People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific Research

University M'Hamed BOUGARA – Boumerdes

Institute of Electrical and Electronic Engineering

Department of Power and Control

Final Year Project Report Presented in Partial Fulfilment of
the Requirements for the Degree of the

MASTER

In **Power Engineering**

Title:

Evolutionary Algorithms-based Optimal Preventive Maintenance Scheduling of Power Systems Generators

Presented by:

Bouchra ELHAZATI

Supervisor:

Prof. A. KHELDOUN

Co-supervisor:

Dr. S. BELAGOUNE

Registration Number:………/2023

ABSTRACT

In many industries that utilize machinery and equipment, the efficient preventive maintenance scheduling, which is a complex optimization problem, plays a crucial role in maintaining their machines and equipment. The preventive maintenance aims to carry out maintenance procedures prior to equipment failure in order to avoid expensive downtime and repairs.

This thesis addresses the optimal Generators preventive-Maintenance Scheduling (GMS) problem in electric power systems that includes several machines. This problem can be solved using a variety of ways, such as metaheuristic methods and mathematical programming. The problem is formulated as a mathematical optimization model using mathematical programming techniques, and the best solution is then found using algorithms. Simulating the maintenance schedule allows you to assess its effectiveness while modeling the equipment and its failure behavior. Metaheuristic methods entail creating maintenance schedules utilizing generalizations or subject-matter expertise. The primary objective of this thesis is to contribute to the performance improvement of a discrete evolutionary algorithm for a reliable and extremely accurate optimization of the discrete objective functions in order to address the issue of the best preventive maintenance scheduling of power systems generators. For planning the generator preventative maintenance, a modern metaheuristic algorithm named "the Discrete Mayfly Optimization (DMFO)" has been designed. This algorithm was proposed as an innovative swarm intelligence optimization algorithm in 2020, it combines the advantages of several existing optimization algorithms. This algorithm has been used in several applications including industrial optimization, ensemble forecasting system, and photovoltaic systems. A First-Bit Flip and Shift (FBFS) strategy for binary vectors, which is a process of manipulating binary vectors, has been first proposed to improve the performance of evolutionary algorithms. The FBFS strategy is a local search strategy that performs small changes to the obtained solutions to help evolutionary algorithms in local optimization and avoiding them from getting stuck in local optima. The proposed technique has been evaluated on a 21-unit test power system with a peak power load demand of 4739 MW in three cases where the total number of the workers available per week is limited. The improved algorithm showed at the end its effectiveness to find a solution for the GMS problem where the Sum of Squares of the Reserves (SSR) of generation is minimized. The results are compared to previous works that used other metaheuristic techniques in order to evaluate the performance of the proposed FBFS-DMFO algorithm and its search process in solving power system GMS problem.

الملخص

في بعض الصناعات التي تستخدم الآلات والمعدات، تلعب جدولة الصيانة الوقائية الفعالة، وهي مشكلة تحسين معقدة، دورًا مهمًا في صيانة أجهزتها ومعداتها. تهدف الصيانة الوقائية إلى تنفيذ إجراءات الصيانة قبل تعطل المعدات من أجل تجنب الأعطال والإصلاحات الباهظة.

تتناول هذه الرسالة المشكلة المثلى لجدولة الصيانة الوقائية للمولدات في أنظمة الطاقة الكهربائية التي تشمل عدة آلات .يمكن حل هذه المشكلة باستخدام مجموعة متنوعة من الطرق، مثل طرق الخوارزميات التطورية والبرمجة الرياضية. تمت صياغة المشكلة كنموذج تحسين رياضي باستخدام تقنيات البرمجة الرياضية، ثم يتم العثور على أفضل حل باستخدام الخوارزميات التطورية. تسمح محاكاة جدول الصيانة بتقييم فعاليتها أثناء نمذجة المعدات وسلوك فشلها. تستلزم الطرق التطورية إنشاء جداول صيانة باستخدام التعميمات أو الخبرة في الموضوع. الهدف الأساسي من هذه الأطروحة هو المساهمة في تحسين أداء خوارزمية تطورية منفصلة من أجل تحسين موثوق ودقيق للغاية للدوال المستهدفة الغير المستمرة من أجل معالجة مسألة أفضل تخطيط للصيانة الوقائية لمولدات أنظمة الطاقة. للتخطيط للصيانة الوقائية للمولدات، تم تصميم خوارزمية تطورية حديثة تسمى "خوارزمية ذباب مايو المنفصلة للتحسين. تم اقتراح هذه الخوارزمية كخوارزمية مبتكرة لتحسين ذكاء السرب في عام 2020، فهي تجمع بين مزايا العديد من خوارزميات التحسين الحالية. تم استخدام هذه الخوارزمية في العديد من التطبيقات بما في ذلك التحسين الصناعي ونظام التنبؤ الجماعي والأنظمة الكهروضوئية. تم اقتراح استراتيجية الانقلاب والتحول للمتجهات الثنائية، لتحسين أداء الخوارزميات التطورية. هذه استراتيجية هي استراتيجية بحث محلية تقوم بإجراء تغييرات صغيرة على الحلول التي تم الحصول عليها لمساعدة الخوارزميات التطورية في التحسين المحلي وتجنب الوقوع في مشكلة محلية. تم تقييم التقنية المقترحة على نظام طاقة اختبار مكون من 21 وحدة مع حمولة قصوى تبلغ 4739 ميجاوات في ثلاث حالات حيث يكون العدد الإجمالي للعمال المتاحين في الأسبوع محدودًا. أظهرت الخوارزمية المحسّنة في النهاية فعاليتها في إيجاد حل لمشكلة جدولة الصيانة الوقائية للمولدات الكهربائية حيث يتم تقليل مجموع مربعات الاحتياطيات للتوليد. تمت مقارنة النتائج بالأعمال السابقة التي استخدمت التقنيات التطورية من أجل تقييم أداء الخوارزمية المقترحة وعملية البحث في حل مشكلة جدولة الصيانة الوقائية للمولدات الكهربائية لنظام الطاقة.

