ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA (ICAI)

Master in Smart Grids

Algorithmic Approaches for Optimal Placement of Flexible Resources in Distribution Networks

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Chapter 1: Introduction

1.1 Project Motivation

The global energy landscape is transitioning towards sustainability and climate change mitigation, with renewable energy playing a critical role. Distributed Generation (DG), which generates electricity close to the point of consumption, is emerging as a key trend. DG technologies, including solar photovoltaic, wind turbines, and bio-energy systems, can reduce transmission losses and enhance power supply reliability[1, 2, 3].

DG integration into current networks offers both benefits and challenges. While DG can decrease energy losses and improve system efficiency, the intermittent nature of renewable-based DGs necessitates sophisticated control strategies for grid stability[1, 4]. Optimization algorithms like Grey Wolf Optimizer and Particle Swarm Optimization are being used to optimize DG placement, sizing, and operation[5, 6].

DG's role is expanding, promising enhanced grid resilience, reduced environmental impact, and increased energy security. It is crucial to integrate these systems into grids using advanced methods and regulatory frameworks to realize the full potential of renewable energy generation[2].

1.1.1 Importance of optimizing hosting capacity in distribution networks

Hosting Capacity (HC) is defined as the maximum amount of generation a power distribution system can accommodate without exceeding operational limits [7]. These limits include voltage stability, thermal capacity of lines, and other critical parameters. HC is a crucial concept, particularly in the integration of renewable energy sources into the grid. When a distribution network reaches its HC, any additional generation can lead to issues such as voltage violations, line overloading, and power quality problems.

Traditionally, power generation was centralized, with electricity being generated at large plants and transmitted over long distances to consumers. Distribution System Operators (DSOs) planned grid investments based on predictable patterns of demand growth and reinforcement needs. However, the increasing penetration of DERs has introduced significant variability and complexity into the grid [8]. This has made traditional grid planning methodologies inadequate for managing the dynamic nature of modern distribution networks. Additionally, unbundling has played a crucial part by splitting the roles each part now can take in the system. In Europe, unbundling impacts Distribution System Operators (DSOs) since it limits their discretion or authority to oversee generation investments. It means that DSOs need to work closely with the generation companies to properly manage the DERs.

The concept of HC was first introduced in 2004 [9]. The initial approach to determining HC was static, considering the worst-case scenarios of maximum generation and minimum demand. This method, while conservative, often underestimates the actual hosting capacity of the grid as it does not account for the temporal variations and uncertainties inherent due to the nature of DERs.

This thesis leverages the previous work of Juan Menéndez Pidal in the Onesait's DERMS project [10] to explore the best algorithms to optimize DG placement within the distribution network. These are considered to bring multiple benefits to the landscape.

1.1.2 Need for efficient allocation of Distributed Generation

Efficient allocation of Distributed Generation (DG) in power systems is vital for several reasons. Optimal placement and sizing of DG units can significantly reduce power losses, leading to economic savings and a more efficient power system [3]. DG also helps maintain voltage levels within prescribed limits, especially in remote areas, improving the stability and reliability of the power supply [11].

Integrating renewable energy sources as part of DG offers environmental benefits, reducing the carbon footprint and aiding in meeting emission reduction targets [2]. DG enhances power supply reliability by providing additional generation sources and increasing system resilience against grid failures [4].

Strategic DG placement can defer costly upgrades to infrastructure, providing economic advantages by optimizing existing grid infrastructure [12]. It can also relieve power line congestion and reduce transmission losses [13]. With the focus on renewable energy integration, proper DG allocation aligns with government policies and maximizes financial incentives for renewable energy adoption [2].

In summary, maximizing DG allocation is significant for technical, economic, strategic, and environmental gains. The selection of appropriate optimization techniques is crucial to effectively achieve these objectives. Efficient DG allocation plays a vital role in modern power distribution systems.

1.2 Objectives of the Thesis

Goal: Develop a metaheuristic algorithm for optimal DG placement and sizing in the power grid

1. **Accelerate connection point requests:** The thesis addresses the surge in connection point requests due to the popularity of renewable energy and Distributed Energy Resources (DERs). It proposes methods to streamline the evaluation and approval of these requests, aiming to focus primarily in those that go in the lines of the optimal configuration.

2. **Long-term planning and minimizing grid reinforcements:** By focusing on strategic placement of DG units, this thesis will provide a tool that will help DSOs faster approve those request that benefit the overall efficiency of the system and reject those which do not. The research will address the need for grid reinforcements due to increasing load demand and DG integration, proposing cost-effective solutions by optimally locating and sizing DG units to utilize existing infrastructure.

