

**T.R.
SAKARYA UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES**

**OPTIMAL DISTRIBUTED GENERATION ALLOCATION AND
SIZING IN A DISTRIBUTION SYSTEM USING HEURISTIC
ALGORITHMS**

MSc THESIS

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Electrical-Electronic Engineering Department

Electrical Engineering Department

JULY 2025

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Thesis Advisor: Assoc. Prof. Dr. Selçuk EMİROĞLU

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The thesis work titled “Optimal Distributed Generation allocation and sizing in a distribution system using heuristic algorithms” prepared by Zahira ABOUMARIA was accepted by the following jury on 04/07/2025 by unanimously/majority of votes as a MSc THESIS in Sakarya University Graduate School of Natural and Applied Sciences, Electrical-Electronic Engineering department, Electrical Engineering programme

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(31/05/2025)

ZAHIRA ABOUMARIA



To my dear parents and my soulmate....





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Zahira Aboumaria



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ABBREVIATIONS

| | |
|----------------|--|
| DG | : Distributed Generation |
| GA | : Genetic Algorithm |
| GBEST | : Global Best (in PSO) |
| GWO | : Grey Wolf Optimization |
| IEEE | : Institute of Electrical and Electronics Engineers |
| KVAR | : Kilovolt-Ampere Reactive (unit of reactive power) |
| KW | : Kilowatt (unit of active power) |
| MATLAB | : Matrix Laboratory (numerical computing environment) |
| NB | : Total number of buses |
| NDG | : Number of Distributed Generation |
| NL | : Number of lines |
| OPENDSS | : Open Distribution System Simulator |
| PBEST | : Personal Best (in PSO) |
| PQ BUS | : Load Bus (specified active and reactive power) |
| PS | : Power System |
| PSO | : Particle Swarm Optimization |
| PU | : Per Unit (normalized unit used in power systems) |
| PV BUS | : Generator Bus (specified active power and voltage magnitude) |
| SLD | : Single Line Diagram |



SYMBOLS

| | |
|----------------------|--|
| \hat{e}_i | : Unit vector in the position i |
| \vec{x}, \vec{x}_p | : Position and hunting position vector of wolves |
| A, C | : Coefficient vectors |
| g_k | : Conductance of line k |
| NB | : Total number of buses |
| $P_{D,j}, Q_{D,j}$ | : Load demand at bus j |
| $P_{DG,i}, Q_{DG,i}$ | : Active and reactive power injected by DG i |
| $P_{L,k}, Q_{L,k}$ | : Active and reactive losses in line k |
| P_{loss} | : Total real power loss in the system (kw) |
| P_{ss}, Q_{ss} | : Active and reactive power from the substation |
| t | : Iteration number |
| T | : Total number of lines in the system |
| V_i | : Voltage at bus i |
| V_i, V_j | : Voltage magnitudes at buses i and j |
| δ_i, δ_j | : Voltage phase angles at buses i and j |



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OPTIMAL DISTRIBUTED GENERATION ALLOCATION AND SIZING IN A DISTRIBUTION SYSTEM USING HEURISTIC ALGORITHMS

SUMMARY

This thesis presents an optimization framework for the allocation and sizing of Distributed Generators (DGs) with reactive power capabilities in unbalanced three-phase distribution systems. The aim is to reduce active power losses and improve voltage profiles while also maintaining phase balance. To achieve the aim, a modified IEEE 37-bus unbalanced distribution feeder is used as the test system, and four metaheuristic algorithms are applied to determine optimal DG placement, capacity, and power factor. These algorithms include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and Pattern Search (PS).

The simulations are carried out using MATLAB linked with OpenDSS. This setup allows the algorithms to interact directly with the distribution system model during the optimization process. The study examines the performance of each algorithm under two operating conditions: unity power factor, where DGs supply only real power, and optimal power factor, where DGs can supply both real and reactive power within allowed limits.

In the unity power factor case, GA achieved the highest reduction in active power loss at 73.85%, followed by GWO (73.78%), PSO (73.32%), and PS (72.98%). In the optimal power factor scenario, GA again performed best, reducing losses by 90.39%. PSO, GWO, and PS followed with reductions of 90.32%, 90.02%, and 88.63%, respectively. These results show the clear benefit of including reactive power support in DG operation.

Voltage profiles were also analyzed for all three phases. Without DGs, voltages dropped significantly, especially at the end of the feeder. With DGs operating at optimal power factor, voltage levels were much more consistent and stayed within acceptable limits. Among all the algorithms, GA consistently delivered the best overall results in terms of both loss reduction and voltage regulation. The findings suggest that optimizing power factor alongside DG location and size can make a meaningful difference in system performance, especially in networks that are unbalanced or weak.

Beyond the improvements in loss reduction and voltage control, the approach used in this study also shows promise for real-world implementation. In addition, the findings also suggest that DG placement should not be based solely on network layout, but also take into account how each unit operates under real system conditions.

Keywords: Distributed Generation, Reactive Power, Power Loss Minimization, Voltage Profile Improvement, Unbalanced Three-Phase System, Genetic Algorithm, Metaheuristic Optimization, MATLAB–OpenDSS Integration, Power Factor Optimization



SEZGİSEL ALGORİTMALAR KULLANILARAK DAĞITIM SİSTEMİNDE OPTİMAL DAĞITIK ÜRETİM YERLEŞİMİ VE BOYUTLANDIRILMASI

ÖZET

Bu tez, reaktif güç yeteneklerine sahip birden fazla Dağıtılmış Üreteç (DG) ünitesinin üç fazlı dengesiz bir dağıtım sisteminde optimum yerleştirilmesi ve boyutlandırılmasını araştırmaktadır. Araştırma, özellikle yük dengesizliği ve gerilim sorunlarının yaygın olduğu gelişmekte olan bölgelerde daha güvenilir, sürdürülebilir ve verimli güç dağıtım ağlarına duyulan artan talep doğrultusunda şekillenmiştir. Tüketim noktasına yakın küçük ölçekli enerji kaynaklarının kullanımı anlamına gelen Dağıtılmış Üretim (DG), iletim kayıplarını azaltma, gerilim kararlılığını artırma ve genel güç kalitesini destekleme potansiyeli nedeniyle giderek daha fazla ilgi görmektedir. Ancak DG'lerin bu potansiyelinden tam anlamıyla faydalanabilmek için uygun boyutlandırma ve yerleştirme yapılmalı ve gerçek ile reaktif güç kapasiteleri birlikte dikkate alınmalıdır.

Bu çalışmanın temel özelliği, DG performansının iki farklı çalışma senaryosunda değerlendirilmesidir: birincisi yalnızca gerçek güç enjeksiyonunu içeren birim güç faktörü durumu ve ikincisi hem gerçek hem de reaktif güç enjeksiyonuna izin veren optimal güç faktörü durumu. DG yerleşim probleminin oldukça doğrusal olmayan ve çok hedefli doğasını ele almak için dört gelişmiş sezgisel optimizasyon algoritması kullanılmıştır: Genetik Algoritma (GA), Parçacık Sürü Optimizasyonu (PSO), Gri Kurt Optimizasyonu (GWO) ve Desen Arama (PS). Bu algoritmalar, karmaşık çözüm uzaylarını ele almadaki etkinlikleri ve mühendislik optimizasyonundaki başarıları nedeniyle seçilmiştir. Her algoritma, asimetrik yapı ve yükleme çeşitliliği açısından gerçekçi bir sistem olan IEEE 37-bus dengesiz dağıtım test besleyicisinde uygulanmıştır.

Simülasyonlar, MATLAB ve OpenDSS'in COM sunucusu arayüzü ile entegre edildiği ortak bir simülasyon ortamında gerçekleştirilmiştir. OpenDSS yük akışı analizini sağlarken, MATLAB optimizasyon algoritmalarını çalıştırmıştır. DG'ler şebeke üzerindeki çeşitli düğümlere yerleştirilmiş ve iki farklı senaryoda (birim ve optimal güç faktörü) güç kayıplarını azaltma ve gerilim profillerini iyileştirme performansları analiz edilmiştir. Birim güç faktörü senaryosunda DG'ler yalnızca gerçek güç enjekte edebilmiştir. Optimal güç faktörü senaryosunda ise DG'ler belirli sınırlar içinde reaktif güç de sağlayabilmiştir.

DG bulunmayan temel senaryoda toplam gerçek güç kaybı 73.81 kW olarak gözlemlenmiş ve gerilim büyüklükleri 0.9664 p.u. ile 1.0607 p.u. arasında değişmiştir. Bu durum, sistemde önemli bir gerilim dengesizliği olduğunu göstermekte ve DG entegrasyonunun etkisinin değerlendirilmesinde referans olarak kullanılmıştır. Birim güç faktörü senaryosunda GA algoritması %73.85'lik kayıp azaltımı ile en yüksek performansı göstermiş ve sistem kaybı 19.302 kW'a düşürülmüştür. GWO %73.78, PSO %73.32 ve PS %72.98'lik azaltımlarla takip etmiştir. Bu sonuçlar, reaktif güç

desteđi olmadan bile dođru yerleřtirme ve boyutlandırmanın sistem verimliliđini artırabileceđini göstermektedir.

