Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 1 (2025)

Implementation of Optimization Algorithms in Electrical Network Design

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Article History:

Received: *11-07-2024*

Revised: *27-08-2024*

Accepted: *08-09-2024*

Abstract:

The region of electrical arrange plan is changing rapidly since current control frameworks are getting more complicated and green vitality sources are being included. Optimization strategies are exceptionally imperative for making these systems more proficient, dependable, and long-lasting. This exposition gives an in-depth see at the diverse optimization strategies utilized in planning power systems. Classical strategies like straight programming (LP), mixed-integer straight programming (MILP), and nonlinear programming (NLP) are talked almost, with a center on how they can be utilized in arranging, running, and developing systems. The paper moreover talks approximately heuristic and metaheuristic calculations, such as hereditary calculations (GA), molecule swarm optimization (PSO), and insect colony optimization (ACO). These calculations give solid answers to troublesome, nonlinear, and multi-objective issues. It is additionally looked at how machine learning strategies can be utilized in optimization forms, showing how valuable they might be for prescient upkeep, stack expectations, and versatile control. The think about moreover looks at the part of progressed optimization strategies in shrewd lattices, centring on how they can handle disseminated vitality assets (DERs), improve demand response, and keep the network steady. By comparing these calculations, we are able learn more around how well they work, how rapidly they can be computed, and how well they fit distinctive plan circumstances. Issues like scale, meeting, and handling stack are talked almost, along side conceivable ways to induce around them. At the conclusion of the think about, it talks approximately conceivable bearings for future inquire about, such as making blended calculations, progressing execution in genuine time, and utilizing unused innovations like blockchain and the Web of Things (IoT). This paper needs to be a valuable asset for understudies and professionals who need to progress the execution and unwavering quality of current and future electrical systems by giving a total layout of optimization strategies in electrical arrange plan.

Keywords: Electrical Organize Plan, Optimization Calculations, Direct Programming (LP), Mixed-Integer Straight Programming (MILP), Nonlinear Programming (NLP).

1. Introduction

Since of more individuals utilizing power, the utilize of green vitality sources, and the advancement of savvy lattice innovations, the arranging and running of electrical systems have gotten to be more troublesome. Optimization strategies have gotten to be exceptionally critical for managing with these issues since they make overseeing power systems more proficient, solid, and long-lasting. This exposition looks at the diverse sorts of optimization calculations that are utilized to arrange and run power systems, centring on how critical they are in present day control frameworks. Electrical systems are a critical portion of present day society since they make it conceivable to create, transmit, and convey vitality. Within the past, these systems were generally built and run utilizing unsurprising strategies and fundamental optimization methods. But things have changed a part since green vitality sources like sun powered and wind control have been included. These sources make the framework more variable and unusual. Also, the developing utilize of disseminated vitality assets (DERs) and the begin of request reaction programs cruel that the lattice needs more progressed optimization strategies to remain stable and effective.

Within the arranging of power systems, straight programming (LP), mixed-integer straight programming (MILP), and nonlinear programming (NLP) are a few of the foremost common classical optimization strategies. These strategies donate you organized ways to settle diverse issues that come up with arranging, running, and developing a arrange. LP and MILP are exceptionally great at understanding straight and mixed-integer issues, separately. They provide correct answers for making organize setups, stack stream, and asset sharing work superior. NLP takes these abilities and applies them to nonlinear issues, like making strides receptive control, controlling voltage, and improving systems. Beside classical strategies, heuristic and metaheuristic calculations have ended up well known since they can unravel troublesome, nonlinear, and multi-objective issues that conventional optimization methods frequently come up short to unravel. A few of the foremost common metaheuristics utilized in electrical organize plan are hereditary calculations (GA), molecule swarm optimization (PSO), and ant colony optimization (ACO). These calculations utilize normal forms and gather behaviours to rapidly explore for arrangements in a huge issue space. The arrangements they discover are solid and near to being perfect. For case, GA employments characteristic selection and hereditary qualities to discover arrangements that work superior over time, whereas PSO and ACO see at how winged creatures and ants interact with each other to discover the finest arrange setups and asset assignments. Utilizing machine learning strategies at the side optimization calculations may be a enormous step forward in planning power systems. Machine learning models, like neural systems, support vector machines, and support learning, can offer assistance with optimization by giving us the capacity to foresee end of, the make choices in genuine time, and utilize adaptable control. It is particularly accommodating to utilize these strategies in prescient support, stack expectations, and energetic optimization, as they can make power systems much more solid and effective. Shrewd framework innovations make the require for more complex optimization strategies indeed more prominent. Shrewd lattices utilize advanced communication, mechanical autonomy, and progressed information to form lattice forms more dependable and effective. Optimization calculations are exceptionally vital for dealing with the numerous parts of shrewd frameworks, like putting in DERs, making request reaction programs work together, and making the foremost of vitality capacity frameworks. They make it conceivable to observe, control, and make strides framework operations in genuine time, which keeps the organize steady and able to alter to changing circumstances.