The optimization model is therefore meant to be used as a tool to help the DSO establish criteria to improve hosting capacity and accelerate the network connection request process. It is not intended to ensure the optimal location for making economic investments, as they are not allowed to take part in the generation business, but rather to assist the DSO in maximizing the capacity of its network. This approach helps delay the need for costly network reinforcements, enhancing the efficiency and reliability of the distribution system.

Chapter 2: State of the Art

The optimal placement and sizing of DG units in power distribution networks have been extensively studied over the past decades [2, 14, 15, 8], driven by the increasing integration of renewable energy sources and the need for enhanced grid stability and efficiency. Numerous optimization algorithms have been proposed and employed to tackle the complex problem of DG placement, each offering unique advantages in terms of computational efficiency and solution robustness.

2.1 Optimisation algorithms

There are several distinct methodologies for addressing the problem of DG allocation in power systems. These methodologies can be broadly categorized into classic optimization approaches, sensitivity analysis-based approaches, metaheuristic-based approaches, and hybrid approaches combining sensitivity analysis with either classic or metaheuristic optimization [15]. Each category has unique strengths and weaknesses, making them suitable for different aspects of DG allocation problems.

- **Classic optimization algorithms**, such as linear programming and non-linear programming, have been applied to DG allocation problems in some cases. These approaches generally lack flexibility as they require pre-conditions like convexity, linearity, and continuity of objective functions, which are often not met in practical scenarios [8]. Despite their rigorous mathematical foundation, classic methods struggle with the non-convex, multi-objective, and mixed-integer nature of real-world power system optimization problems [8].
  - **Strengths**: Rigorous and well-understood mathematical framework. Suitable for problems that meet the necessary pre-conditions of convexity and linearity.
  - **Weaknesses**: Limited flexibility, often require simplifications that may not accurately capture the complexities of power systems. May be applicable only to small-scale problems.

- **Sensitivity Analysis-Based Approaches**, focus on finding the optimal location for DG units by using a sensitivity index to identify the most sensitive locations. While sensitivity analysis offers low computational time, the degree of optimality of the solutions is uncertain, and these methods typically do not determine the optimal size of DG units, therefore, need to be combined with other methods [15].
  - **Strengths**: Low computational time. Effective for quickly identifying potential locations for DG units.
  - **Weaknesses**: The optimality of the solutions is often unknown. Limited to determining only the location, not the size, of DG units.
- **Metaheuristic algorithms**, are population-based stochastic approaches that do not impose pre-conditions on objective functions or constraints. These methods are highly effective in solving DG allocation problems and are among the most commonly used approaches. However, they can sometimes converge to false local optima rather than the global optimum, prompting ongoing research to address this premature convergence issue [8].
  - **Strengths**: High flexibility with no need for convexity or linearity. Capable of handling complex, multi-objective, and non-linear optimization problems.
  - **Weaknesses**: Risk of converging to local optima instead of the global optimum. May require significant computational resources for large-scale problems and even then, you can end up with sub-optimal solutions and not the best of them.
- **Hybrid Approaches**, combine sensitivity analysis with either classic or metaheuristic optimization algorithms. Sensitivity analysis is first used to reduce the search space by identifying appropriate locations for DG units. Then, a classic or metaheuristic optimization algorithm is applied to determine the optimal size of the DG units. This reduces the complexity of the problem [16] since the optimization algorithm does not need to handle a mixed-integer problem.

- **Strengths**: Combines the low computational time of sensitivity analysis with the flexibility of optimization algorithms. Reduces the search space, making the optimization process more efficient.
- **Weaknesses**: Relies on the initial accuracy of sensitivity analysis for effective performance. May still face challenges related to the convergence and accuracy of the optimization algorithm.

This review provides a chronological examination of key methodologies and findings in the field, highlighting the evolution of optimization techniques and their application to various power system objectives, such as minimizing power losses, improving voltage stability, and accommodating uncertainties in renewable energy output. The following section detail the significant contributions and advancements in DG optimization, drawing insights from a diverse array of studies to present a comprehensive state-of-the-art perspective. Table 2 includes the most relevant data of all reviewed articles.