Optimal g faktr senaryosunda iyileřtirmeler daha da belirgin hale gelmiřtir. GA algoritması bu senaryoda %90.39'luk kayıp azaltımı ile toplam kaybı 7.103 kW'a dřrmřtir. PSO %90.32, GWO %90.02 ve PS %88.63'lk bařarı elde etmiřtir. Bu performans artıřları, reaktif gcn gerilim desteđi ve teknik kayıpların azaltılmasındaki kritik roln gstermektedir. DG'lerin hem aktif hem de reaktif gc sađlamasına izin verilmesi, sistemin daha iyi gerilim reglasyonu elde etmesini ve dđmler arasında daha tutarlı gerilim deđerleri sađlamasını mmkn kılmıřtır. Ayrıca, bu alıřma DG'lerin sistemde neden olduđu gerilim profilinin dzeltilmesinde ve gc kayıplarının azaltılmasında optimal gc faktrnn daha etkili olduđunu ortaya koymuřtur.

c fazın (A, B ve C) gerilim profilleri izilmiř ve analiz edilmiřtir. Temel durumda gerilim byklkleri, zellikle řebekenin c dđmlerinde nemli lcde dalgalanma gstermiřtir. DG'ler birim gc faktryle alıřtıđında gerilim seviyeleri iyileřmiř fakat bazı blgelerde ařırı gerilim gzlenmiřtir. Optimal gc faktr senaryosunda ise daha dzgn ve kararlı bir gerilim profili elde edilmiřtir. Faz A'da, GA algoritması ile gerilim 0.9986 ile 1.0363 p.u. arasında kalmıřtır. Benzer řekilde Faz B ve C'de de gerilimler daha dar aralıklarla korunmuř ve genel sistem gerilim kararlılıđı sađlanmıřtır. Bu durum, sistemde ařırı gerilim ve dřk gerilim sorunlarının azaltılmasına katkı sađlamıřtır.

Ayrıca analizler gstermiřtir ki optimal gc faktr senaryosu yalnızca kayıpları azaltmak ve gerilim profillerini iyileřtirmekle kalmamıř, aynı zamanda fazlar arasında dengeyi de artırmıřtır. Gerek hayattaki dađıtım sistemlerinin karřılařtıđı bařlıca sorunlardan biri olan yk dengesizliđi, reaktif gc desteđiyle nemli lcde azaltılmıřtır. Sezgisel algoritmaların kullanımı, karmařık zm uzayında etkili gezinmeyi mmkn kılmıř ve GA, hem yakınsama hızı hem de son zm kalitesi aısından diđerlerinden stn performans gstermiřtir.

Algoritma davranıřı aısından GA, zm iyileřtirmede gcl smr kabiliyetleri ile ne ıkmıřtır. PSO, sr zekası ilkesine dayalı olarak hızlı yakınsama gstermiř fakat bazen yerel optimumlarda takılmıřtır. GWO, keřif ve smr arasında iyi bir denge sađlayarak liderlik hiyerarřisini arama srecine bařarıyla entegre etmiřtir. PS algoritması ise nfus temelli olmamasına rađmen, belirli durumlarda kararlı lokal arama yetenekleriyle makul bařarı gstermiřtir. Ancak kresel arama yeteneđinin sınırlı olması nedeniyle daha karmařık problemlerde yetersiz kalmıřtır.

IEEE 37-bus test sistemi seimi, alıřmanın geerliliđi aısından olduka nemli olmuřtur. Tek fazlı ve c fazlı yklerin karıřımı, farklı bađlantı trleri ve dzensiz hat empedansları ile bu sistem, nerilen optimizasyon modellerini deđerlendirmek iin gereki bir test ortamı sunmuřtur. OpenDSS ile dođru gc akıřı hesaplamaları yapılırken, MATLAB'in esnekliđi algoritmaların entegrasyonu ve sonu analizini kolaylařtırmıřtır. Bu simlasyon ortamı, aynı zamanda algoritmaların uygulanabilirliđini test etmek ve karřılařtırmalı performanslarını deđerlendirmek aısından byk avantaj sađlamıřtır.

Bu alıřmanın en nemli katkılarından biri, DG planlamasında reaktif gc esnekliđinin gz ardı edilmemesi gerektiđini aıka gstermesidir. Geleneksel alıřmalar ođunlukla yalnızca aktif gce odaklanırken, bu arařtırma reaktif gcn dahil edilmesinin sistem performansını nemli lcde artırabileceđini somut verilerle ortaya koymuřtur. Gzlemlenen gerilim kararlılıđı ve gc kaybı iyileřtirmeleri bu yaklařımı

doğrulamakta ve planlama uygulamalarının güncellenmesi gerektiğini göstermektedir. Bununla birlikte, optimal güç faktörünün gerilim profili üzerindeki olumlu etkisi, sistemin güvenilirliğini ve kullanıcı memnuniyetini artıracak şekilde pratik uygulamalara dönüşebilir.

Ayrıca algoritmaların görelî performansı da dikkate değerdir. GA en etkili algoritma olarak öne çıkarken, optimal güç faktörü koşullarında GA, PSO ve GWO arasındaki farkların az olması, uygulama gereksinimlerine göre tümünün geçerli seçenekler olduğunu göstermektedir. PS ise biraz daha düşük performansa sahip olmasına rağmen, yerel arama gereken karma algoritmalarda faydalı olabilir.

Sonuçlar ayrıca farklı algoritmaların güçlü yönlerini birleştiren hibrit yaklaşımların potansiyeline işaret etmektedir. Örneğin, GA-PSO hibriti, GA'nın sağlam yakınsama davranışını, PSO'nun hızlı keşfiyle birleştirerek daha iyi sonuçlar verebilir. Gelecek çalışmalar algoritmalar içinde dinamik veya uyarlanabilir parametre ayarlamalarını da değerlendirerek dayanıklılığı ve ölçeklenebilirliği artırabilir.

Bu çalışmanın bazı sınırlamaları arasında ekonomik ve çevresel faktörlerin dahil edilmemesi yer almaktadır. Ayrıca IEEE 37-bus test sistemi sağlam bir kıyas ölçütü sunsa da, gerçek dünya şebekeleri daha karmaşık topolojilere, zamanla değişen yüklerle ve rastgele yenilenebilir kaynaklara sahip olabilir. Modelin bu tür unsurları içerecek şekilde genişletilmesi daha kapsamlı planlama araçları ortaya çıkarabilir.

Buna rağmen, bu çalışma özellikle zayıf ya da dengesiz şebekelere sahip bölgelerde sistem planlayıcıları için değerli içgörüler sunmaktadır. Gelişmiş sezgisel tekniklerin, DG kapasitelerinin kapsamlı bir şekilde anlaşılmasıyla uygulandığında, sistem güvenilirliği, verimliliği ve kararlılığına önemli katkılar sağlayabileceğini göstermektedir. Reaktif güç desteğine yapılan vurgu, inverter tabanlı DG'lerin artan penetrasyonuna sahip modern dağıtım sistemleri için oldukça önemlidir.

Sonuç olarak, bu tez, dengesiz dağıtım sistemlerinde DG'lerin yerleştirilmesi ve boyutlandırılması için teknik olarak sağlam ve pratik açıdan geçerli bir çerçeve sunmaktadır. Birden fazla sezgisel algoritmanın gerçekçi koşullar altında karşılaştırılması ve iki operasyonel senaryo altında analiz edilmesi, güç sistemi optimizasyonu alanına önemli katkılar sağlamaktadır. Bulgular, DG planlamasında reaktif güç kapasitesinin dahil edilmesinin önemini vurgulamakta ve modern güç sistemlerinin çok hedefli doğasının sezgisel yaklaşımlarla ele alınabileceğini doğrulamaktadır.

Güç sektörü hızla daha dağınık ve yenilenebilir kaynaklara dayalı bir yapıya doğru evrilirken, bu çalışmadan elde edilen bulgular son derece zamanında ve uygulanabilir niteliktedir. Elde edilen sonuçlar, büyük altyapı yatırımları olmadan dağıtım ağı performansını artırmak isteyen kamu hizmetleri ve politika yapıcılar için bir yol haritası sunmaktadır. Ayrıca geliştirilen metodolojiler ve araçlar, dağıtılmış enerji kaynakları, akıllı şebeke teknolojileri ve entegre enerji sistemlerini içeren diğer planlama problemlerine de uygulanabilir niteliktedir.