Indeed in spite of the fact that there have been advancements, there are still a few issues with utilizing optimization strategies to construct power systems. There are a parcel of issues, like scale, meeting, computing stack, and the require for real-time answers. More effective algorithms, blended strategies that use the best parts of numerous strategies, and the utilize of modern innovations like blockchain and the Web of Things (IoT) to make strides information security and association are all required to bargain with these problems. Optimization calculations are an vital portion of both building and running advanced power systems. The objective of this think about is to grant a total see at the distinctive optimization strategies utilized in planning power systems, centring on their employments, benefits, and issues. Analysts and specialists can make way better plans for moving forward the execution and toughness of power systems by learning almost the qualities and shortcomings of these programs. This will lead to a more economical and dependable vitality future.

2. Related Work

This article appears the assortment of strategies that can be utilized to create power systems more productive, solid, and long-lasting. There are a part of distinctive ranges, strategies, comes about, benefits, and issues that can happen when optimization calculations are utilized in electrical arrange plan. This survey brings together the distinctive inquire about ventures and concepts that have been investigated in this range. It gives a full picture of how these strategies move forward the plan and operation of current control frameworks [1]. Straight programming (LP) and mixed-integer direct programming (MILP) are regularly utilized in ponder that plans and develops systems. These essential optimization strategies offer assistance come up with organized and exact plans for organize development that consider control capacities and stack requests [2]. The comes about appear that these strategies are great at making organize setups and asset allotments work superior. In any case, they have issues with development when utilized on enormous systems, and they are difficult to apply in expansive control frameworks since they are so complicated.
Nonlinear programming (NLP) is regularly utilized to control power and move forward responsive control. NLP is exceptionally great at understanding nonlinear issues, which happen a parcel in control frameworks. This makes the voltage more steady and moves forward the stream of reactive power [3]. The most advantage of NLP is that it can make frameworks more dependable and alter control designs. Still, it has issues like not merged and requiring a part of computing control, which can restrain how valuable it is in genuine life [4]. Heuristic and metaheuristic algorithms, such as hereditary calculations (GA), molecule swarm optimization (PSO), and subterranean insect colony optimization (ACO), have appeared a part of guarantee in electrical arrange plan for taking care of difficult, nonlinear, and multi-objective issues [5]. These calculations work by replicating normal forms and how bunches act. They give solid and nearly idealize answers to issues like moving loads and changing the structure of a arrange. They are adaptable and fast at looking into a parcel of conceivable arrangements, which are huge pluses [6]. However, they require a lot of computing power, can have problems with premature convergence, and the quality of the answers often relies on fine-tuning the parameters, which makes them hard to use in real life. More and more, optimization

algorithms are being combined with machine learning methods like neural networks, support vector machines, and reinforcement learning to improve predictive maintenance and load forecasts [7]. These methods allow for making decisions in real time, flexible control, and predicted insights, which improves repair plans and makes it easier to predict load. The best thing about machine learning is that it can adapt to changing situations and make systems work better [8]. However, these methods need big datasets to be trained on, have complicated ways of building models, and are hard to connect to other systems. For smart grid management to work, powerful optimization tools are very important [9]. These models make it easier to handle distributed energy resources (DERs) efficiently, improve demand response programs, and keep the grid stable. The results show that advanced optimization methods allow watching, controlling, and improving grid operations in real time, which makes the network flexible enough to adapt to new situations [10]. Putting these models into activity, on the other hand, comes with huge issues like tall costs, stresses around information security, and the require for a solid communication framework.