Résumé

Dans certaines industries qui utilisent des machines et des équipements, la planification efficace de la maintenance préventive, qui est un problème d'optimisation complexe, joue un rôle crucial dans la maintenance de leurs machines et équipements. La maintenance préventive vise à effectuer des procédures de maintenance avant la panne de l'équipement afin d'éviter des temps d'arrêt et des réparations coûteux.

Cette thèse aborde le problème optimal de planification de la maintenance préventive des générateurs (GMS) dans les systèmes d'alimentation électrique comprenant plusieurs machines. Ce problème peut être résolu de différentes manières, telles que les méthodes méta heuristiques et la programmation mathématique. Le problème est formulé comme un modèle d'optimisation mathématique à l'aide de techniques de programmation mathématique, et la meilleure solution est ensuite trouvée à l'aide d'algorithmes. La simulation du planning de maintenance permet d'évaluer son efficacité tout en modélisant l'équipement et son comportement en cas de panne. Les méthodes méta heuristiques impliquent la création de calendriers de maintenance en utilisant des généralisations ou une expertise en la matière. L'objectif principal de cette thèse est de contribuer à l'amélioration des performances d'un algorithme évolutif discret pour une optimisation fiable et extrêmement précise des fonctions objectives discrètes afin de répondre à la problématique de la meilleure planification de la maintenance préventive des générateurs des systèmes électriques. Pour planifier la maintenance préventive des générateurs, un algorithme méta-heuristique moderne nommé "l'algorithme d'optimisation discrète de Mayfly (DMFO)" a été conçu. Cet algorithme a été proposé comme algorithme innovant d'optimisation de l'intelligence en essaim en 2020, il combine les avantages de plusieurs algorithmes d'optimisation existants. Cet algorithme a été utilisé dans plusieurs applications, notamment l'optimisation industrielle, le système de prévision d'ensemble et les systèmes photovoltaïques. Une stratégie First-Bit Flip and Shift (FBFS) pour les vecteurs binaires a d'abord été proposée pour améliorer les performances des algorithmes évolutionnaires. La stratégie FBFS est une stratégie de recherche locale qui effectue de petites modifications des solutions obtenues pour aider les algorithmes évolutifs dans l'optimisation locale et éviter qu'ils ne restent bloqués dans les optima locaux. La technique proposée a été évaluée sur un système électrique de test de 21 unités avec une charge maximale de 4739 MW dans trois cas où le nombre total de staff disponibles par semaine est limité. L'algorithme amélioré a montré à la fin son efficacité pour trouver une solution au problème GMS où la Somme des Carrés des Réserves (SSR) de génération est minimisée. Les résultats sont comparés

à des travaux antérieurs qui utilisaient d'autres techniques méta-heuristiques afin d'évaluer les performances de l'algorithme FBFS-DMFO proposé et de son processus de recherche dans la résolution du problème GMS du système électrique.

Dedication

I would like to dedicate this project to who have been significant sources of love, support, and inspiration in my life:

To my wonderful mother **Mrs. NACERA D.** the greatest mother in this world, you are the epitome of strength, resilience, and unconditional love. Your belief in me and measureless support have been my guiding light throughout this journey. Your sacrifices, encouragement, and nurturing have shaped me into the person I am today. This achievement is a testament to the values you instilled in me. Without your endless love and encouragement, I would never have been able to complete my graduate studies. You have selflessly sacrificed for my happiness, you have put my needs above your own. I love you and I appreciate everything that you have done for me. I dedicate this project with too much love and pride to you my mama.

To the father of my husband **Mr. LEZGHAD B.** may your soul rest in peace. You were a pillar of wisdom and kindness, and your presence in our lives will always be cherished. I ask God to make you one of the people of Paradise. This project is dedicated to your memory.

To my two beautiful amazing sisters IMEN and AMINA. **IMEN**, you have taught me to be strong, from the earliest days of our childhood, you have been there for me, supported me, stood by my side, helped me a lot, guided me with wisdom, love and pride. I owe so much of who I am to you. Thank you dear sister for all that you do. **AMINA**, you have been my confidante and my best friend, through every challenge, you help me transcend it. Your encouragement and your words of wisdom always lift me up when I am down. My sisters, you are my pillars of support and my closest confidantes. Your presence has filled my life with laughter, joy, and endless inspiration. I am grateful for the bond we share and I dedicate this achievement to our sisterhood.

To my nephew, little angel, **Yasser M.** you hold a special place in my heart. I am honored to be your maternal aunt, and I am excited to watch the great things you will accomplish. May this project serve as a reminder of the love I have for you.

To my beloved husband **Mr. SABIR B.** you are my partner and my biggest source of strength. You entered my life and brought joy and light, you have stood by me in my moments of doubt, you have always lifted me up and helped me find my way. Thank you for understanding the challenges I faced during this project and for being my source of motivation. I am grateful to have you by my side and I wish you were with me during my master defense. This dedication is a testament to our love and partnership, with you, my heart is forever fulfilled.

To my best friend and my roommate **CHAHINEZ S.** and my close friend **NAJAH B.** you have been my companions on this journey. Your presence brings fun to my days and comforts me in times of distress. I will always appreciate of the bond we share and the immeasurable impact you have had on my life. Your unwavering friendship, encouragement have been invaluable.

Acknowledgement

First and foremost, I am deeply thankful to **God** for granting me the strength, guidance, and perseverance throughout this journey. Thank you, **ALLAH**, for the blessings you have bestowed on my life. You have provided me with more than I could ever have imagined. You have given me family and friends who bless me every day with kind words and actions.

I would like to extend my utmost appreciation to my supervisor, **Prof. A. KHELDOUN**, their invaluable guidance, their expertise, feedback and mentorship have been instrumental in shaping the direction of this project. I am grateful for providing valuable, insights and helping me refine my project.

I would like to express my sincere gratitude to my co-supervisor, **Dr. S. BELAGOUN**, for their valuable contributions and their guidance that have been instrumental in enhancing the quality of my work. I am thankful for their patience and willingness to share his knowledge, which greatly enriched my project experience.