Chapter 3: Aligment with the SDGs

The Sustainable Development Goals (SDGs) were established by the United Nations (UN) in 2015 with the aim of achieving a cleaner, more sustainable, and inclusive future by 2030 [17]. These 17 goals provide a roadmap for addressing global challenges, including poverty, inequality, climate change, and environmental degradation. This project aligns with several of these goals, as detailed below:

- SDG 7: Affordable and Clean Energy
- SDG 9: Industry, Innovation, and Infrastructure
- SDG 11: Sustainable Cities and Communities
- SDG 13: Climate Action

Figure 3.1: Sustainable Development Goals [17]

This project aligns with several key SDGs, particularly SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). By optimizing the placement of flexible resources in distribution networks, the project supports the integration of renewable energy, enhances grid efficiency, and contributes to building a sustainable and resilient energy infrastructure. These efforts are essential for achieving a sustainable future and addressing the pressing challenges posed by climate change and urbanization.

Chapter 4: Methodology

4.1 Research Approach

This thesis follows a step-by-step research approach to analyze and assess algorithms for flexible resource deployment in distribution networks. It covers both theoretical and practical aspects, from the initial hypothesis to final testing.

First, a literature review identifies current optimization techniques for DG placement in power systems, highlighting their pros and cons, identifying potential gaps and setting the stage for developing new methods.

Next, data on the distribution network, such as grid configuration, load characteristics, and generation data, is collected. The right tools and software for simulation and analysis are chosen at this stage.

The essence of the work lies in the definition of the problem for a metaheuristic algorithm through a power flow. This involves outlying the objective function to achieve the goals of the optimization process. This function is defined to optimize different factors such as, minimizing power losses, improving voltage profile, reducing cost and maximizing the penetration of renewable energy resources. Additionally, other aspects might need to be considered like specific parameter tunning for each algorithm or setting boundary conditions and constraints.

Then, decision variables and constraints are defined based on the network features and optimization goals. Variables often include the location and size of DG units, while constraints cover voltage and thermal limits.

The final step involves comparing suitable algorithms to select and integrate into MINSAIT's service the best one based on performance, computational complexity, and fit for the distribution network.

Throughout the research, iterative testing and validation ensure the robustness and reliability of the proposed solutions, aiming to provide practical recommendations for optimizing DG placement.

4.2 Project Management

The project is set to be executed over a three-month period, from May 2024 to August 2024. The following Gantt chart (Figure 4.1) outlines the timeline for each task:

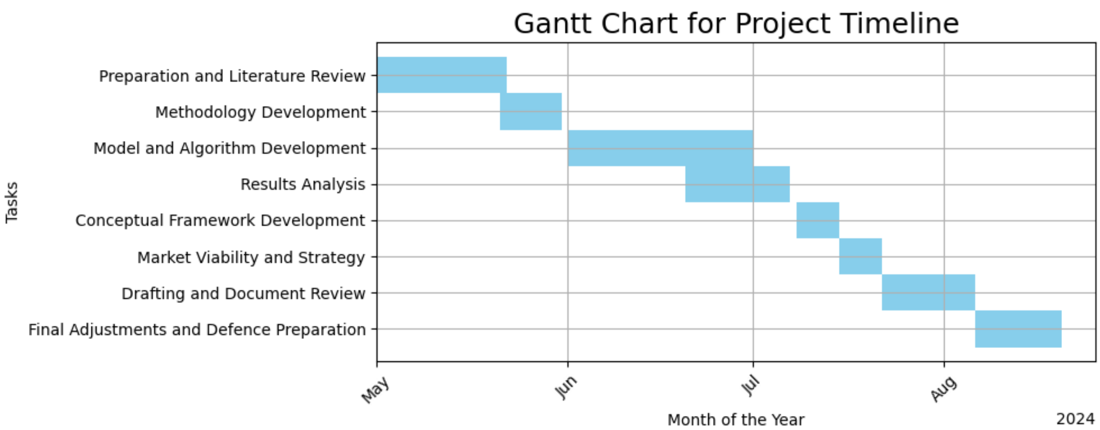

Figure 4.1: Gantt Chart for project timeline

The project commences in May with a focus on preparation and literature review. This involves extensive reading and analysis over a two-week period. Methodology includes selecting appropriate models and algorithms that will guide the subsequent stages of the project.

In June, the primary task is the development and implementation of the selected models and algorithms in MATLAB. The theoretical models will be translated into functional code, with adjustments made as needed.

July is dedicated to analyzing the results from the implemented models. With the understanding of the optimal model, the development of the conceptual framework and architecture for integrating the model into MINSAIT's service will begin. This task involves outlining the structure and design of the final algorithm, ensuring that all components work together seamlessly.

The final month, August, focuses on bringing the project to completion. The final document will be drafted and a review conducted over the next two weeks. In the last week, final adjustments will be made based on feedback and preparation for the project defense will be carried.