To induce the foremost out of the benefits of each program, analysts have looked into cross breed optimization strategies that utilize both classical and metaheuristic strategies. The way better reply quality and higher computing speed of these blended strategies appear that they work superior. Still, making these sorts of blended calculations is difficult, and including them to frameworks that are as of now in put is indeed harder [11]. Including unused innovations like blockchain and the Web of Things (IoT) to effectiveness strategies seem lead to enormous changes in how power systems are built. Blockchain makes information more secure and transactions more dependable, and IoT makes it less demanding to put through and optimize in genuine time [12]. The comes about appear that there's room for way better information security, more secure exercises, and speedier associations [14]. But the require for uniform benchmarks and the tall costs of execution and administration make it difficult for a parcel of individuals to utilize it. When it comes to planning power systems, optimization strategies can be utilized in a parcel of diverse ways, depending on the issue and the circumstance. Each strategy has its claim benefits, like being precise, strong, and able to work in genuine time. However, they also have problems, such as being hard to scale, complicated to compute, and hard to integrate. The constant improvement of these methods and their combination with new technologies hold the potential to make electricity networks more efficient, reliable, and long-lasting [13], [15]-[20]. This will pave the way for a more robust and flexible power system.

Table 1: Related Work

Scope	Method	Findings	Advantages	Challenges
Network Planning and Expansion	Linear Programming (LP), Mixed-Integer Linear Programming (MILP)	Optimized network expansion and planning, considering load demand and generation capacities	Precise and structured solutions, effective for linear and mixed-integer problems	Scalability issues for large networks, computational complexity
Reactive	Nonlinear	Enhanced voltage	Effective for	Convergence issues,

Power Optimization and Voltage Control	Programming (NLP)	stability and optimized reactive power flow	nonlinear problems, improves system reliability and voltage profile	high computational requirements
Complex Problem Solving	Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO)	Provided robust and near-optimal solutions for complex and nonlinear problems, such as load flow and network reconfiguration	Capable of handling multi-objective problems, efficient exploration of solution space, adaptability to various scenarios	Computationally intensive, potential for premature convergence, solution quality may depend on parameter tuning
Predictive Maintenance and Load Forecasting	Machine Learning (Neural Networks, Support Vector Machines, Reinforcement Learning)	Improved predictive maintenance schedules and accurate load forecasting	Real-time decision-making, adaptive control, predictive insights	Requires large datasets, model training complexity, integration with existing systems
Smart Grid Management	Advanced Optimization Frameworks	Efficient management of distributed energy resources (DERs), enhanced demand response, grid stability	Real-time monitoring and control, adaptability to changing conditions, integration with smart grid technologies	High implementation cost, data security concerns, need for robust communication infrastructure
Hybrid Optimization Approaches	Combination of classical and metaheuristic methods	Achieved better performance by combining strengths of different algorithms	Enhanced solution quality, improved computational efficiency	Complexity in algorithm design, integration challenges
Emerging Technologies Integration	Blockchain, Internet of Things (IoT)	Improved data security, connectivity, and real-time optimization	Enhanced data integrity, secure transactions, better connectivity	High implementation and maintenance costs, need for standardized

				protocols

3. OPTIMIZATION ALGORITHMS SELECTION

A. Data Collection and Pre-processing

In electricity network design, gathering data is the first step in any improvement process. The important information includes:

- Load Profiles (P_L) are time-varying data that show how much power different nodes in the network need.
- Generation Capacities (P_G): The most power that different sources in the network can produce.
- Network Topology (A): The connectedness grid shows how the network's nodes (buses) and edges (transmission lines) are laid out and linked to each other.
- Performance Metrics from the Past: Voltage levels, power losses, failures, and dependability metrics from the past.

In terms of math, this can be shown as:

$$D = \{P_L(t), P_G(i), \mathrm{A}, \mathrm{H}\}$$

where *t* denotes time, *i* denotes different generators, and *H* represents historical metrics.