I would like to express my deepest appreciation and heartfelt appreciation to my mother **Mrs. D. NACERA**. Your support, encouragement, and belief in my abilities have been a source of motivation throughout this journey. Your sacrifices, understanding, and caring have been the key to my success. Thank you for your unconditional love that knows no bounds. Thank you for always being my biggest cheerleader and for being there for me every step of the way. I am truly blessed to have your love and help that have played a significant role in the successful completion of my project.

LIST OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATION

Acronyme	Meaning
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
DCJO	Discrete Chaotic Jaya Optimization
DE	Differential Evolution
DICS	Discrete Integer Cukoo Search
DMFO	Discrete Mayfly Optimization
DPSO	Discrete Particle Swarm Optimization
FA	Firefly Algorithm
FBFS	First-Bit Flip and Shift
GA	Genetic Algorithm
GMS	Generator Maintenance Scheduling
GWO	Grey Wolf Optimization
HCT	Hill Climbing Technique
HGS	Hunger Games Search
HSGA	Hybrid Scatter-Genetic Algorithm
LC-JAYA	Logistic Chaotic-JAYA
LOLE	Loss Of Load Expectation
MDPSO	Modified Discrete Particle Swarm Optimization
MFO	Mayfly Optimization
MS-MDPSO	Multiple Swarms-Modified Discrete Particle Swarm Optimization
PSO	Particle Swarm Optimization
SA	Simulated Annealing
SDV	Standard Deviation
SOS	Symbiotic Organisms Search
SSR	Sum of Squares of the Reserves
TMS	Transmission Maintenance Scheduling

LIST OF SYMBOLS

Acronyme	Meaning
$\boldsymbol{t}$	Index of periods; $t\epsilon\tau$
Chapter 2	
$\boldsymbol{\tau}$	Total number of planned horizons
$\boldsymbol{i}$	Index of the number of generators; $i = 1, \ldots, N$;
$\boldsymbol{N}$	Total number of generators
$\boldsymbol{P_{i,t}^{max}}$	Maximum output power of generator i in MWs in period t
$\boldsymbol{P_{i,t}}$	Generated output power of generator i in MWs in period t
$\boldsymbol{N_t}$	Set of the total generators under maintenance in period t
$\boldsymbol{N_i}$	The outage duration of maintenance of generator i
$\boldsymbol{a_{i,t}}$	The set of maintenance weeks stages of generator i within period t; $a_{i,t} \in \{k_{i,t}, k_{i,t} + 1, \ldots, k_{i,t} + N_i - 1\}$;
$\boldsymbol{k}$	The index of maintenance stage; $k\epsilon a_{i,t}$
$\boldsymbol{k_{i,t}}$	Starting week of maintenance of generator $i$in period t
$\boldsymbol{C_{i,t}}$	Variable of maintenance start for generator $i$in period t; if generator i: $\begin{cases} \text{on maintenance} C_{i,t} = 1 \\ \text{otherwise} C_{i,t} = 0 \end{cases}$
$\boldsymbol{D_t}$	The load power demand in MWs within period t
$\boldsymbol{L_{i,t}}$	Workforce needed for maintaining generator $i$in period t
$\boldsymbol{P_t}$	The total generating capacity within period t
$\boldsymbol{\rho}$	The sum of the squares of the reserves
$\boldsymbol{\mu_t}$	The minimum reserve capacity within period t
$\boldsymbol{AL_t}$	The available workforce within period t
$\boldsymbol{\alpha}$	The workforce violation
$\boldsymbol{\beta}$	The load power demand violation
$\boldsymbol{L}$	The total number of violated constraints
$\boldsymbol{l}$	The index of violated restriction
$\boldsymbol{C_l}$	The weight of the violation V_l
$\boldsymbol{C_R}$	The weight coefficient associated with SSR of generation
$\boldsymbol{C_M}$	The weight coefficient associated with the total workforce violation
$\boldsymbol{C_L}$	The weight coefficient associated with the total load violation
Chapter 3	
$\boldsymbol{i}$	The individual mayfly
$\boldsymbol{x_i^t}$	The actual position of the male mayfly
$\boldsymbol{y_i^t}$	The actual position of the female mayfly
$\boldsymbol{v_i^t}$	The velocity a mayfly
$\boldsymbol{a_1}$	The positive attraction constant for the social role
$\boldsymbol{a_2}$	The positive attraction constant for the social role
$\boldsymbol{\beta}$	The visibility factor of the mayflies
$\boldsymbol{N}$	The total number of males in the mayfly swarm

r_p	The Cartesian distance between the mayfly actual position and the individual best position
r_g	The Cartesian distance between the mayfly actual position and the global best position
p_{best_i}	The individual best position for mayflies
g_{best}	The global best position for mayflies
r	A random number, $r \in [-1, 1]$
d	The nuptial dance coefficient
X_{ij}	Individual best position or global best position
r_{mf}	The Cartesian distance between male and females mayflies
f_l	A random walk coefficient
L	A random value within a specific range
V_{max}	The maximum velocity of a mayfly
g	The gravity coefficient
g_{max}	The maximum value of the gravity coefficient
g_{min}	The minimum value of the gravity coefficient
n	The number of iteration
n_{max}	The maximum number of iteration
δ	A constant value, $0 < \delta < 1$
σ	The standard deviation of the normal distribution
N_n	The standard normal distribution

GENERAL INTRODUCTION

The provision of uninterrupted electrical energy to clients is currently the most crucial aspect of power networks. Unwanted power system infirmities are mostly caused by various electric power system failures, which might occur at improbable times and in varied locations within the various parts as well as pauses. The clients' service would be interrupted as a result of this unwelcome outage. In order to lessen and prevent the recurrence of these failures and to ensure that the power systems are operating in an efficient and dependable manner, it is crucial to establish an effective maintenance strategy. Corrective and preventive processes are used to carry out maintenance.