4.2.1 Possible Obstacles and Mitigation Strategies

During the course of this project, several obstacles may arise (see Table 4.1).

Table 4.1: *Obstacles and Mitigation Strategy*

Obstacle	**Mitigation Strategy**
Literature Access Issues	Utilize university library resources, online databases, and request interlibrary loans. Schedule regular consultations with advisors.
Algorithm Complexity	Break down implementation into smaller tasks. Seek help from peers or advisors. Allocate extra time for unforeseen difficulties.
Data Availability	Identify multiple data sources early. Use data cleaning and preprocessing techniques. Consider using synthetic data.
Technical Challenges	Maintain regular backups and use version control systems. Allocate time for troubleshooting and debugging. Seek technical support from software documentation and user communities.
Time Management	Create a detailed weekly schedule and stick to it. Set specific goals for each week and review progress regularly. Prioritize tasks to avoid procrastination.
Market Analysis Complexity	Collaborate with Minsait's marketing experts or seek guidance from their business advisors. Use market research reports and industry publications to inform the analysis.

4.3 Description of Tools Used

- **MATLAB/Simulink:** A powerful computational platform used for developing and testing optimization algorithms. Provides extensive libraries and toolboxes for power system modeling, simulation, and analysis.
- **MATPOWER:** An open-source power system simulation tool that integrates seamlessly with MATLAB. Used for performing power flow analysis, optimal power flow calculations, and other network studies.
- **Opensource Toolboxes:** MATALABs File Exchange Toolboxes will provide the foundational model for the different metaheuristic algorithms to compare and implement.

Testing data will be obtained of IEEE Test Bus Systems. On the other hand, real-world data for integration testing will be provided by Minsait.

Table 2: *Existing research works on DG allocation problem from viewpoint of used optimisation algorithms.*

Ref	Algorithm	Objective(s)	Dec Variables	Constraints	Main findings
[18]	Power Flow	-	Type, Size, Location	Voltage stability, reactive power limits	Identifies sensitive buses for DG placement, enhancing voltage stability, reducing losses, and improving power transfer capacity.
[19]	CSA	Power Loss, VSI	Size, Location	Voltage limits, system capacity	Cuckoo Search algorithm outperforms other methods in reducing power losses and improving voltage stability.
[16]	LSF, SA	Power Loss, VSI	Size, Location	Voltage, thermal, power limits	Efficiently determines optimal DG placements, reduces power losses, and improves voltage stability and profiles.
[20]	NSGAII	Minimize costs, losses, outage costs; maximize investments	Size, Location	Technical and economic constraints	NSGAII optimizes DG placement balancing cost, losses, reliability, and investment, handling uncertainties probabilistically.
[21]	PSO	Minimize power loss	Type, Size, Location, PF	Voltage, current, power flow limits	PSO optimizes DG placement, reducing power distribution losses significantly, especially with Type III DGs.
[22]	MTLBO	Minimize power losses	Size, Location	Not specified	MTLBO reduces power losses efficiently compared to traditional methods, with less computational effort.
[23]	CCG	Minimize costs, maximize profits	Type, Size, Location	Voltage, power, DG output constraints	Comprehensive optimization model considering economic, operational, and environmental aspects under uncertainty.
[24]	SQP, BAB	Minimize power losses	Type, Size, Location	Voltage, stability, power factor limits	Reduces real power losses and optimizes DG distribution efficiently.
[25]	PSO	Minimize losses, improve voltage	Size, Location	Voltage, power balance, DG capacity limits	PSO effectively schedules DGs, enhancing performance and reducing losses under various load scenarios.
[26]	SQP	Minimize energy losses, cost of energy	Type, Size, Location, Battery Capacity	Voltage, battery operation constraints	DG and battery storage integration reduces energy losses and COE, crucial in standalone microgrid operation.
[27]	VSI	Minimize power loss, improve voltage	Type, Size, Location	Load growth, voltage, stability margins	VSI method outperforms others in optimal DG placement, addressing load growth impacts and improving voltage profiles.
[28]	MINLP	Minimize losses, generation costs	Size, Location	Voltage, line capacity, placement restrictions	Approach reduces search space and computational time, achieving near-optimal solutions quickly.
[13]	MINLP, MP-OPF	Maximize DG capacity	Size	Voltage rise, thermal overload, grid configuration constraints	Static and dynamic reconfigurations significantly increase DG hosting capacity without extensive grid reinforcements.
[29]	GA, PSO, SA, Hybrid	Optimize cost, efficiency, reliability	Type, Size, Hybrid systems	Cost, renewable resource availability, technology constraints	AI methods optimize hybrid energy systems' performance and cost-effectiveness, enhancing system design and operation.
[6]	GWO	Minimize reactive power losses	Size, Location	Voltage stability, power system constraints	GWO outperforms other algorithms in DG placement, reducing reactive power loss and improving voltage profiles.
[11]	Analytical, GA	Minimize system losses	Location, P, PF	Power flow, voltage limits, power factor	Hybrid approach minimizes system losses more effectively than using only GA or analytical methods.
[30]	FA, CSA	Improve dynamic stability	Size, Location (UPFC)	Dynamic stability constraints	Hybrid FA and CS approach optimizes UPFC placement and minimizes costs, enhancing dynamic stability.