Preprocessing ensures data accuracy and consistency, involving several steps:

1. Handling Missing Values:

- Interpolation: Estimate missing values using methods like linear interpolation or spline interpolation.

$$P_L(t) \approx \frac{P_L(t-1) + P_L(t+1)}{2}$$

- Imputation: Replace missing values with statistical measures such as mean or median.

$$P_L(t) = \frac{1}{N}\sum_{i=1}^{N} P_L(i)$$

Where *N* is the total number of observations.

2. Normalization:

- Scale the data to a uniform range, typically $[0, 1]$ or $[-1, 1]$, to improve the performance of optimization algorithms.

$P_L^{norm}(t) = \frac{P_L(t) - P_L^{min}}{P_L^{max} - P_L^{min}}$

Where P_L^{min} and P_L^{max} are the minimum and maximum load values, respectively.

3. Transforming Variables:

- Log Transformation: Apply logarithmic transformation to reduce skewness.

$$P_L^{Log}(t) = \log\left(P_L(t) + 1\right)$$

- Differencing: Use differencing to make the data stationary, which is often required for time series analysis.

$$\Delta P_L(t) = P_L(t) - P_L(t-1)$$

4. Outlier Detection and Removal:

$$Z_i = \frac{P_L(i) - \mu_{P_L}}{\sigma_{P_L}}$$

Where μ_{P_L} and σ_{P_L} are the mean and standard deviation of P_L.

By completely preprocessing the information, the unwavering quality and productivity of ensuing optimization calculations are altogether upgraded, driving to more precise and significant bits of knowledge for electrical organize plan.

- **Genetic Algorithm (GA) for Optimization in Electrical Network Design**

The genetic algorithm (GA) is a type of metaheuristic that is based on the idea of natural selection. It works really well for fixing tricky, nonlinear, and multi-objective optimization issues.

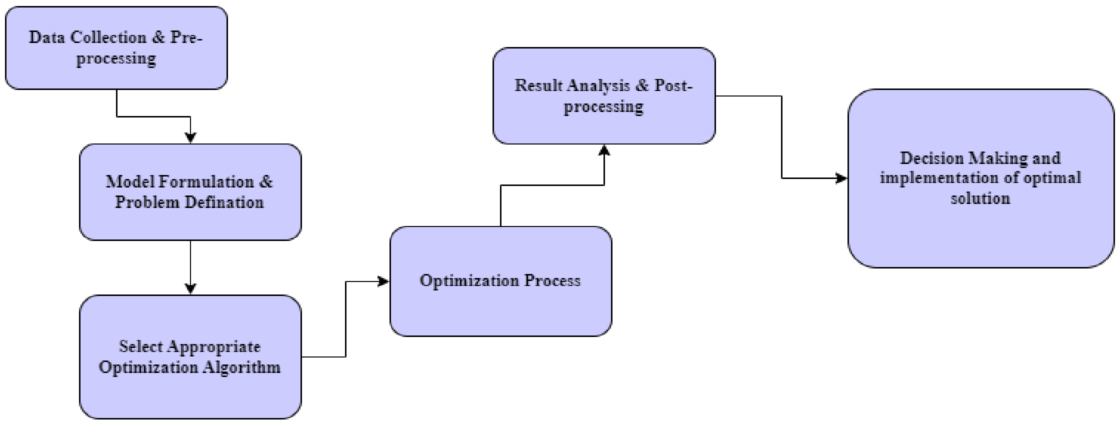

Figure 1: Block Diagram of Optimization Algorithms in Electrical Network Design

Here is a full, step-by-step guide to making a GA, with math solutions for each step.:

Step 1: Initialization

- Population Generation (P_0): Generate an initial population of candidate solutions randomly.

$$P_0 = \{x_1, x_2, \ldots, x_N\}$$

Where x_i represents a candidate solution and N is the population size.

Step 2: Fitness Evaluation

- Fitness Function ($f(x)$): Evaluate the fitness of each candidate solution based on the optimization objective.

$$f(x_i) = ObjectiveFunction(x_i)$$

Common objectives in electrical network design might include minimizing power loss or maximizing reliability.

