within the group is chosen as the ideal position worldwide g when an initial configuration that meets all the criteria is obtained. After that, the procedure for iteration is executed. The following routines are used to update the particle locations and velocities randomly in each iteration.

$$v_j \text{â†} \ W v_j + C_1 R_1 (q_j - z_j) + C_2 R_2 (g - z_j), \quad z_j \text{â†} \ z_j + v_j \qquad (8)$$

The values of R_1, $R_2$are arbitrary integers drawn at random from the range [0,1]. The jth particle's velocity is denoted asv_j. The symbol for the mass of inertia is W. The constants of acceleration are C_1 andC_2.

The inertia weight W has a positive effect on algorithm convergence and search accuracy; a lower W is good for escaping local optima, while a greater W is good for leaping out of them. Finding the sweet spot between search speed and accuracy requires a good value of W. This research uses an adaptive inertia weight W modification approach. A greater starting number of 0.9 was set at the start of the loop, decreasing linearly to 0.4.

The method checks if the new particle locations and velocities satisfy the requirements and enhance the objective function value after receiving them. Both requirements must be met for the swarm to update the solution. Everything else is the same. The new global optimum position g is determined by taking the best swarm position once all particles have been updated. The algorithm's best answer is represented by the swarm's globally best position g after each iteration.

3.2. Solution Procedure

The transmission and generation scheduling model concept are shown in Figure 1. The primary issue is planning optimization, and the operating optimization, sub-problem, is handled using possible planning scheme solutions and fed back to the main problem. An ideal solution that meets the needs of both levels is achieved in the two-level scheduling issue by an iterative collaboration among program scheduling and source-storage planning systems.

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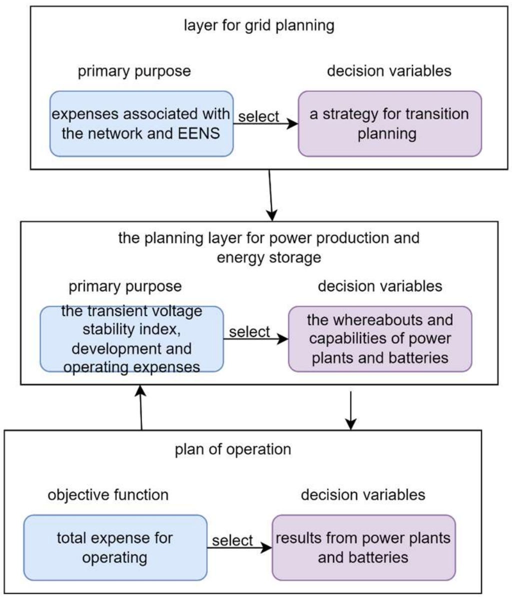

Figure 1: Generation-Transmission Planning Schematic

The two-layer power group and distribution planning model are addressed using the modified weight-adaptive PSO algorithm. Here's the solution procedure.

1. Grid planning solution procedure:
   - Start with population X's initial specifications and come up with N grid planning designs.
   - A selection of the stellar individuals from particle populations X are chosen for mutation and crossover in order to generate N revised grid design schemes, with the overarching goal of maximizing the cost of line construction and system dependability.
   - Power supply, storage of energy planning, and operational issue resolution all need input conditions for the N grid building schemes, which should be transferred to the lower-level recording.
   - Assess particle population X's fitness and iterative termination condition. Searching stops and the optimum solution is produced if the criterion is satisfied. Otherwise, step 2 is repeated after updating the population.

2. Formulation of a strategy for energy storage and power generation:

- Based on subdivision community X of the network building plan from the top layer, create the particle population Y for conventional, new energy, and energy storage access location and investing capacity.
- Applying the technique of Monte Carlo to a model of wind speeds and solar energy intensities for each period, a fuzzy C-means algorithm for clustering is used to group the data collected fresh energy output scenarios, and multiple characteristic scenarios are obtained, taking into account the ambiguity of the output that is produced of new energy units.
- Based on the results of the new energy unit and the probability of common situations, improve the operating strategy for each generating unit and storage of energy in investment systems. Next, figure out how much it will cost to run the system based on the traditional unit scheduling plan and the wind/solar power plan.
- Determine the particle population Y's fitness using the planning scheme's transient voltage stability index, the operative cost of the system, and the investment cost of energy production and storage, which make up the complete optimization goal. Follow steps 4 if you've hit the iterative termination condition; if not, go back to step 1 and update the population.
- Send back to the top layer the value of the primary goal purpose. Revise the best planning strategy based on the most recent best value of the goal function.