Bu bağlamda, çalışmada önerilen optimizasyon modeli, sadece gerilim kararlılığı ve kayıp azaltımı açısından değil, aynı zamanda gerçek sistem uygulamalarında kullanılabilirliği açısından da güçlü bir potansiyel sunmaktadır. Simülasyon sonuçları, özellikle GA algoritmasıyla elde edilen yüksek yakınsama başarısı ve düşük güç kaybı değerleriyle, önerilen yaklaşımın sahada uygulanabilir teknik çözümler üretme kapasitesini ortaya koymuştur. Özellikle optimal güç faktörü ayarının sisteme entegre edilmesi, yalnızca algoritmaların performansını artırmakla kalmamış, aynı zamanda

gerilim profili üzerinde doğrudan ve ölçülebilir bir iyileştirme sağlamıştır. Bu durum, DG yerleşim stratejilerinin sadece topolojik değil, aynı zamanda operasyonel parametrelerle birlikte değerlendirilmesi gerektiğini göstermektedir.

Anahtar Kelimeler: Dağıtılmış Üretim, Reaktif Güç, Güç Kaybı Azaltma, Gerilim Profili İyileştirme, Dengesiz Üç Fazlı Sistem, Genetik Algoritma, Sezgisel Optimizasyon, MATLAB–OpenDSS Entegrasyonu, Güç Faktörü Optimizasyonu



1. INTRODUCTION

Background of The Study

1.1. The increasing demand for electricity combined with the need for more sustainable and efficient energy systems, has led to growing interest in distributed generators (DG). DG refers to the decentralized production of electricity using small-scale Energy source located near the point of consumption. Integrating DG units into power distribution networks offers multiple benefits such as reduced transmission losses, enhance voltage stability, improved power quality, and better reliability [1, 2, 3].

However, achieving these benefits depends significantly on the optimal allocation and sizing of DG units with the network. This is particularly challenging in three-phased unbalanced distribution systems, where first loading, line impedance, and voltage conditions vary across phases. Such unbalanced conditions are common in a real-world power network, especially in developing regions and they complicate the process of DG planning and optimization [4, 5, 6].

Moreover, many studies have focused primarily on the real power contributions of DGs, overlooking the potential advantages of utilizing their reactive power capabilities. Reactive power support is essential for maintaining voltage profiles and improving the efficiency of the system. Without considering both the active and reactive power, the integration of DGs may lead to suboptimal or even adverse impacts on the distribution network.

To address the complexity of this planning problem, heuristics algorithms have emerged as powerful tools. These algorithms such as genetic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO), and Pattern Search (PS) have been successfully used to solve optimization problems that are too complex for classical methods. They are particularly well suited for non-linear, non-convex, and multi-objective problems, making them ideal for solving DG allocation and sizing challenges in unbalanced systems [7, 8, 9].

This thesis builds upon these advancements by incorporating both real and reactive power capabilities in DG modeling and comparing the performance of four metaheuristic algorithms under different power factor scenarios. The study aims to enhance voltage regulation, reduce power losses, and address phase unbalance, while providing insights into the comparative strengths of each algorithm.

Statement of The Problem

1.2. The integration of distributed generators into power distribution systems presents both opportunities and challenges. In unbalanced three-phased systems, improper placement and sizing of DGs can lead to increased power losses, poor voltage regulation, and phase imbalance. Additionally, the reactive power capabilities of DGs are often neglected, despite their significant role in supporting voltage profiles and improving overall system stability.

Most existing approaches either assume a balanced network, focus solely on active power contribution, or use classical optimization methods that may not handle the complexity of real-world networks effectively there is, therefore a pressing need for an advanced optimization strategy that addresses these limitations.

1.3. **Objectives of The Study**

Main objectives:

To develop a heuristic-based optimization model for the optimal allocation and sizing of multiple DGs with reactive power capabilities in a three-phase unbalanced distribution system.

Specific objective:

- To model a realistic three-phase unbalanced radial distribution system.
- To implement four heuristic algorithms GA, PSO, GWO, and PS for DG allocation and sizing.
- To evaluate system performance under unity and optimal power factor scenarios.
- To analyse the impact of DG integration on active power losses, voltage profile, and phase balance.

- To compare the optimization performance, convergence behaviour, and solution quality of the algorithms.

Scope of the Study

This study is limited to

- 1.4.
- Modeling and simulation using MATLAB and OpenDSS.
 - Implementation of GA, PSO, GWO, and Pattern Search algorithms.
 - Optimization based on active power loss reduction, voltage profile improvement, and phase balance.
 - Evaluation under both unity power factor and optimal power factor operation.
 - Economic cost and environmental impact assessments are beyond the scope of this work.

1.5.

Significance of the Study

This research contributes to the development of efficient planning methods for power distribution systems, particularly in unbalanced configurations. By integrating reactive power support into the optimization model and evaluating the comparative performance of multiple metaheuristic algorithms, the study offers practical guidance for system planners and operators.

It highlights the value of reactive power in improving voltage regulation and reducing technical losses, and emphasizes the effectiveness of advanced heuristic techniques especially GWO, in solving complex DG planning problems. The findings are expected to be relevant to relevant parties in enhancing the reliability and efficiency of modern distribution systems.



2. LITERATURE REVIEW

Introduction

2.1. Distributed Generation (DG) refers to the decentralized production of electricity by small-scale technologies located close to the load centers. It has become a prominent component of modern power systems, offering benefits such as improved voltage support, reduced transmission losses, enhanced power quality, and increased system reliability [1], [2]. DG units can utilize renewable sources such as solar photovoltaic, wind, and biomass, or non-renewable sources like micro-turbines and diesel generators.

The concept of DG emerged as a response to the limitations of centralized generation, particularly in rural or load-end regions where grid expansion is economically unviable. The liberalization of electricity markets and technological advancements in power electronics have also accelerated DG deployment globally [10].

DG integration contributes significantly to peak shaving, loss reduction, and deferred investment in transmission and distribution infrastructure. However, it also introduces technical challenges such as reverse power flows, voltage fluctuations, and coordination of protection systems [11]. These challenges necessitate comprehensive planning and optimization for effective DG deployment.

2.2. Over the last two decades, regulatory frameworks and incentives in many countries have encouraged DG growth, especially from renewable sources. This aligns with global sustainability goals and climate change mitigation strategies [12]. The next sections discuss the technical dimensions of DG integration in more detail.

Voltage Profile Improvement and Power Loss Minimization

One of the primary motivations for integrating DG into power distribution networks is its ability to enhance voltage profiles and reduce power losses. Traditional distribution systems, particularly radial networks, often suffer from voltage drops and real power losses due to long feeder lines and centralized generation [3]. Strategically placed DG

units can inject power closer to the load centres, thus improving the voltage profile along the feeders and significantly minimizing technical losses [13].

Several studies have quantitatively demonstrated the effectiveness of DG in reducing active and reactive power losses. For example, [14, 15] proposed a DG placement strategy aimed at reducing losses while improving voltage regulation. Their method showed that DG placement at optimal locations can lead to significant improvements in both energy efficiency and voltage stability. Similarly, [16] employed evolutionary technique to optimize DG location and size, achieving substantial power loss reduction.

Recent developments have incorporated advanced algorithms like the Bacterial Foraging Optimization Algorithm (BFOA) and Firefly Algorithm, which have been shown to outperform traditional methods in finding loss-minimizing DG configurations [17], [18]. These methods not only focus on loss reduction but also maintain acceptable voltage limits throughout the network.

Moreover, studies such as those by [19] and [20] show that simultaneous optimization of DG size and location can lead to a balanced trade-off between improved voltage profile and minimized power losses. These outcomes are especially relevant in systems with high penetration of renewables, where voltage regulation becomes critical.

Thus, the strategic deployment of DG, guided by optimization techniques and validated by real-system modelling, remains a proven method for improving voltage profiles and minimizing losses in distribution systems.

2.3.

Reactive Power and Power Quality in Distribution System

L Reactive power plays a crucial role in maintaining voltage stability and overall power quality in distribution systems. Distributed Generation (DG), particularly those based on inverter technologies, can be configured to provide reactive power support, thereby contributing to local voltage regulation and reducing the burden on central reactive power compensators [21].

Integration of DG into distribution systems can both improve and degrade power quality, depending on the nature of the DG source and system conditions. Inverter-based DG units, when equipped with appropriate control strategies, can mitigate issues such as voltage flicker and reactive power imbalance [22]. However, without proper

design, DG integration may lead to harmonic distortions, particularly when nonlinear loads are involved [23].

Total Harmonic Distortion (THD) is a key power quality index influenced by the presence of distributed energy resources. Several studies have examined the effect of DG on harmonic levels in radial systems, concluding that strategic placement and filtering techniques are essential to maintain THD within IEEE-519 harmonic standards [24, 25].