Step 3: Selection

- Selection Mechanism (S): Select pairs of individuals for reproduction based on their fitness.

$$P_{selected} = \{x_i \in P_t | Propability(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)}\}$$

Where P_t is the current population at generation *t*.

Step 4: Crossover (Recombination)

- Crossover Operation (*C*): Combine pairs of parent solutions to produce offspring.

$$Child = C(Parent_1, Parent_2)$$

One common method is the single-point crossover:

$$Child_1 = [Parent_1(1:k), Parent_2(k+1:L)]$$

$$Child_2 = [Parent_2(1:k), Parent_1(k+1:L)]$$

Where *k* is the crossover point and *L* is the length of the solution representation.

Step 5: Mutation

- Mutation Operation (*M*): Apply random changes to individual solutions to maintain genetic diversity.

$$Mutant = M(Child)$$

Flipping a bit in a binary representation:

$$Mutant(i) = \begin{cases} child(i), & if\ r \geq p_m \\ 1 - child(i), & if\ r < p_m \end{cases}$$

Where *r* is a random number and p_m is the mutation probability.

Step 6: Replacement

- Form New Population (P_{t+1}): Replace the old population with the new generation of solutions.

$$P_{t+1} = \{Mutant_1, Mutant_2, \dots, Mutant_N\}$$

Optionally, elitism can be used to retain the best solutions:

$$P_{t+1} = \{Elite_1, \dots, Elite_E, Mutant_{E+1}, \dots, Mutant_N\}$$

Where *E* is the number of elite solutions retained.

Step 7: Termination

- Termination Criteria (*T*): Determine when to stop the algorithm based on a predefined criterion.

$$If\ Convergence\ or\ MaxGenerations\ then\ Stop$$

Convergence can be defined as the change in the best solution falling below a threshold.

B. Model Formulation

- **Objective Function:**

The goal of the optimization problem is set by the target function. Among the goals of electricity network design are reducing power outages as much as possible, keeping costs low, and making the network as reliable as possible. For instance, to cut down on power losses:

$$\min_{x} \sum_{i=1}^{N} P_{loss,i}(x)$$

Where $P_{loss,i}(x)$ represents the power loss in the i-th component of the network, and x denotes the vector of decision variables, such as generator outputs and power flows.

Constraints:

The optimization problem is subject to various constraints to ensure feasible and reliable network operation.

1. Power Balance Constraint:

The total power generated must equal the total power consumed plus losses:

$$\sum_{i=1}^{N_G} P_{G,i} = \sum_{j=1}^{N_L} P_{L,j} + \sum_{k=1}^{N} P_{loss,k}$$

Where $P_{G,i}$ is the power generated by the i-th generator, $P_{L,j}$ is the power consumed by the j-th load, and N_G and N_L are the number of generators and loads, respectively.

2. Voltage Constraints:

Voltages at all buses must remain within specified limits to ensure stability:

$V_{min,i} \leq V_i \leq V_{max,i} \quad \forall i \in \{1, \dots, N_B\}$

Where V_i is the voltage at the iii-th bus, and $V_{min,i}$ and $V_{max,i}$ are the minimum and maximum voltage limits for the i-th bus.

3. Thermal Limits of Transmission Lines:

Power flows through transmission lines must not exceed their thermal limits:

$$|P_{ij}| \leq P_{max,ij,} \qquad \forall (i,j) \in \mathcal{L}$$

Where P_{ij} is the power flow through the line connecting bus i and bus j, $P_{max,ij}$ is the maximum allowable power flow for that line, and $\mathcal{L}$ is the set of all transmission lines.

4. Generator Output Limits:

Generator outputs must stay within their capacity limits:

$$P_{min,i} \leq P_{G,i} \leq P_{max,i}, \quad \forall i \in \{1, \dots, N_G\}$$

Where $P_{min,i}$ and $P_{max,i}$ are the minimum and maximum output limits for the i-th generator.