4. CASE STUDY

Two separate cases are defined using the IEEE-33 standards as a foundation in order to compare and contrast and prove that the procedure works. Scenario 1 is all about optimizing the generation planning system. Scenario 1 solely plans power production and energy storage, not the grid structure, to separate these two possibilities. In contrast, Scenario 2 looks at power production and energy storage as well as the planning of the grid layer by implementing the suggested plan model.

4.1 Parameters for Optimization

Table 1 contains the optimization parameters. Energy storage power is only one example of a limitation where upper and lower bounds are

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detailed below. The generation planning construction and operations expenses may be determined using the multi-stage heuristic technique suggested in Section 3. There is a 5% discount rate. At 10,000 CNY/MWh, the cost coefficient of wasted load Ň is defined. With 100 generations and a population size of 100, the PSO algorithm is ready to run.

Table 1: Operating system limits

Optimization Criteria	Value
An energy storage device's maximum discharge power	251
Energy storage capacity at its maximum charging point	199
Thermal power unit minimum power	251
Thermal power unit minimum power	99
Gas turbine maximum power	301
The gas turbine's minimal power	99

4.2 Optimization Object Outcomes

In Table 2 you can see the best outcomes. Here are two examples of how much generation planning may cost. The best schemes of Scenario 2 outperform Scenario 1 in economic terms, In Scenario 1, the transient stability of voltage index ρ is 0.53, whereas in Scenario 2, the recommended transmission and generation planning approach reduces it to 0.16. Result shows considerable improvement in system transient voltage stability.

Table 2: Planning expenses for generation in various optimization scenarios

scenario	CNY	Thermal power (CNY)	(CNY) PV cost	(CNY) Wind turbine cost	(CNY) Gas turbine cost	(CNY) Total cost
1 scenario	3588	4310	1336	2909	6816	52,275
2 scenario	3222	2843	1336	2909	7245	52,031

4.3 Analysis of Two Scenarios' Planning Outcomes

Figure 2 shows transmission planning findings for two situations. The graph shows Scenario 2's proposed expansion lines as a dashed line.

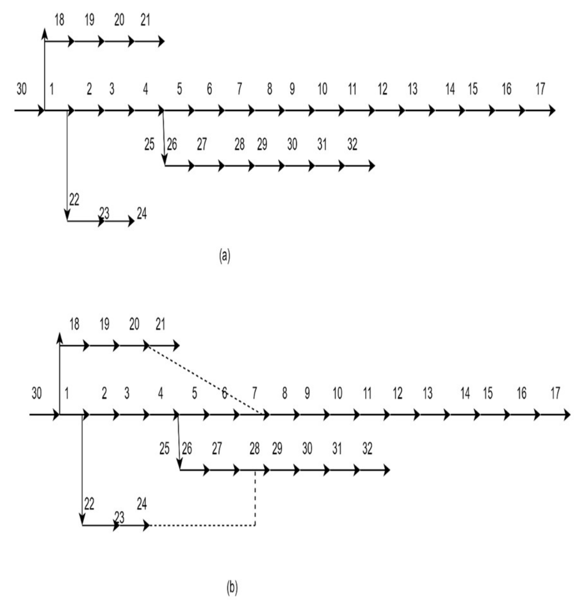

Figure 2: Transmission forecast. a) The system framework of Scenario 1; b) optimum grid planning strategy of Scenario 2.

Table 3 also shows where the energy storage units and generators are in each of those cases.

Table 3: Different optimization possibilities for generator and energy storage access

Scenario	Storage Energy	Turbine Gas	Thermal Power Unit	PV	Turbine Wind
Scenario 1	(13,18)	(3,22)	(27.10)	(15,7)	(25,21)
Scenario 2	(13.33)	(4,25)	(29,10)	(21,8)	(30,17

Based on the first scenario, the following nodes are occupied by various components: 13 and 18 for energy storage, 3 and 22 for gas turbines, 27 and 8 for thermal power units, 15 and 7 for PV units, and 25 and 21 for wind turbines. In the second scenario, the suggested planning model is put into action with the following nodes: 13 and 33 for energy storage, 4 and 25 for gas turbines, 29 and 10 for thermal power units, 21 and 8 for PV units, and 30 and 17 for wind turbines.