To address harmonic and reactive power challenges, devices such as Distribution Static Compensators (DSTATCOM) and Active Power Filters (APFs) are often deployed. [21] demonstrated how optimal placement of APFs using advanced optimization methods like the Adaptive Grey Wolf Optimizer can significantly improve power quality indices in systems with nonlinear DG. Similarly, [11] explored the joint allocation of DG and DSTATCOM to ensure voltage stability while mitigating harmonic distortion.

In addition to compensating reactive power, modern DSTATCOMs can dynamically adjust their output based on load conditions, making them well-suited for systems with high DG variability. Their deployment, particularly alongside inverter-based DGs, can enhance voltage support, reduce THD, and ensure compliance with power quality standards [26].

Therefore, effective integration of DG with reactive power compensating devices is essential not only for voltage control but also for ensuring a high-quality power supply

2.4. in evolving distribution systems.

Optimization Techniques for DG Placement and Sizing

Optimal placement and sizing of Distributed Generation (DG) units is crucial for maximizing their technical and economic benefits. Numerous optimization techniques have been developed to address this complex problem, which involves minimizing power losses, enhancing voltage profiles, and ensuring system reliability under a set of nonlinear and multi-objective constraints [27].

Among the earliest techniques, Genetic Algorithms (GA) have been widely adopted for their ability to handle complex, multi-dimensional search spaces. [28] applied GA to reduce energy losses and improve voltage stability in radial distribution systems,

demonstrating improved network efficiency. Similarly [9] investigates the optimization problem using GA and Particle Swarm Optimization (PSO), where GA outperforms PSO in the process.

Particle Swarm Optimization (PSO), inspired by social behaviour of organisms, has gained popularity for its simplicity and fast convergence. [29, 30] introduced PSO, and its adaptations have been used in DG planning studies to optimize both location and size of generation units. Studies such as those by [31] and [32] have shown that PSO provides effective results when integrated with power flow constraints.

Hybrid methods combining PSO with other heuristics like Simulated Annealing and Differential Evolution have also been developed to enhance solution quality and avoid local optima. [33] proposed a hybrid GA-SA algorithm that outperforms single-algorithm methods in identifying optimal DG configurations. Similarly, as proposed by [34, 35] other hybrid methods like GWO – PSO surpasses conventional single algorithm techniques in optimization domain evidenced by the rate of convergence and objective function. Taking into account active power losses, reactive power compensation, and the objective function value in DGs, the hybrid method GA-PSO demonstrated superior effectiveness in identifying optimal solutions [36].

In addition to widely adopted metaheuristic techniques, Pattern Search (PS) methods have emerged as reliable alternatives for constrained optimization in power systems, particularly when gradient information is unavailable or costly to compute. Recent advancements, such as the adaptive PS framework developed by [37], demonstrate that these methods can effectively handle large-scale optimization problems through dimension-wise adaptation and mesh control.

Other bio-inspired methods include the Bacterial Foraging Optimization Algorithm (BFOA), used by [10], and the Firefly Algorithm as demonstrated by [11], both of which are effective for multi-objective optimization problems.

Recent advancements feature metaheuristics like Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and Symbiotic Organism Search (SOS), which have been shown to outperform traditional methods in terms of convergence speed and solution diversity [38, 39].

Each optimization algorithm has unique strengths, and their performance often depends on problem complexity, network size, and constraint handling. Consequently,

the trend has moved towards hybrid and adaptive algorithms capable of balancing exploration and exploitation in DG planning tasks.

Thus, the field of optimization in DG planning continues to evolve, providing increasingly sophisticated tools to achieve efficient and stable integration of distributed energy resources.

Research Gaps and Motivation

While significant research has been conducted on the integration of Distributed Generation (DG) into distribution systems, several critical gaps remain in the literature, particularly concerning the application of DG in realistic, unbalanced network conditions.

Firstly, most studies tend to focus solely on the active power injection capabilities of DGs, aiming to reduce power losses or improve voltage profiles. However, they often neglect the potential benefits of incorporating reactive power support. This omission limits the voltage regulation capacity and overall efficiency improvements that could be achieved, particularly in weak or heavily loaded sections of the grid.

Secondly, although unbalanced three-phase distribution systems are common in real-world scenarios especially in developing regions, many optimization frameworks in the literature rely on simplified balanced network models. These idealized assumptions overlook the critical phase-specific dynamics and voltage imbalances that arise in practical operation, reducing the applicability of such models.

Thirdly, numerous heuristic and metaheuristic algorithms have been proposed for DG sizing and allocation. However, comparative studies evaluating the performance of multiple algorithms under the same network configuration are limited. This restricts the ability of planners and researchers to objectively choose the most effective algorithm for their specific applications.

Finally, full-system simulations that jointly evaluate voltage regulation, loss minimization, and the influence of reactive power in unbalanced networks are scarce. Most existing studies isolate individual objectives or assume fixed operating conditions, failing to capture the interconnected and dynamic nature of real distribution systems.

This thesis addresses these gaps by proposing a detailed optimization framework that integrates DGs with both active and reactive power capabilities into a realistic three-phase unbalanced network (modified IEEE 37-bus system). It applies and compares Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), ensuring a robust and comprehensive analysis of performance in terms of power loss reduction, voltage profile improvement, and algorithm efficiency.



3. RESEARCH METHODOLOGY

Introduction

3.1. This chapter presents the detailed methodology adopted for the optimal allocation and sizing of multiple Distributed Generators (DGs) with reactive power capabilities in a three-phase unbalanced distribution system. The aim of this study is to minimize real power losses and enhance voltage profiles through the integration of heuristic optimization techniques. The entire methodological flow is designed to closely follow the simulation and experimental design reported in the published article.

The methodology integrates mathematical modelling, simulation, and optimization, combining tools such as MATLAB and OpenDSS to implement and evaluate different optimization techniques. These techniques include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO), which are tested for performance in optimizing the DG parameters.

3.2.

Research Design and Methodological Approach

The research employs a quantitative methodology grounded in computational modelling and numerical optimization. This choice is due to the inherently technical and mathematical nature of power system studies, particularly in evaluating distributed generation in unbalanced distribution networks.

The methodological steps include:

- System modelling using the IEEE 37-bus unbalanced radial distribution feeder.
- Power flow analysis using OpenDSS.
- Heuristic optimization using MATLAB.
- Evaluation of two DG operating scenarios: unity power factor and optimal power factor.

Each step involves data preprocessing, constraint formulation, objective function implementation, and simulation result analysis. The study's technical depth requires a

deterministic system model and precise variable control to evaluate DG effects on voltage stability and power loss.

The use of heuristic algorithms is justified by the nonlinear and multi-modal nature of the optimization problem, which makes conventional deterministic approaches impractical. The algorithms used are known for their ability to escape local minima and converge to near-optimal solutions in complex search spaces.

The IEEE 37-bus system, widely regarded for its representation of realistic unbalanced network conditions, serves as the test system. This feeder includes various load types and phase imbalances, making it suitable for examining the impact of DGs on network performance.

The following sections detail the mathematical formulation of the optimization problem, including objective function and constraints, as well as the configuration of the test system and implementation of the optimization algorithms.

Problem Formulation

3.3.

In power distribution systems, real power losses significantly impact energy efficiency and system performance. The optimization problem addressed in this study focuses on reducing these losses by determining the most suitable locations, sizes, and power factors of multiple DG units.

The formulation incorporates both the minimization of active power loss and the satisfaction of physical and operational constraints such as voltage limits and DG capacity bounds. The objective function is designed to capture the real power losses across all branches in the network based on bus voltages and phase angles.

3.3.1. Objective function

The total real power losses in the network are calculated using the following equation:

$$\min P_{LOSS} = \sum_{k=1}^T g_k (V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)) \quad (3.1)$$

where:

- P_{loss} = total real power loss in the system (kW)

- g_k = conductance of line kk
- V_i, V_j = voltage magnitudes at buses i and j
- δ_i, δ_j = voltage phase angles at buses i and j
- T = total number of lines in the system

This objective function is non-linear and non-convex due to the trigonometric dependency on phase angles and the presence of voltage magnitudes as variables. Minimizing this function results in improved network efficiency.

3.3.2. Constraints

The optimization problem is subject to the following constraints:

Voltage Constraints:

$$V_{min,i} \leq V_i \leq V_{max,i}, \quad i = 1, 2, \dots, NB \quad (3.2)$$

Where NB is the total number of buses, and V_i is the voltage at bus i .