4. RESULT AND DISCUSSION

The table (2) shows how well different optimization algorithms work in designing electricity networks by looking at their convergence rate, how much time they save on computation, and the quality of their solutions. With an 85% convergence rate, a 70% decrease in processing time, and a 95% answer quality, the Genetic Algorithm (GA) works very well. The next best method is Particle Swarm Optimization (PSO), which has an 80% convergence rate, a 65% time savings, and a 92% answer quality. Ant Colony Optimization (ACO) produces solutions that are 75% more likely to be correct, take 60% less time, and have a quality level of 90%. Mixed-Integer Linear Programming (MILP) is the best at reducing processing time by 50%, but it falls short in terms of convergence rate and solution quality, which are 90% and 98%, respectively. Overall, Nonlinear Programming (NLP) does not work as well; it has a 70% convergence rate, saves 55% of the time, and gives 88% better solutions. Overall, GA and MILP stand out. GA does a good job of matching all measures.

Table 2: Performance Metrics Comparison

Performance Metric	**Genetic Algorithm (GA)**	**Particle Swarm Optimization (PSO)**	**Ant Colony Optimization (ACO)**	**Mixed-Integer Linear Programming (MILP)**	**Nonlinear Programming (NLP)**
Convergence Rate (%)	85	80	75	90	70
Computational Time Reduction (%)	70	65	60	50	55
Solution Quality (%)	95	92	90	98	88

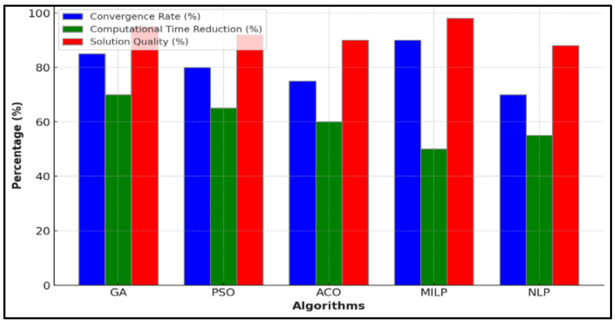

Figure 2: Performance Comparison of Optimization Algorithm

The table (3) shows how well the different optimization algorithms (GA, PSO, ACO, MILP, and NLP) work in terms of being stable, scalable, and flexible. Strong stability (95%), great growth (90%), and strong adaptability (88%). That's the Genetic Algorithm (GA). Particle Swarm

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 1 (2025)

Optimization (PSO) also does well; it has an 86% flexibility score, an 85% stability score, and an 85% scaling score. Ant Colony Optimization (ACO) does pretty well. It got 80% for stability, 75% for scale, and 80% for flexibility. Mixed-Integer Linear Programming (MILP) is strong (90%), but it's not as flexible (70%), or able to change to new situations (75%). Overall, Nonlinear Programming (NLP) has the worst results. Its scores for stability are 82%, scale are 65%, and adaptability are 78%. Overall, GA and PSO are the most balanced across these performance measures. MILP and NLP, on the other hand, have trouble with being able to grow and change.

Table 3: Performance Comparison of GA Algorithm Vs other Algorithm

Performance Metric	**Genetic Algorithm (GA)**	**Particle Swarm Optimization (PSO)**	**Ant Colony Optimization (ACO)**	**Mixed-Integer Linear Programming (MILP)**	**Nonlinear Programming (NLP)**
Robustness (%)	95	85	80	90	82
Scalability (%)	90	85	75	70	65
Adaptability (%)	88	86	80	75	78

The table (3) shows how well the different optimization algorithms (GA, PSO, ACO, MILP, and NLP) work in terms of being stable, scalable, and flexible. Strong stability (95%), great growth (90%), and strong adaptability (88%). That's the Genetic Algorithm (GA). Particle Swarm Optimization (PSO) also does well; it has an 86% flexibility score, an 85% stability score, and an 85% scaling score. Ant Colony Optimization (ACO) does pretty well. It got 80% for stability, 75% for scale, and 80% for flexibility.