The optimal Generator Maintenance Scheduling (GMS) problem's primary function in power systems is to create an ideal schedule for the preventive maintenance of the generator portion units. An ideal GMS increases the operational reliability of power systems, increases the lifespan of the generators, and lowers the cost of generator maintenance. An optimization problem is how the GMS problem is put forth. This issue should be resolved by ensuring the power systems' dependability at low operating costs while also satisfying the load's power consumption and workforce limitations. Since precise mathematical techniques have been applied in the past to find exact answers to small-scale problems, the GMS problem has been researched for a long time. These traditional mathematical methods, however, have a number of drawbacks and suffer from excessive computing demands as system dimension rises. For medium-scale power systems, traditional approximate approaches have been used to get around the shortcomings of accurate methods. For wide-area systems with large dimensions, they do, however, only provide approximations of the solutions and need a significant computational effort.

Modern techniques based on metaheuristic optimization have recently played a significant role in resolving the GMS problem and overcoming the shortcomings of approximate techniques. In this thesis, a proposed Binary vector First-Bit Flip and Shift (FBFS) strategy with the Discrete Mayfly Optimization (DMFO) algorithm are used to schedule the preventive maintenance of the generators used in electric power systems. To enhance both the exploration and exploitation phases, the suggested algorithm is based on the FBFS and DMFO strategies. The GMS problem is modeled using an objective function of the Sum of Squares of the Reserves (SSR) of generations as the dependability requirement. By minimizing an evaluation function comprised of the weighted sum of the objective function and the penalty function for violating the constraints, the optimization process is carried out.

The suggested strategy has been applied in a 21-unit test system over a planned horizon of 52 weeks, where the highest generation is 5688 MW, the peak load is 4739 MW, and limited workforce available each week to do the maintenance chores. Multiple statistical tests have been used to compare the proposed method to current methods used in comparable works. The acquired results demonstrate the suggested algorithm's superiority over other current methods for tackling the GMS problem. Currently, this method may be depended upon to address issues with the scheduling of maintenance for power system generators.

1. STATE OF THE ART

1.1. Motivation

Today, it is crucial to provide consistent, dependable electricity due to the growing demand for electrical energy. One of the most important factors of supplying reliable electrical energy to the necessary industrial and urban loads is the scheduling of generating unit maintenance [1].

The goal of maintenance is to increase the lifetime of power generation facilities or at least to increase the interval between failures that could result in expensive repairs. The frequency of service outages and their effects can also be decreased with an efficient maintenance schedule. In order to make a power system operates economically and with high reliability [2]. Power generation companies (GENCOs) use a variety of maintenance techniques to accomplish their goals in terms of quality and cost [3]. The two basic types of maintenance are corrective and preventive. Corrective maintenance refers to corrective actions carried out following a failure to return the operation to its previous operational state. The term "preventive maintenance" refers to procedures used to keep an asset's operability at a satisfactory level. Generation maintenance scheduling (GMS) in power systems is to set up a schedule for generation units to perform preventive maintenance to lower the possibility of failure. Furthermore, the generating units must be taken out of operation for a duration ranging from a few hours to many weeks, regardless of the type of maintenance done. The decision is then based on a variety of factors, including the impact of maintenance outages on the system as a whole, reliability, the loss of services, the company's reputation, and the loss of revenue [3], [4].By performing periodic preventative maintenance, power system equipment remains in proper functioning. There is no guarantee that the best or nearly best schedule will be found when the duty of generator maintenance is carried out manually by human professionals who create the plan based on their knowledge of the system and experience. The goal of maintenance scheduling is finding the sequence of scheduled outages of generating units over a particular period of time such that the level of energy reserve is maintained [5]. Such a type of schedule is crucial since decisions made in one planning activity have an immediate impact on others. Modern power systems have experienced growing electrical energy demand and corresponding system size growth, which results in a rise in the number of generators and a decrease in reserve margins. Constrained GMS optimization problem complexity has increased as a result for such a huge power system [5].Finding the best schedule for generation preventive maintenance is difficult because there are more restrictions, more power system generators, and more customer demand. As a result, there are more variables to consider, which makes it more challenging to find the best solution, as demonstrating in [5].

Conventional optimization approaches have been used to study the GMS problem for many years. However, due to the significant computing effort required to arrive at the solution, old methodologies had many limitations. In this situation, metaheuristics have replaced traditional computational methods in order to deal with the GMS problem while maintaining high levels of solution performance. This thesis is based on using a metaheuristic approach to schedule the maintenance of generators in large-scale power systems, which involves minimizing an evaluation function made up of the sum of two weighted functions for the generation's Sum of Squares of Reserves (SSR) and the penalty function for violating constraints [6].

1.2. Literature Review

GMS problems have historically been resolved using conventional means. To solve the maintenance scheduling difficulties, the authors in[7]–[9]provided a stochastic programming method, whereas authors in [10] and [11] employed decomposition techniques. According to authors in [2], [12], [13], maintenance scheduling problems in small dimension problems can be solved precisely with a minimal number of repetitions using traditional methods or exact methods such mathematical approaches to optimization. Numerous mathematical techniques, such as integer programming in [14]mixed integer programming presented in [14] dynamic programming in [15], Successive approximation dynamic programming applied in [16] and branch and- bound demonstrated in [17]. Authors in [18]provided a mathematically aided differential evolution strategy to address the power system maintenance scheduling problem. Nevertheless, as the system size and variables expand because of the expansion of the solution space, conventional approaches have to deal with long computational and operating times. They require precise constraint formulations that are lacking in the current system.

In the past, approximate methods have been used to get around various problems caused by traditional mathematical methods. When compared to conventional procedures, these approaches are relatively quick to implement and take only a short time to run. In [19], researchers demonstrated that approximate methods had overcome the challenges posed by the complexity of the problem, the nonlinear or non-differentiable objective functions [1], and the discrete form of the variables to solve the problem of excessive computational and running time in the absence of powerful computers. The GMS problem was solved by the researchers in[20] even though the constraints were not satisfied and the units schedule was not in any particular order. For the thermal GMS problem, researchers in [21] suggested a heuristic-guided depth first search approach by converting the scheduling operation to a tree searching problem and using heuristic rules to find the solution quickly by satisfying the smallest reserve between total generation and load's power demand. The Lagrangian-Relaxation method has been applied by authors in [22], [23] for short-term maintenance scheduling in thermal power plants and electric power systems, respectively. However, as demonstrated in [12], the goal of approximation methods is to find at least approximate solutions rather than necessarily precise ones [24]. They take into account each generator independently and arrange the generation units consecutively in accordance with a predetermined order. They sometimes fail to offer effective solutions. As stated in [13], approximate approaches need a significant computing effort for a wide area system with a large dimension since they perform a significant number of iterations where the objective function is assessed and the constraints are confirmed. The performance of approximate methods can be improved by integrating them with more recent metaheuristic optimization techniques [19].