Power Balance Equations:

$$P_{ss} + \sum_{i=1}^{NDG} P_{DG,i} = \sum_{j=1}^{NB} P_{D,j} + \sum_{k=1}^{NL} P_{L,k} \quad (3.3)$$

$$Q_{ss} + \sum_{i=1}^{NDG} Q_{DG,i} = \sum_{j=1}^{NB} Q_{D,j} + \sum_{k=1}^{NL} Q_{L,k} \quad (3.4)$$

Where;

- P_{ss}, Q_{ss} : active and reactive power from the substation
- $P_{DG,i}, Q_{DG,i}$: active and reactive power injected by DG i
- $P_{D,j}, Q_{D,j}$: load demand at bus j
- $P_{L,k}, Q_{L,k}$: active and reactive losses in line k

DG Output Bound:

$$\sum_{i=1}^{N_{DG}} P_{DG,i} \leq \sum_{j=1}^{N_B} P_{D,j} \quad (3.5)$$

This ensures that the total real power injected by DGs does not exceed the total system demand.

DG Capacity Limits:

$$P_{DG,min,i} \leq P_{DG,i} \leq P_{DG,max,i} ; i = 1, \dots, N_{DG} \quad (3.6)$$

This restricts the size of each DG unit within its minimum and maximum capacity.

Power Factor Constraints:

$$P_{f_{DG,min,i}} \leq P_{f_{DG,i}} \leq P_{f_{DG,max,i}} ; i = 1, \dots, N_{DG} \quad (3.7)$$

These constraints allow flexibility in the reactive power capabilities of the DGs while maintaining realistic operation ranges.

Together, these mathematical models represent the physical and operational realities of integrating DGs in distribution systems and form the basis for the optimization process implemented in this study.

3.4.

Test System Description

The IEEE 37-node test feeder is adopted as the case study system in this research. It is a standard benchmark system used extensively in distribution system analysis, particularly suited for studies involving unbalanced loading and radial network configurations. The feeder exhibits characteristics commonly found in practical power distribution systems such as asymmetrical line impedances, uneven phase loading, and a mix of single-phase and three-phase loads [40].

System Characteristics:

- Topology: Radial, unbalanced three-phase distribution network
- Number of buses (NB): 37
- Nominal voltage: 4.8 kV (line-to-line)

- Load distribution: Mixture of wye and delta-connected loads
- Load type: Residential and light commercial
- Number of lines (NL): 36 segments
- Load size: Approximately 2547 kW and 1201 kVAR

This system provides a realistic framework to assess how multiple DG units, when optimally sized and placed, can affect system losses and voltage profiles.

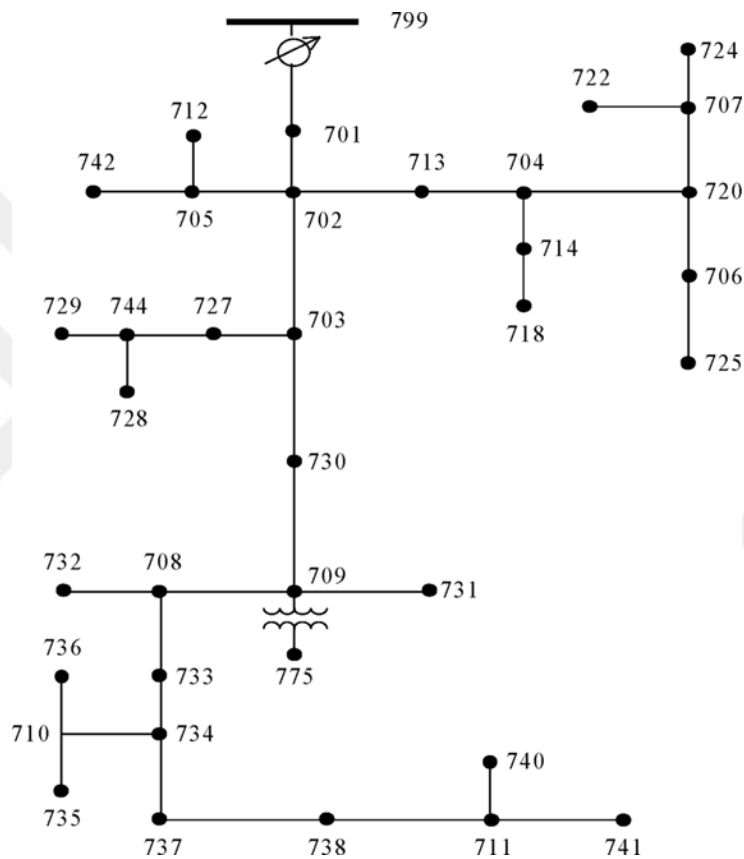


Figure 3.1: Single line diagram of IEEE 37 Test Feeder [40]

Figure 3.1 is the single-line diagram of the IEEE 37-node test feeder which represents a radial distribution system commonly used for evaluating unbalanced power flow and distributed generation studies. The feeder originates from a substation at node 799 and branches into a network of 37 buses, including both three-phase and single-phase nodes. It features a mix of wye- and delta-connected loads and varying line configurations, accurately reflecting the complexity of real-world distribution systems. The diagram highlights the network's asymmetry, with uneven phase distribution and line impedances, making it ideal for testing optimization algorithms under realistic

operating conditions. This structure allows researchers to analyse voltage drops, power losses, and the impact of DG placement across a diverse range of nodes.

Modelling Tools:

The system is modelled and simulated using OpenDSS [41], an open-source power distribution system simulator developed by the Electric Power Research Institute (EPRI). MATLAB [42] is used for the implementation of optimization algorithms and interfacing with OpenDSS to run simulations and retrieve results.

DG Placement Approach:

For this study, various DG placements are simulated, including both fixed and optimally determined locations. In the fixed scenario, DGs are installed at buses 17, 30, and 32 based on prior knowledge of weak voltage areas. In the optimization scenarios, the location, size, and power factor of the DGs are determined using the applied heuristic algorithms.

3.5. Optimization Algorithms

The study applies three state-of-the-art heuristic optimization techniques to solve the DG allocation and sizing problem: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO). Each of these algorithms operates on a population of potential solutions and uses natural or social-inspired mechanisms to guide the search toward optimal configurations [43].

3.5.1. Genetic Algorithm (GA)

Genetic Algorithm is a biologically inspired search method that simulates the process of natural selection and genetics [44]. A population of candidate solutions (chromosomes) is evolved through a series of generations using selection, crossover, and mutation operators.

- **Initialization:** Randomly generate initial population of chromosomes, each encoding DG location, size, and power factor.
- **Selection:** Choose the fittest individuals for reproduction based on fitness function (i.e., total power loss).

- **Crossover:** Combine selected parents to produce offspring with mixed characteristics.
- **Mutation:** Introduce random modifications to maintain diversity.
- **Termination:** Stop after a defined number of generations or when improvement is negligible.

Concisely, the flowchart in **Figure 3.2** illustrates the operational steps of the Genetic Algorithm (GA) used for optimization. It begins by initializing a population of candidate solutions, each representing a potential configuration of DG parameters. The fitness of each solution is evaluated based on the objective function. The best-performing individuals are selected to undergo crossover and mutation operations, producing a new generation of solutions. This process repeats iteratively, with the algorithm checking at each cycle whether a stopping criterion such as maximum generations or convergence threshold is met. Once satisfied, the algorithm terminates and returns the optimal solution.

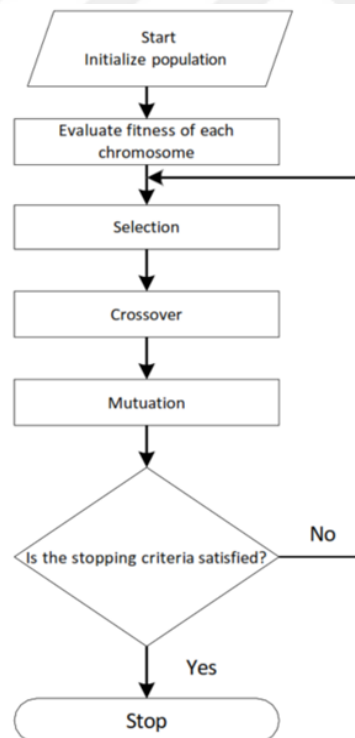


Figure 3.2. GA Flowchart

3.5.2. Particle swarm optimization (PSO)

Inspired by the social behaviour of birds and fish, PSO optimizes by having a swarm of particles explore the search space [28]. Each particle adjusts its position based on its own experience and that of neighbouring particles.

- **Initialization:** Randomly generate initial positions and velocities for each particle.
- **Fitness Evaluation:** Compute power loss for each particle's configuration.
- **Position Update:**

$$x_i^{new} = x_i^{old} + v_i \quad (3.8)$$

- **Velocity Update:**

$$v_i^{new} = w \cdot v_i^{old} + c_1 \cdot r_1 \cdot (Pbest_i - x_i^{old}) + c_2 \cdot r_2 \cdot (Gbest_i - x_i^{old}) \quad (3.9)$$

If any particle's personal best;

$$Pbest_i^{new} = \begin{cases} x_i^{new}, & \text{if } f(X_i^{k+1}) < f(Pbest_i^{old}) \\ Pbest_i^{old}, & \text{otherwise} \end{cases} \quad (3.10)$$

has a better fitness, the global best is then updated;

$$Gbest_i^{new} = \begin{cases} Pbest_i^{new}, & \text{if } f(Pbest_i^{new}) < f(Gbest^{old}) \\ Gbest^{old}, & \text{otherwise} \end{cases} \quad (3.11)$$

- **Termination:** End the iteration when convergence or a maximum number of steps is reached.