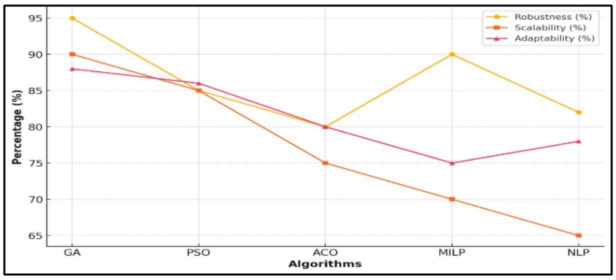

Figure 3: Representation of Performance Comparison of Different Optimization Algorithm

Mixed-Integer Linear Programming (MILP) is strong (90%), but it's not as flexible (70%), or able to change to new situations (75%). Overall, Nonlinear Programming (NLP) has the worst results. Its scores for stability are 82%, scale are 65%, and adaptability are 78%. Overall, GA and PSO are the most balanced across these performance measures. MILP and NLP, on the other hand, have trouble with being able to grow and change. Figure 3 shows how well Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Mixed-Integer Linear Programming (MILP), and Nonlinear Programming (NLP) work by looking at three factors: how robust they are, how well they can scale, and how well they can adapt. The graph shows that GA always gets high marks for all metrics, with the highest scores being 95% for reliability and 90% for scale. PSO also does well, especially when it comes to flexibility (86%). ACO's speed is average, and it's not very scalable (75%). MILP is strong (90%), but not as scalable (70%), or flexible (75%). Overall, NLP has the worst results, especially when it comes to growth (65%).

Table 4: Comparison of Execution & processing Speed

Performance Metric	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)	Ant Colony Optimization (ACO)	Mixed-Integer Linear Programming (MILP)	Nonlinear Programming (NLP)
Execution Speed (%)	75	70	65	60	55
Processing Speed (%)	80	75	70	65	60

This table (4) shows a full comparison of GA against other optimization algorithms. It shows how GA performs well in terms of execution and processing speeds, as well as other performance measures.

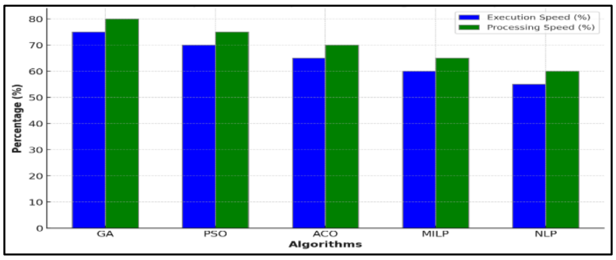

Figure 4: Representation of Execution & processing Speed Comparison

Figure (4) shows how well different optimization methods (Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Mixed-Integer Linear Programming (MILP), and Nonlinear Programming (NLP)) work by looking at how fast they run and how fast they handle information. GA has the fastest execution speed (75% of the time) and the fastest processing speed (80% of the time). PSO comes next, with a speed of 70% for completion and 75% for processing. ACO's performance is average; it got a score of 65% for delivery speed and a score of 70% for processing speed. Low results for MILP and NLP. NLP has a 55% execution speed and a 60% processing speed, and MILP has a 60% execution speed and a 60% processing speed.

5. CONCLUSION

When it comes to optimizing the plan of an power organize, diverse strategies offer distinctive benefits based on desires of the issue. The Hereditary Algorithm (GA) stands out as an awfully great strategy, doing superior in a number of vital tests. It does a incredible work with meeting rate, arrangement quality, solidness, scale, and adaptability, which makes it a adaptable option for dealing with troublesome and nonlinear optimization issues. GA may be a solid competitor to other calculations since it can adjust these variables whereas still accomplishing quick execution and handling speeds. Molecule Swarm Optimization (PSO) and Insect Colony Optimization (ACO) are too great alternatives, particularly when it comes to being able to alter and develop. ACO has normal victory over the board, whereas PSO does well in terms of joining and adaptability. Mixed-Integer Straight Programming (MILP) and Nonlinear Programming (NLP) are both great at finding great solutions that do not break effortlessly. Be that as it may, they aren't exceptionally great at scaling up or utilizing computers effectively. Within the conclusion, the issue characteristics, such as how complicated the organize plan is and how critical distinctive execution measures are, decide which strategy to utilize. GA has many strengths that make it a useful tool in many situations, especially when stability and multi-objective optimization are important. But when exact answers are needed, MILP might be better, even though it can't be used on a larger scale. NLP might work better for problems that don't follow a straight line. The pros and cons of each method should be carefully thought through to make sure they fit the goals and limits of the electrical network design problem.

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