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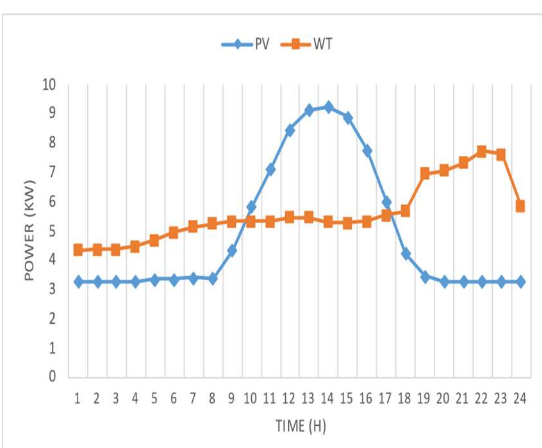
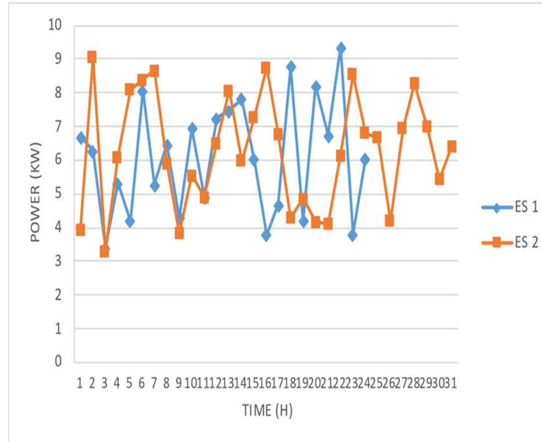
4.4 Results for Optimal Operation

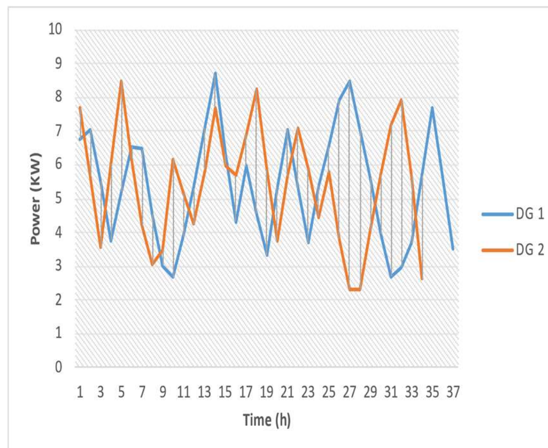
Moreover, the ideal outcomes of the procedure in Scenario 2 are computed and examined. Following is a graphic depicting the operational systems of the energy storing units and generators in the second scenario's ideal planning scheme. The time axis, or abscissa, in Figure 3 represents a single instant in a 24-hour period. The power value, shown as the ordinate, is measured in kilowatts (kW). Figure 3a shows that power from solar cells is at its highest during the day, whereas power from wind turbines is at its highest during the night. The power requirement is met by efficiently using the results of new energy resources. As shown in Figure 3b, energy storage units can be fine-tuned so that they may add to the power supply. The energy storage units linked to nodes 13 and 33 each have their own power curve that shows the output. According to the effective limits, the energy and control curves chance the restraints. The outputs of thermal power units and gas turbines, separately, which are also familiar to fit the power supply in the optimum preparation system. In order to maximize the energy supply and fulfil the needs in the system, the findings show that the suggested planning perfect is successful in combining various sources of power and storing units. Below are some visual representations of the outcomes of optimizing the power flow. Time of day is represented by the x-axis coordinates and the total amount of nodes in the system is represented by the y-axis coordinates in the picture. As shown in Figure 4, the power profile shows the magnitude of the voltage at every bus in the electrical system. System stability and dependability are guaranteed by maintaining the ideal voltage profile within the permitted range.