Figure 3.3 is the flowchart representing the Particle Swarm Optimization (PSO) process. It begins by initializing a swarm of particles with random positions and velocities. Each particle's fitness is then evaluated using the objective function. Based on performance, the personal best of each particle and the global best among all particles are updated. Subsequently, particle velocities and positions are adjusted to guide the search toward optimal regions. This cycle continues until a stopping criterion

such as a maximum number of iterations or convergence threshold is satisfied, at which point the algorithm terminates and outputs the best-found solution.

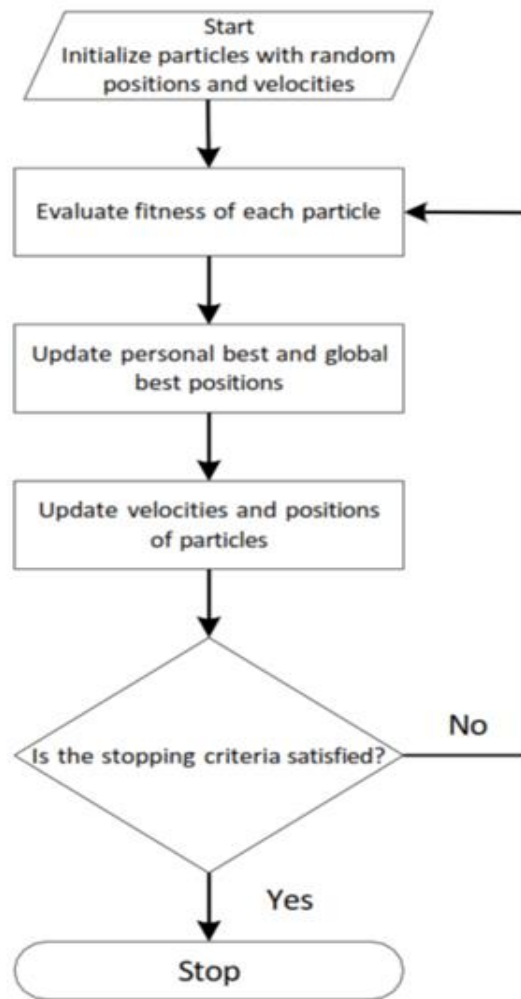


Figure 3.3. PSO Flowchart

3.5.3. Pattern Search (PS):

Pattern Search (PS) is a derivative-free optimization technique categorized under direct search methods [43]. Unlike population-based heuristics, PS performs a systematic local search by exploring the neighbourhood of the current solution using a pre-defined search pattern or mesh. It does not require gradient information, making it well-suited for problems with discontinuous or non-differentiable objective functions.

PS is particularly effective in fine-tuning solutions obtained from other methods or when a fast, stable convergence is desired.

The algorithm begins with an initial solution and iteratively evaluates candidate points around it. If a better solution is found, the search moves in that direction; otherwise, the mesh size is reduced to refine the local search.

$$\begin{aligned}x^u &= x + h_i \hat{e}_i \\x^d &= x + h_i \hat{e}_i\end{aligned}\tag{3.12}$$

From the above \hat{e}_i is the unit vector in the position i and step size is initially:

$$h = x_{max} - x_{min}$$

The iteration continues and it updates x to be the best of the three options (x , x_u , x_d), where x is:

$$x = \operatorname{argmin}(f(x), f(x^u), f(x^d))\tag{3.13}$$

The flowchart in figure 3.4. summarizes the procedural steps of the Pattern Search (PS) algorithm as previously described.

Pattern Search begins by setting algorithmic parameters such as mesh size, expansion and contraction factors, and maximum iterations. The search starts from an initial point and constructs pattern directions to generate new mesh points in the solution space. Each candidate is evaluated using the objective function. The process checks whether the stopping criteria have been met. If not, it evaluates whether the new mesh improves the solution. Based on this, the mesh is either expanded (if successful) or contracted (if not), and the search continues until convergence is achieved.

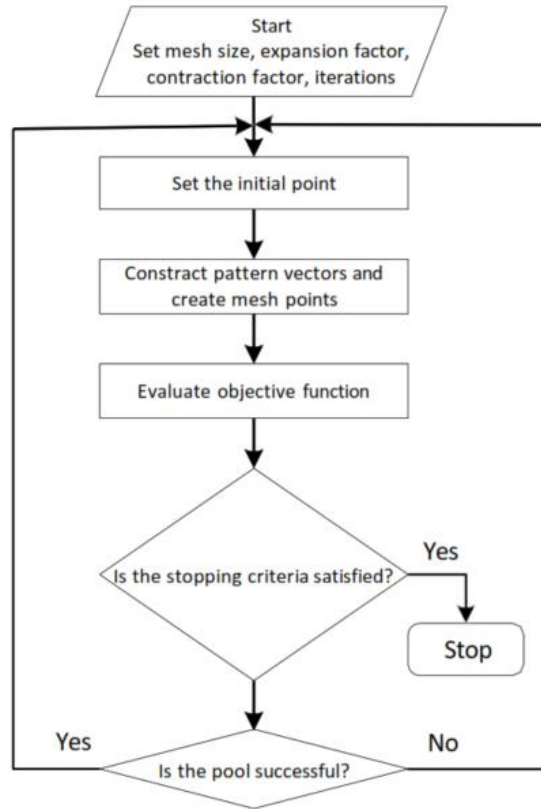


Figure 3.4. Pattern Search Flowchart

3.5.4. Grey Wolf Optimization (GWO)

GWO mimics the leadership hierarchy and hunting mechanism of grey wolves in nature [45]. The population is divided into four levels: alpha, beta, delta, and omega, with alpha guiding the search.

- **Leadership Assignment:** Alpha (best), beta (second), delta (third) leads the population.
- **Encircling Prey:** Wolves adjust their positions around the best solutions.
- **Position Update:**
- **Exploration and Exploitation:** Controlled by coefficient vectors A and C that shrink over time.

$$\vec{D} = |\vec{c} \cdot \vec{x}_p(t) - \vec{x}(t)| \quad (3.14)$$

$$\vec{x}(t+1) = \vec{x}_p(t) - \vec{A} \cdot \vec{D}$$

where;

t : is the iteration number

\vec{x} and \vec{x}_p Position and hunting position vector of wolves

A and C are coefficient vectors.

Position of optimal wolves can be calculated following the equation below;

$$\begin{aligned} \vec{D}_\alpha &= |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_1 \cdot \vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \\ \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_1 \cdot \vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_1 \cdot \vec{D}_\beta \\ \vec{X}(t+1) &= \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \end{aligned} \quad (3.15)$$

All four algorithms are applied to the same problem formulation and evaluated on their effectiveness in minimizing power losses and improving voltage profiles in the test system.

Figure 3.5 present a flowchart that illustrate the operational steps of GWO algorithm as described above.

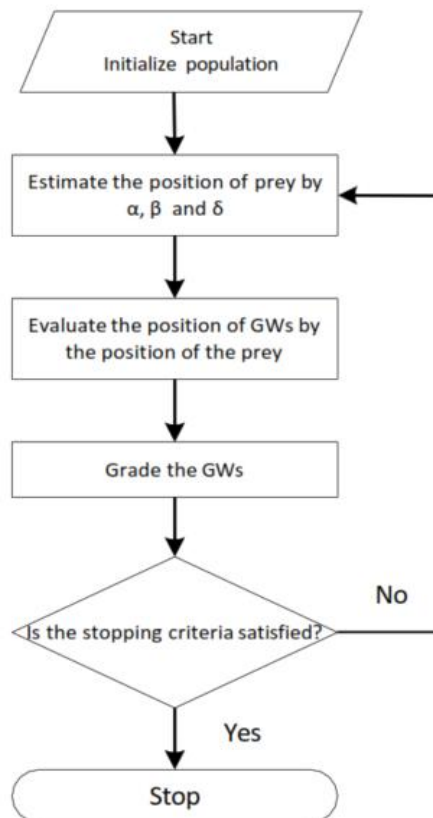


Figure 3.5. GWO Flowchart

GWO begins by initializing a population of candidate solutions (grey wolves). The algorithm estimates the prey's position using the top three wolves: alpha, beta, and delta. Based on this, all wolves update their positions relative to the estimated prey location. Each solution is then evaluated, and the wolves are ranked according to fitness. This process like previous algorithms repeats its process until a stopping criterion such as maximum iterations or convergence threshold is met, at which point the best solution is returned.

Simulation Setup

3.6. This section outlines the configuration of the simulation environment, and the experimental setup used to implement the optimization process.