Recent studies have praised meta-heuristic algorithms for their ability to solve GMS problems [25]. They are bio-inspired by the collective thinking of living groups as hawks, ants, lions, wolves, fishes, etc.[26]. They outperform the aforementioned techniques [1]. The researchers in[27] presented a Genetic Algorithm (GA) for the optimization and solution of the GMS problem in power systems. This algorithm was tested in practice on the Macedonian power system by minimizing the objective function of the yearly Load Expectation Loss (LOLE), in which all constraints were included and verified and the suggested approach demonstrated enhanced power systems reliability when compared with approximate methodologies. By minimizing cost objective functions, the Simulated Annealing (SA) algorithm was presented in [28], [29] to solve the GMS problem in both the thermal power plant and the electric power system. SA demonstrated its effectiveness and produced good outcomes in both cases. Researchers in[25] used a strategy based on SA to solve the GMS problem by optimizing a reliability objective function; the method was tested on a 32-unit thermal test system. Authors in [30] introduced the Ant Colony Optimization (ACO) strategy for solving the GMS problem, which has been treated as an economic cost optimization problem. The approach has been tested on a test system with 6 producing units, and it has proven successful. The GMS problem was solved using the Artificial Bee Colony (ABC) algorithm in [31], which included the use of cost and reliability criterion objective functions. The method demonstrated its effectiveness in both 21-unit and 49-unit test systems. In order to solve the GMS problem in electric power systems, researchers in [32] demonstrated the usefulness of the Tabu search algorithm, which was tested on both 4-unit and 22-unit test systems. This approach was applied to minimize two objective functions: the total generators operating cost and levering the reserve, where the same constraints were put to use and verified, including the maintenance completion constraint, the workforce size constraint, the priority constraint, and the levering the reserve. The ACO algorithm has been introduced and demonstrated in [33], where the researchers came to the conclusion that it is more effective than standard techniques. It has been tested in a hydropower test system where typical constraints have been used and verified. According to [34], a Modified Discrete Particle Swarm Optimization (MDPSO) technique was used to find the best GMS solution while taking into account the load's power requirements and workforce constraints. MDPSO offered superior solutions to GA and DPSO techniques. The technique was tested on two different systems, a 49-unit system feeding the Nigerian national grid and a 21-unit test system. Multiple Swarms-DPSO (MS-MDPSO) technique for solving the GMS problem was described by [5]. It was tested on both 21-unit and 49-unit test systems, and it was contrasted with the MDPSO method. Also, a Discrete Integer Cuckoo Search (DICS) optimization algorithm has been described in [26]. In[35], a GA was proposed to address the GMS problem through the optimization of an economic cost objective function over a scheduled 25-week time horizon. The GA was evaluated using a test system with 19 generating units. By minimizing a reliability objective function, a modified ABC algorithm has been developed in [36] to solve the GMS problem. It has demonstrated its effectiveness on both 13-unit and 21-unit test systems.

The GMS problem in power systems has been solved using crossbred or hybrid strategies that combine metaheuristics and approximation methodologies [1]. In [37], a discrete Particle Swarms Optimization-Genetic Algorithm (PSO-GA) hybrid technique was utilized to address the GMS problem by optimizing an objective function for the reliability criterion, and it was evaluated on 5-unit and 21-unit test systems. PSO-GA and PSO-Shuffled Frog Leaping hybrid strategies have been presented in [2] in order to handle the GMS problem by optimizing objective functions of both economic cost and reliability requirements. Thermal power systems with IEEE 24-bus and 32 generating units were used to test these two strategies. They showed strength in resolving this problem. Using a 21-unit test system, a Hybrid Scatter-Genetic Algorithm (HSGA) has been used to solve the GMS problem as presented in [38]. It has been compared to GA, DPSO, and MDPSO approaches. For the purpose of tackling both GMS and TMS problems in electric power systems, the researchers of [39] suggested a hybrid method that combines a meta-heuristic approach with a local search methodology termed the Hill Climbing Technique (HCT). In [24], a hybrid GA-SA strategy was developed, and it was demonstrated that this methodology is more reliable than both conventional GA and SA methods. In [40], the researchers presented a hybrid SA/ACO technique that uses a 21-unit test system to solve the GMS problem. This hybrid method has been compared to GA, SA, and ACO methods and has proven to be successful in solving the GMS problem. Researchers in [1] suggested a strategy combining GA and HCT in order to address the GMS problem. The GMS problem has proven to be amenable to all the methods listed above, but metaheuristics have proven to be the most effective in doing so, and they have overcome all the previous difficulties and limitations that traditional methods had in the past. The GMS problem's historical advancements are outlined in Table 1.1 below.