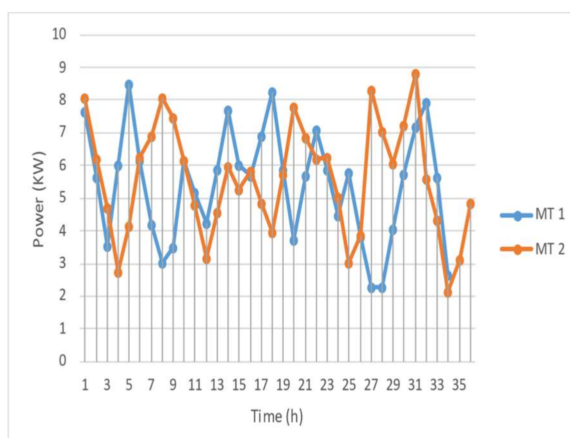
(a)



(b)



(c)



(d)

Figure 3: Generator and storage of energy system operation schemes: (a) fresh energy resource outputs, (b) energy storage unit outputs, (c) thermal power unit outputs, (d) gas turbine outputs.

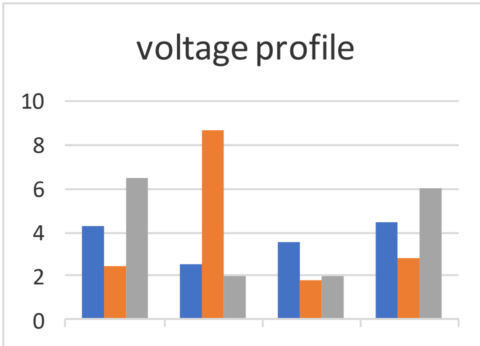
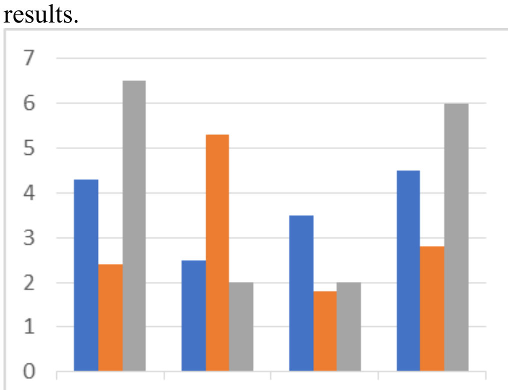
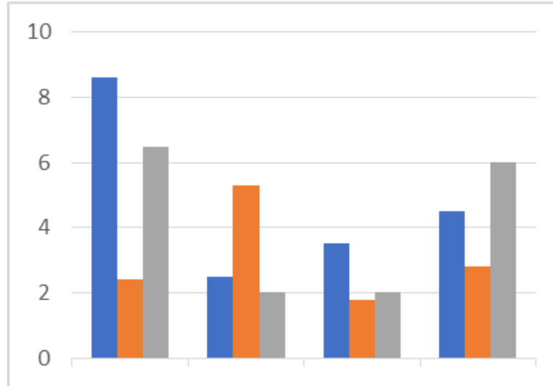


Figure 4: Power Graph

Power transfer efficiency and voltage stability may be achieved by distributing both reactive and active power flows optimally, as shown in Figures 5 and 6. The amount of active and reactive power per unit of time for each node on a one-day time scale are represented by the associated z-axis coordinates. The improved system reduced overload and underutilization of certain system components by distributing power evenly across the various lines of transmission and generators, as measured by active power flow. The findings show that the electrical network transmission and generation scheduling issue is successfully addressed by the suggested optimization strategy, which also improves the system's operating reliability and efficiency. Future methods for planning and operating power systems may be informed by the results.



Figures 5: Power Transfer in Action



Figures 6: Flow of Reactive Power

5. CONCLUSION

Taking into account dependability and temporary voltage constancy, this work introduces a unique two-layer optimization model for generation and transmission preparation that addresses the difficulties of integrating renewable energy sources. To account for all expenses associated with building the grid, the transmission planning layer formulates an objective function that takes both the building cost and the EENS cost into account. The goal function is created at the layer responsible for planning energy production and storage by taking the operational and construction expenses as well as the transient stability index into account. In addition, in order to guarantee the practicability of building and operating, the limitations of producer output, building capacity, transient constancy, system power flow, etc., are thoroughly addressed. The complicated nonlinear issue is solved using a two-layer iterative approach that is built on adaptive PSO. Evidence from real-world applications shows that the suggested approach may improve grid planning, power storage device placement and capacity, and generator set efficiency. To enhance the optimization effect, future research may consider uncertainties' effects on power system planning's dependability and transient voltage stability, such as changes in load demand. This paper's model may be extended and used as an analogy to apply the suggested strategy in real systems.

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