Software Integration:

- **OpenDSS** is used as the simulation engine for load flow analysis. It models the IEEE 37-bus test feeder and computes power flows, bus voltages, and line losses.
- **MATLAB** is used for algorithm implementation, including GA, PSO, and GWO routines. It interfaces with OpenDSS using a COM server API that allows issuing simulation commands and retrieving results programmatically.

Scenario Design:

Two primary simulation scenarios are evaluated:

1. **Unity Power Factor Case:** DGs are allowed to inject only real power (reactive power = 0), representing a simplified design constraint.
2. **Optimal Power Factor Case:** DGs operate at adjustable power factors within a specified range to provide both real and reactive power support. This allows for voltage regulation and reduction in reactive power losses.

Algorithm-Specific Parameters (Control Parameters):

The Genetic Algorithm was implemented with a population size of 50, a crossover rate of 0.8, and a mutation rate of 0.05. The selection process was based on roulette wheel strategy, and elitism was applied to retain the best solution across generations. The algorithm was executed for a maximum of 100 generations. These parameters were

selected to ensure effective exploration and preservation of high-quality solutions during the optimization process.

For PSO, the swarm size was set to 50 particles. The inertia weight started at 1.0 and was gradually reduced by a damping factor of 0.99. The cognitive and social acceleration coefficients were both set to 2.0. The algorithm ran for 100 iterations, with velocity and position update equations guiding each particle toward the global and personal best solutions. These settings were chosen to balance global search behaviour with local refinement.

Pattern Search employed an initial mesh size of 0.1. The expansion factor (β) and contraction factor (γ) were set to 2.0 and 0.5, respectively. The search was conducted over a maximum of 100 iterations, consistent with the other algorithms. The pattern directions followed coordinate basis moves, and the step size was adaptively updated based on improvement criteria. This configuration allows PS to effectively perform localized search and fine-tuning in the solution space.

GWO was configured with 50 search agents and 100 maximum iterations. The leadership hierarchy (alpha, beta, delta, omega) guided the optimization through encircling and hunting mechanisms. The convergence control parameter 'a' was linearly decreased from 2 to 0 during the iterations to transition from exploration to exploitation. This parameter configuration is based on established GWO literature and ensures adaptive convergence behaviour.

These parameters are tabulated in **Table 3.1**, which shows the control parameters and their corresponding values.

Input Representation:

Each candidate solution includes DG location(s), real power output (kW), and power factor. These values are encoded as:

- Integer values for DG bus numbers (1–37)
- Continuous values for DG size and power factor within defined bounds

Fitness Evaluation:

Each solution is evaluated based on the total real power losses in the network. The OpenDSS engine calculates losses after applying each DG configuration. The optimization objective is to minimize these losses while satisfying all constraints.

Termination Criteria:

The optimization process is terminated when either:

- The number of generations/iterations reaches the maximum value, or
- The improvement in fitness value falls below a pre-set threshold over consecutive iterations.

Table 3.1. The control parameters used in the simulation of optimization algorithms

| Algorithm | Parameter Description | Value |
|------------------|--|--------------------|
| GA | Population size, Elite count, Crossover rate, Scaling factor | 50, 0.05, 0.8, 0.4 |
| PSO | Swarm size, Inertia Coefficient (w), Cognitive Coefficient (c_1), Social Coefficient (c_2), Inertia Damping Weight | 50, 1, 2, 2, 0.99 |
| PS | Mesh Contraction Factor (γ), Mesh Expansion Factor (β) | 0.5, 2 |
| GWO | Number of Search Agents | 50 |



4. RESULTS AND DISCUSSIONS

Introduction

4.1. This chapter presents the results obtained from the optimization of Distributed Generator (DG) allocation and sizing in the IEEE 37-bus unbalanced test feeder. The simulations were conducted to evaluate the performance of four optimization algorithms Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and Pattern Search (PS) under two operational scenarios: unity power factor and optimal power factor. Each algorithm was assessed based on its ability to reduce real power loss.

The analysis begins with a base case simulation without DG integration, which serves as a reference for comparative evaluation. Subsequent sections discuss the simulation environment, power loss reduction, and voltage improvements achieved by each algorithm. This chapter follows the simulation framework and result structure presented in the published article [46], using the same test system, algorithms, and performance evaluation criteria.

4.2.

Simulation Environment

4.3. All simulations were performed using MATLAB R2022a interfaced with OpenDSS. The IEEE 37-bus radial unbalanced test feeder was modelled in OpenDSS, and optimization algorithms were executed via MATLAB. The interface between the two platforms was implemented using a COM server, enabling the transfer of control variables and real-time simulation feedback. The test system was configured with a total load of 2547 kW and 1201 kVAR, and DG units were allowed to operate either at unity or optimal power factor depending on the scenario.

Base Case Analysis

Before integrating DG units, the base case was simulated to determine the initial system conditions. The total real power loss recorded in the system without any DG

integration was 73.81 kW. The voltage magnitude across buses ranged from 0.9664 p.u. (V_{min}) to 1.0607 p.u. (V_{max}), indicating significant voltage imbalance and drops in certain areas of the feeder. This base case serves as the benchmark for evaluating the performance of the optimization algorithms.

Power Loss Reduction

Power loss reduction is a primary performance indicator in the integration of Distributed Generators (DGs) within power distribution systems. The presence of DGs near the load centers helps reduce the current flow in the distribution lines, which directly translates to a reduction in real power losses. This section presents the total active power loss recorded for each algorithm under two scenarios: unity power factor and optimal power factor.

The base case, without DGs, exhibited a total active power loss of 73.81 kW. **Table 4.2** and **Table 4.4** illustrates the real power losses achieved by each algorithm. Under unity power factor, where DGs are restricted to supplying only real power, GA achieved the most significant reduction at 73.85%, followed closely by GWO (73.78%), PSO (73.32%), and PS (72.98%). Under optimal power factor, where DGs contribute both real and reactive power, the reduction in losses was markedly higher. GA once again led with 90.39% loss reduction, followed by PSO (90.32%), GWO (90.02%), and PS (88.63%).

These results align with existing literature that highlights the advantages of optimal reactive power coordination in loss minimization [47], [18], [23]. The superior performance of GA under both scenarios is consistent with previous findings, particularly in [18], where GA was shown to provide excellent convergence and solution quality for DG placement problems.

Table 4.1. DG Locations and Sizes for Each Algorithm under Unity Power Factor

| Algorithm | DG 1 (Node, Size (kW)) | DG 2 (Node, Size (kW)) | DG 3 (Node, Size (kW)) | DG 4 (Node, Size (kW)) |
|-----------|------------------------|------------------------|------------------------|------------------------|
| GA | (737, 637.94) | (703, 853.35) | (701, 584.06) | (707, 351.24) |
| PSO | (736, 747.3) | (744, 303.75) | (727, 1012.7) | (718, 290.64) |
| PS | (734, 863.78) | (701, 659.63) | (713, 663.71) | (722, 269.88) |
| GWO | (737, 610.71) | (730, 508.18) | (701, 1052.0) | (722, 284.91) |

Table 4.2. Active Power Loss (kW) and Loss Reduction Percentage for Each Algorithm under Unity Power Factor

| Algorithm | Power Loss (kW) | Loss Reduction (%) |
|-----------|-----------------|--------------------|
| GA | 19.302 | 73.85% |
| PSO | 19.693 | 73.32% |
| PS | 19.940 | 72.98% |
| GWO | 19.354 | 73.78% |

Table 4.3. DG Locations and Sizes for Each Algorithm under Optimal Power Factor

| Algorithm | DG 1 (Node, Size (kW)) | DG 2 (Node, Size (kW)) | DG 3 (Node, Size (kW)) | DG 4 (Node, Size (kW)) |
|-----------|------------------------|------------------------|------------------------|------------------------|
| GA | (737, 656.27) | (703, 743.66) | (701, 791.74) | (722, 255.6) |
| PSO | (737, 518.16) | (709, 559.14) | (701, 896.94) | (720, 480.83) |
| PS | (738, 341.44) | (733, 631.19) | (701, 772.38) | (704, 711.38) |
| GWO | (738, 435.93) | (733, 432.84) | (702, 1267.0) | (722, 247.75) |

Table 4.4. Active Power Loss (kW) and Loss Reduction Percentage for Each Algorithm under Optimal Power Factor

| Algorithm | Power Loss (kW) | Loss Reduction (%) |
|-----------|-----------------|--------------------|
| GA | 7.103 | 90.39% |
| PSO | 7.122 | 90.32% |
| PS | 8.412 | 88.63% |
| GWO | 7.384 | 90.02% |

The above values were derived from repeated simulations and averaged across multiple runs to ensure consistency. **Table 4.1** and **Table 4.3** shows each of the DGs' locations and sizes for each algorithms. It is observed from comparing **Table 4.2** and **Table 4.4** that enabling reactive power flexibility in DG operation significantly improves the ability of all algorithms to minimize system losses, confirming the importance of optimal power factor consideration in planning studies.