Method type	Algorithm	Criterion	Type of the test system	Size of the test power system	Ref.
Exact	Branch-and-bound	Reliability	-	7-unit test system	[17]
	Integer programming	Economic cost	Thermal	15-unit test system	[41]
	Dynamic programming	Reliability and Economic cost	-	21-unit test system	[15]
	Successiveapproximation dynamic programming	Economic cost	Thermal (Fossil-fuelled)	20-unit test system	[16]
	Stochastic programming	Reliability and Economic cost	Hydro-Thermal	Southern Brazilian 48-unit test system	[8]
	decomposition methods	Economic cost	-	5-unit test system	[10]
	decomposition methods	Economic cost	-	IEEE-RTS, 32 Generating units, 23 bus, 38 transmission line test system	[42]
	Mathematical approach assisted differential evolution	Economic cost	-	4-unit and 22-unit test system	[18]
Approximate	Lagrangian-Relaxation	Economic cost	-	10-unit test system	[22]
	Heuristic 1	Reliability	-	21-unit test system	[24]
	Lagrangian-Relaxation		-		[23]
	Heuristic 2	Reliability	-	21-unit test system	[24]
	Heuristic-guided depth-first search	Reliability	Thermal	10-unit test system	[21]
Metaheuristic	Discrete Particle Swarm Optimisation (DPSO)	Reliability and Economic cost	Hydrothermal	21-unit test system and 49-unit system feeding the Nigerian National Grid	[34]
	Simulated Annealing (SA)	Economic cost	Thermal	29-unit test system	[29]
	Simulated Annealing (SA)	Economic cost	-	15-unit and 30-unit and 60-unit test systems	[28]
	Modified - DPSO (MDPSO)	Reliability and Economic cost	Hydrothermal	21-unit test system and 49-unit system feeding the Nigerian National Grid	[34]
	Ant Colony Optimisation (ACO)	Reliability	Hydro	Tasmania power system with two catchment areas and five power stations of 8 generating units each.	[33]
	Genetic Algorithm (GA)	Economic cost	Thermal	29 generating units	[35]

	Genetic Algorithm (GA)	Reliability	Thermal	29-unit Macedonian test power system	[27]
	Tabu search	Reliability and Economic cost	-	4-unit test system and 22-unit test system	[32]
	Multiple Swarms-MDPSO (MS-MDPSO)	Reliability and Economic cost	Hydrothermal	21-unit test system and 49-unit system feeding the Nigerian National Grid	[5]
	Discrete Integer Cuckoo Search (DICS) optimisation	Reliability	-	21-unit test system	[26]
	Ant Colony Optimisation (ACO)	Reliability	Thermal	32 generating units test system	[25]
	Ant Colony Optimisation (ACO)	Economic cost	-	6 generating units test system	[30]
	Artificial Bee Colony (ABC)	Reliability and Economic cost	Thermal	21-unit test system and 49-unit system feeding the Nigerian National Grid	[43]
	Modified Artificial Bee Colony	Reliability	-	13-unit and 21-unit test systems	[36]
Hybrid	GA + local search Hill Climbing Technique (HCT)	Reliability	-	33-unit test system	[1]
	GA + SA	Reliability	-	21-unit test system	[24]
	Evolutionary programming + HCT	Economic cost	-	IEEE 30-bus, 6 generating units, 41 transmission lines	[39]
	GA+ Heuristic	Reliability	-	21-unit test system	[24]
	GA+ SA+ Heuristics	Reliability	-	21-unit test system	[24]
	SA + ACO	Reliability	-	21-unit test system	[40]
	Hybrid Scatter-Genetic Algorithm (HSGA)	Reliability	-	21-unit test system and IEEE RTS 9 generating units test system	[38]
	Hybrid PSO + GA and Hybrid PSO–Shuffled Frog Leaping	Reliability and Economic cost	Thermal	IEEE 24-bus, 32 generating units test system	[2]
	Hybrid Discrete PSO + GA	Reliability	-	5-unit and 21-unit test systems	[37]

Table 1.1: The related works to solve the generator maintenance-scheduling problem.

The past few years have seen an increase in the usage of a novel approach called DMFO algorithm by researchers to solve different optimization problems. The DMFO method is found to have a fast convergence rate compared to other optimization methods, such as the Symbiotic Organisms Search (SOS), PSO, and Differential Evolution (DE). The DMFO algorithm will be used in cooperation with a proposed FBFS strategy to solve the GMS problem. Moreover, the results done in this thesis conclude that the FBFS-DMFO algorithm is a reliable and effective optimization technique compared with others.

1.3. Thesis Objectives

One of the primary motivations for using an improved FBFS-DMFO algorithm to solve generator maintenance problems is its ability to handle effectively optimization tasks in complex and dynamic systems. The GMS plays a crucial role in ensuring the reliable and efficient operation of power systems. It involves determining the optimal time and duration for performing maintenance activities on generators while minimizing the impact on power supply and maximizing the availability of the system. The FBFS-DMFO algorithm's ability to balance exploration and exploitation, along with its stochastic nature, makes it well suited for addressing the uncertainty and dynamic nature of GMS. By leveraging the algorithm's adaptive search capabilities, it becomes possible to find optimal maintenance schedules that minimize downtime, reduce maintenance costs, and enhance the overall reliability and performance of power systems. The FBFS-DMFO algorithm offers a promising approach for tackling the GMS problem and can contribute to more efficient and effective maintenance strategies in the power industry. This thesis is the study of finding an effectives solution for the GMS problem using this improved FBFS-DMFO algorithm.

1.4. Thesis Organization

This thesis is divided as follows; General introduction, Chapter 1 which represents a background of all the previous works dealing with GMS problems. Chapter 2 provides a mathematical formulation of the GMS problem; the objective function, the evaluation function and its restrictions. Chapter 3 describes general concepts about DMFO algorithm and the FBFS local search strategy. Chapter 4 presents the 21-unit test system data; obtained results and discussion. A general conclusion is drawn at the end and the suggestions for more study will be provided.

2. MAIN PROBLEM IN POWER SYSTEM

2.1. Introduction

The process of planning preventive maintenance for power generators is essential today in order to increase the reliability of power systems generators, which have necessary to continuously supply customer demand for electricity without interruption, and prevent their possible future electrical failures. Power generators' preventive maintenance planning assures that the generating reserve should be kept to a minimum and must be as small as possible at the end of the overall maintenance horizon. The planning process necessitates the best possible use of the available workforce, with the workforce required for maintenance tasks to be as efficient and minimal as possible while meeting a number of constraints, including those related to the maintenance window, load power demand, resource allocation, and reserve boundary. Therefore, the solution to the problem of scheduling generator maintenance should be economical and reliable. This chapter covers the difficulties of scheduling preventive maintenance for the generation section of power systems.