Ref	Algorithm	Objective(s)	Dec Variables	Constraints	Main findings
[31]	ALOA	Minimize power losses, improve voltage	Size, Location	Voltage limits, power conservation, line capacity	ALOA reduces power losses and improves voltage profiles under various loading conditions.
[32]	War Optimization	Minimize power losses	Size, Location	Voltage, power balance, DG capacity	War Optimization outperforms other metaheuristics in reducing power losses and improving voltage stability.
[33]	OBOSA, GWO, ALO	Minimize power losses	Number, Location	Voltage, penetration level, power balance constraints	OBOSA is faster and more accurate than GWO and ALO in minimizing active power losses.
[34]	DE	Minimize power losses	Number, Size, Location	Voltage, power, placement constraints	Method minimizes active power losses with strategic DG placement and sizing, analyzing loss behavior with increasing DG units.
[5]	GWO	Improve voltage, minimize losses	Size, Location	Voltage differences, load patterns	GWO optimizes DG siting and sizing, enhancing voltage stability and reducing losses under different load variations.
[35]	PSO	Minimize losses, improve voltage	Size, Location	Voltage, loadability, power conservation	Integrating PV-DG and BESS via reconfiguration improves system resilience and efficiency under varying conditions.
[36]	CSA-PSO	Minimize cost, losses	Size, Location	Voltage stability, power balance	CSA-PSO reduces costs and power losses effectively when allocating RDGs on specific buses.
[37]	Hybrid PPSO, GSA	Minimize energy loss, maximize voltage stability	Size, Location	Power conservation, DG limitations	Hybrid algorithm reduces energy loss and improves voltage stability better than other metaheuristic techniques.
[38]	COA	Minimize power loss, tap changes	Size, Location	Voltage, tap changes, PV-DG constraints	COA achieves lower losses, minimal regulator tap changes, and higher PV penetration capacity compared to other methods.
[7]	SOCP	Maximize hosting capacity	Size, Location, OLTC settings	Voltage stability, power flow, operational limits	Model increases hosting capacity by optimally reallocating DG units and reconfiguring the grid.
[3]	MOBOSA, GWO, SSA	Minimize power loss	Size, Location	Voltage Stability	Model optimized DF placement with significant energy loss reduction. Robust management of variable generation uncertainties.
[39]	GA, SFLA, JAYA	Minimize losses, voltage deviations	Size, Location	Loss minimization, voltage stability, DG operational limits	Jaya Algorithm outperforms GA and SFLA in DG placement and sizing to minimize losses and voltage deviations.
[40]	EO	Maximize PV capacity	Size, Location	Voltage, reverse power flow, PV output variations	EO outperforms other algorithms in optimal PV planning, considering reverse power flow and smart inverter controls.
[41]	ANFIS, GA, EPSO	Minimize power loss, voltage inconsistency	Type, Size, Location	Voltage profile, power loss, DER type, PF impacts	ANFIS reduces real power loss significantly and improves voltage profiles, requiring fewer iterations for optimal results.
[42]	Fuzzy, GA	Enhance RE penetration, reduce losses	Type, Size, Location + EVs	Voltage, power flow, sizing and location constraints	Combining fuzzy logic for sizing and genetic algorithms for location optimizes RES and EV integration, improving stability and reducing losses.
[43]	PSO, TTA, AOA	Minimize power losses	Location, P	Voltage, thermal, DG placement restrictions	TTA and AOA perform better than PSO under minimal population, but PSO is better with larger population and iterations.
[44]	GWO	Minimize supply costs	Size, Dispatch, Load Strategies	Demand response, technical operation constraints	GWO minimizes costs by optimizing generation and load management, showing substantial cost reductions compared to traditional methods.

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