Voltage Profile Improvement

Maintaining acceptable voltage levels at all load points is a critical requirement in power distribution networks. The integration of DGs can significantly improve voltage profiles by injecting power closer to the load, thereby reducing voltage drops along long feeder lines. This section evaluates the voltage magnitude performance of the four optimization algorithms under unity and optimal power factor scenarios.

This improvement is due to the additional reactive power support provided under optimal PF, which helps mitigate voltage sags more effectively than real power injection alone. Thus, optimal power factor operation offers superior voltage regulation in Phase B, especially in sections of the network that are more vulnerable to voltage instability.

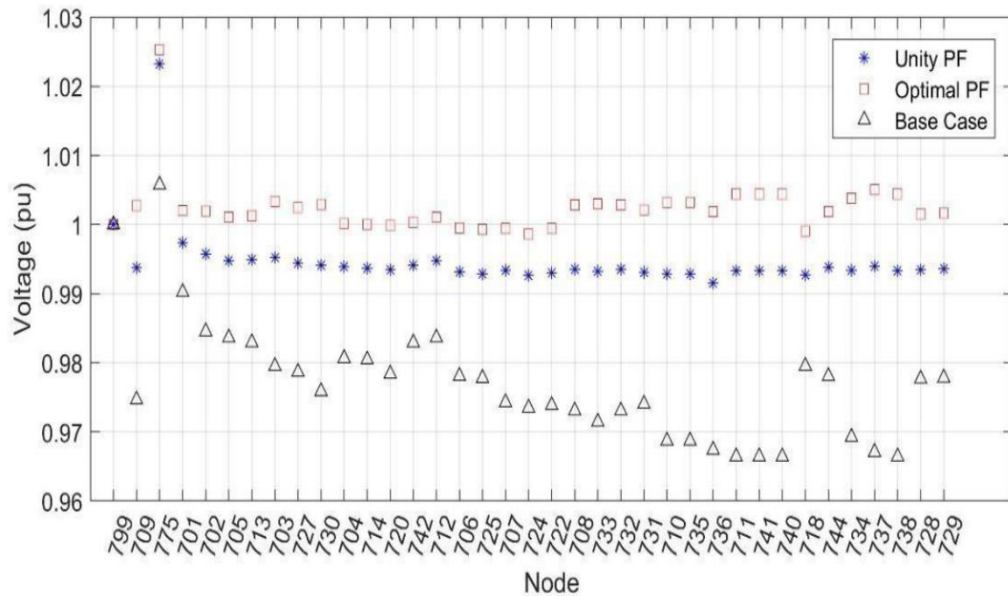


Figure 4.2. Phase B voltage profile across all nodes for three scenarios: the base case without DGs, and cases where DGs operate at unity and optimal power factor.

Figure 4.3 illustrates the voltage profile of Phase C. In the base case (triangles), the voltage levels drop significantly below nominal across a wide portion of the feeder, indicating poor voltage support and potential undervoltage violations. When DGs are operated at unity power factor (blue stars), the voltage is noticeably improved and held consistently around 1.02 p.u., though without reactive compensation. The optimal power factor case (red squares) further elevates and stabilizes the voltage profile, maintaining values between 1.03 and 1.04 p.u. across most nodes. This demonstrates the effectiveness of reactive power support in mitigating voltage drops and enhancing overall system voltage performance in Phase

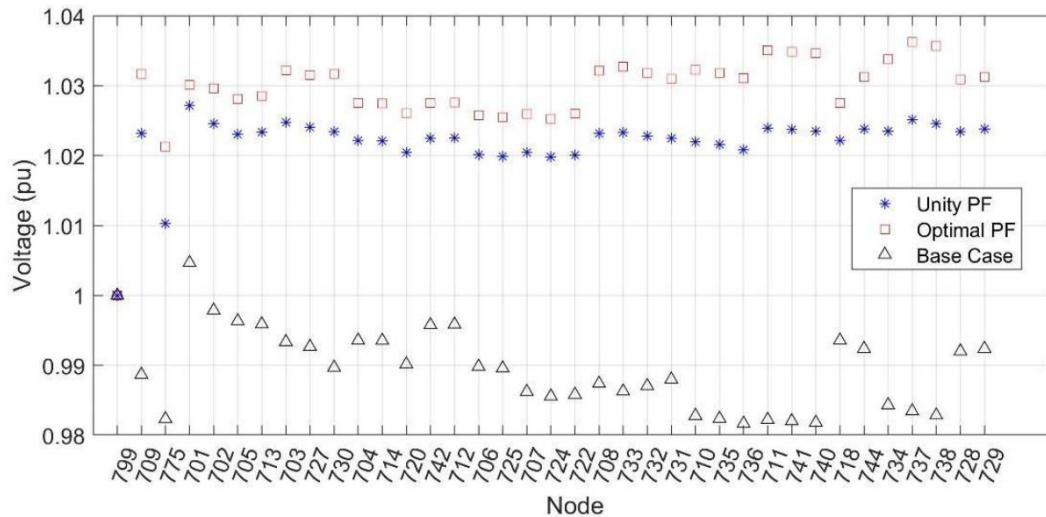


Figure 4.3. Phase C voltage profile across all nodes for three scenarios: the base case without DGs, and cases where DGs operate at unity and optimal power factor.

In summary, the base case, without any DGs, showed a wide variation in bus voltages, ranging from 0.9664 p.u. to 1.0607 p.u., highlighting the need for voltage correction mechanisms. After optimization, all algorithms demonstrated improvement, with optimal power factor scenarios yielding tighter voltage regulation.

Table 4.5 and **Table 4.6** summarizes the minimum and maximum bus voltage magnitudes observed for each algorithm. Under unity power factor, the improvements were marginal, as DGs could only inject real power. GA produced the best range (0.9915–1.0477 p.u.), closely followed by PSO and GWO. Under optimal power factor, where reactive power support is enabled, the voltage range was significantly improved. GA once again demonstrated superior performance, tightening the voltage range to 0.9986–1.0363 p.u., followed by PSO and GWO, with PS showing competitive performance as well.

Table 4.5. Voltage Magnitude Range Across All Buses under unity power factor

| Algorithm | Min Voltage (p.u.) | Max Voltage (p.u.) |
|-----------|--------------------|--------------------|
| GA | 0.9915 | 1.0477 |
| PSO | 0.9916 | 1.0475 |
| PS | 0.9915 | 1.0478 |
| GWO | 0.9903 | 1.0478 |

Table 4.6. Voltage Magnitude Range Across All Buses under optimal power factor

| Algorithm | Min Voltage (p.u.) | Max Voltage (p.u.) |
|------------------|---------------------------|---------------------------|
| GA | 0.9986 | 1.0363 |
| PSO | 0.9987 | 1.0362 |
| PS | 0.9983 | 1.0370 |
| GWO | 0.9982 | 1.0361 |

The results demonstrate that voltage regulation benefits are more pronounced when DGs are permitted to operate at optimal power factor. The difference between the minimum and maximum bus voltages was reduced in every case. This improvement contributes directly to increased voltage stability and reliability, which are essential metrics for system planners and utilities. Such trends are consistent with earlier findings in the literature, where reactive power optimization has been shown to improve voltage profiles in both balanced and unbalanced networks [48].



5. CONCLUSION

This study looked into how to best place and size Distributed Generators (DGs) that can supply both real and reactive power in a three-phase unbalanced distribution network. Using a test setup that closely mimics real-world conditions especially in places like developing countries where such unbalanced systems are common, four popular heuristic algorithms were tried: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Pattern Search (PS), and Grey Wolf Optimization (GWO).

These algorithms were implemented to perform under two conditions: when DGs were allowed to supply only real power (unity power factor) and when they were allowed to provide both real and reactive power (optimal power factor), the results were then compared. It turned out that letting the DGs provide reactive power made a big difference. The voltage across the network was more stable and power losses dropped significantly. Specifically, GA achieved a maximum power loss reduction of 90.39% and maintained a voltage range of 0.9986–1.0363 p.u. under optimal power factor settings, followed closely by PSO, GWO, and then PS.

One of the key findings is that reactive power matters a lot when it comes to keeping voltages steady and reducing system losses. Also, the study showed that algorithms like GA and GWO can be very useful tools for planning DG placement in unbalanced networks.

In simpler terms, for engineers and planners working in areas with complex or less-than-ideal grid setups, this work shows that combining real and reactive power in your DG strategy along with the right optimization method can lead to better-performing systems.

Moving forward, future research could look into additional goals like cutting costs or improving environmental outcomes. It might also be worth exploring hybrid versions of these algorithms to handle even bigger or more dynamic power systems more efficiently.



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