2.2. Generators Preventive Maintenance Scheduling Problems

Preventive maintenance for generators is typically needed within a specified planning horizon; this horizon is commonly long, ranging from 8 weeks to 5 years, separated into various time intervals of weeks. Preventive maintenance aims to increase the expected lifespan of generating units, to ensure a secure operating state, minimize the risks of unexpected outages produced by defective generators, lower maintenance costs, and provide highly reliable power-system generation components. The GMS problem signifies that all restrictions have been met and the objective function has reached its ideal state. There is a common reliability requirement that maintains a specific level of generating reserve during the period of planned operation for those who are working with reliability criteria. Therefore, our thesis is focused on reducing the SSR of generation[6].

2.2.1. The Objective Functions of the Generator Maintenance Scheduling Problem

The nonlinearity feature identifies GMS difficulties. It is possible to solve GMS problems and arrive at the best timetable for preventative planned maintenance by optimizing a predetermined objective function connected to the generation component of electric power systems. In addition, solving the GMS problem requires designing a maintenance schedule that indicates the beginning and end times for maintaining generation part units as well as the number of workers and resources needed while minimizing SSR and verifying restrictions[6].

During the scheduling process, generators are either being maintained or not. For decision $C_{i,t}$, generators can be expressed as a binary variable that equals either 1 when generator is undergoing repair within period t or 0 if it is not. Each generator must be recovered from maintenance within a predetermined period using specific and unique resources. The most significant restrictions taken into account in this thesis are the maintenance window, the workforce and the load demand. The terminology used to describe the GMS problem's mathematical model is shown in Table 2.1.

Table 2.1: The terminology of generator maintenance scheduling mathematical model.

Nomenclature			
t	Index of periods; $t\epsilon\tau$	N_i	The outage duration of maintenance of generator i;
τ	Total number of planned horizons;	$k_{i,t}$	Starting week of maintenance of generator $i$in period t,
i	Index of the number of generators; $i = 1, \dots, N$;	$C_{i,t}$	Variable of maintenance start for generator $i$in period t; if generator i: $\begin{cases} \text{on maintenance} C_{i,t} = 1 \\ \text{otherwise} C_{i,t} = 0 \end{cases}$;
N	Total number of generators;	D_t	The load power demand in MWs within period t;
$P_{i,t}^{max}$	Maximum output power of generator i in MWs in period t;	$L_{i,t}$	Workforce needed for maintaining generator $i$in period t;
$P_{i,t}$	Generated output power of generator i in MWs in period t;	P_t	The total generating capacity within period t;
N_t	Set of the total generators under maintenance in period t;	ρ	The sum of the squares of the reserves;
$a_{i,t}$	The set of maintenance weeks stages of generator i within period t; $a_{i,t} \in \{k_{i,t}, k_{i,t}+1, \dots, k_{i,t}+N_i-1\}$;	μ_t	The minimum reserve capacity within period t;
k	The index of maintenance stage; $k\epsilon a_{i,t}$	AL_t	The available workforce within period t;

The maintenance window restriction determines the outage duration and periods for each generator to be under maintenance[5], [6], [26]. Consider next equation (Eq. 2.1):

$\forall t\epsilon\tau$and $\forall i\epsilon N$;

$$\sum_{t\epsilon\tau} C_{i,t} = N_i \tag{2.1}$$

Where, $C_{i,t} = \begin{cases} 1 \; if k \in a_{i,t}; \\ 0 \; if k \notin a_{i,t}; \end{cases}$

The workforce restriction determines that the total workers can be used to perform a maintenance assignment in a certain period t cannot be greater than the whole available workforce [5], [6], [26]. Consider next equation (Eq. 2.2)

$\forall t\epsilon\tau$and $\forall i\epsilon N$;

$$\sum_{i\epsilon N_t}\sum_{K\epsilon a_{i,t}} C_{i,k}L_{i,t} \leq AL_t \tag{2.2}$$

Where, $\sum_{i\epsilon N_t}\sum_{K\epsilon a_{i,t}} C_{i,k}L_{i,t}$ implies that the total workforce needed within period t and AL_t implies the available workforce within period t.

The load demand restriction determines that the produced power should correspond with the load demand [5], [6], [26]. Consider next equation (Eq. 2.3)

$$\sum_{i=1}^{N} P_{i,t}^{max} - \sum_{i\epsilon N_t}\left(\sum_{k\epsilon a_{i,t}} C_{i,k}P_{i,k}\right) \geq D_t + \mu_t \tag{2.3}$$

Where, $\sum_{i=1}^{N} P_{i,t}^{max}$ stands for the maximum total generated power of the electric power system within period t, $\sum_{i\epsilon N_t}\left(\sum_{k\epsilon a_{i,t}} C_{i,k}P_{i,k}\right)$ stands for the total generation power loss due to prescheduled outage within period t, $\sum_{i=1}^{N} P_{i,t}^{max} - \sum_{i\epsilon N_t}\left(\sum_{k\epsilon a_{i,t}} C_{i,k}P_{i,k}\right)$ stands for the total generated capacity P_t of the electric power system during maintenance tasks within period t and $\sum_{i=1}^{N} P_{i,t}^{max} - \sum_{i\in N_t}\left(\sum_{k\in a_{i,t}} C_{i,k}P_{i,k}\right) - D_t$ stands for the total reserves capacity during the planned period horizon which should be optimal and at minimum value μ_t [5], [6], [26]. Consider next equation (Eq. 2.4)

$\forall t\epsilon\tau$ and $\forall i\epsilon N$;

$$\mu_t = \sum_{i=1}^{N} P_{i,t}^{max} - \sum_{i\epsilon N_t}\left(\sum_{k\epsilon a_{i,t}} C_{i,k}P_{i,k}\right) - D_t \tag{2.4}$$

The objective function based on the reliability criterion presented in previous work [5], [6], [24], [26], [34], [38], [43]–[45] is the focus of this thesis. A comparison between production and consumption should be done after each period to keep the total SSR in electric power systems generation to a minimum level or estimate. The reserve requires to be reduced to a minimum. Production needs to keep up with demand. By minimizing the SSR objective function, the GMS problem is then effectively solved. Consider next equations (Eq. 2.5 and Eq. 2.6)

$\forall t\epsilon\tau$ and $\forall i\epsilon N$;

$$F_{obj} = \rho = \sum_{t\epsilon\tau} \mu_t^2 \tag{2.5}$$

$$Min(F_{obj}) = Min(\rho) = Min\left(\sum_{t\epsilon\tau} \mu_t^2\right) \quad (2.6)$$

This objective function, represented by (Eq. 2.5), is based on the reliability criterion and aims to ensure that, regardless of load variations, there is always a sufficient balance between power generation and load power demand. To do this, the utilities usually provide a spinning reserve by producing more power than the load power demand, which improves the system's reliability at a low operational cost. Minimizing the SSR can be a successful strategy when there is significant variation in the reserve. This is utilized as an objective function to be minimized in this application. By reducing the SSR during the whole operational scheduling period, as demonstrated in (Eq. 2.6), the reliability criterion GMS problem will be resolved. A general mathematical model for a general GMS problem expressed as a quadratic 0–1 programming problem is defined by equations (Eq. 2.1) (Eq. 2.6). Additional restrictions could be placed on the power system's local maintenance and reliability. There may be increased worry about the generators' insufficient supply during planned maintenance outages. As a result, the SSR of the generating units is minimized while formulating the reliability criterion GMS issue. The reliability of the power system is measured by the sum of the squares of the reserves, or the objective value. The reserve margin is distributed more evenly and the reliability is higher as the objective values decrease. The test GMS problem's average reserve level provides the lower bound of the desired value, providing a constant reserve margin throughout the scheduling period.

Heuristic methods and traditional mathematical techniques like Integer programming or Dynamic programming are the traditional approaches to such situations. However, despite being effective, these old strategies frequently have problems when it comes to their applicability to significant issues. Due to their ability to resolve complex optimization issues, it is preferable to take into account the usage of metaheuristic techniques for the general mathematical model of the GMS problem[6].

2.2.2. The Evaluation Function of the Generator Maintenance Scheduling problem

Modeling the GMS problem as an optimization issue using a minimum cost evaluation function is recommended. Two weighted functions make up the evaluation: a weighted objective function and a weighted penalty function for violating the constraints [5], [6], [24], [26], [34], [38], [43]–[45]. However, the final maintenance plan might not meet the workforce, load, and maintenance window requirements, as the workforce number may exceed the maximum available workforce and the load demand may exceed the entire generating capacity when maintenance operations are being performed. Therefore, the objective function in (Eq. 2.5) should include additional penalties for the workforce violation given by (Eq. 2.7) and the load demand violation given by (Eq. 2.8). To prevent any crossing of limitations, these penalties are reduced together with the target function. Equation (Eq. 2.7) can be used to calculate the workforce violation α [5], [6], [26], as demonstrated below:

$$\alpha = \sum_{i\epsilon\tau} \left(\sum_{k\epsilon N_t} \sum_{k\epsilon a_{i,t}} C_{i,k} L_{i,k} - AL_t \right) \tag{2.7}$$

Where, α is calculated during the times when the total workforce needed to complete the maintenance chores exceeds the available workforce. In other words when $\sum_{i\epsilon\tau}\left(\sum_{k\epsilon N_t}\sum_{k\epsilon a_{i,t}} C_{i,k}L_{i,k}\right)$ is greater than AL_t. If not, workforce violation does not exist.

According to [5], [6], [26] the load demand violation β is computed in the next equation (Eq. 2.8):

$$\beta = D_t - \left(\sum_{i=1}^{N} P_{i,t}^{max} - \sum_{i\epsilon N_t} \left(\sum_{k\epsilon a_{i,t}} C_{i,k} P_{i,k} \right) \right) \tag{2.8}$$

Where, β is calculated during the times when the load demand to complete the maintenance chores exceeds the generating capacity. In other words when D_t is greater than $\sum_{i=1}^{N} P_{i,t}^{max} - \sum_{i\epsilon N_t}\left(\sum_{k\epsilon a_{i,t}} C_{i,k}P_{i,k}\right)$. If not, load demand violation does not exist.

Every time a constraint is broken, a penalty value is proportionate to the amount by which the constraint is violated [5], [6], [24], [26], [34], [38], [43]–[45]. Consider next equation (Eq. 2.9):

$$Penaltycost = \sum_{l=1}^{L} C_l \times V_l = C_1 \times V_1 + C_2 \times V_2 + \ldots + C_L \times V_L \tag{2.9}$$

Where, L is the total number of violated constraints and l is the index of violated restriction number, C_l is the weight of the violation V_l.

According to [5], [6], [24], [26], [34], [38], [43]–[45], if both constraints of the workforce and the load's power demand are violated, the penalty function for these violations is represented in next equation (Eq. 2.10)

$$Penaltycost = C_M \times \alpha + C_L \times \beta \tag{2.10}$$

To describe the GMS problem, we assume a minimization problem of an evaluation function (E), also known as a crisp evaluation function, as mentioned in[46]. This function is a weighted sum of the objective function (ρ) and the penalty function for violating the constraints (α and β) [5], [6], [24], [26], [34], [38], [43]–[45]. This evaluation function is represented in next equation (Eq. 2.11):

$$E_{best} = Min[C_R \times \rho + C_M \times \alpha + C_L \times \beta] \tag{2.11}$$

Where, E_{best} stands for the best evaluation function value, ρ stands for the SSR of generation. α stands for the total workforce violation, β stands for the total violation during service time, C_R stands for the weight coefficient associated with SSR of generation. C_M stands for the weight coefficient associated with the total workforce violation and C_L stands for the weight coefficient associated with the total load demand violation.

The weighting coefficients are chosen so that penalty values for violations of the constraints dominate over the objective function, and to ensure that the violation of the relatively hard load constraint results in a higher penalty value compared to the relatively low workforce constraint [5], [6], [24], [26], [34], [38], [43]–[45].

2.3. Conclusion

The reliability criterion of an evaluation of a weighted sum of the goal function and the penalty function of violations of the constraints has been used to define and model the GMS problem mathematically. The objective function is based on the sum of the squares of the generation reserves. The penalty function is set for any violation of the load power demand and the workforce constraints, as well as when the load power demand during maintenance exceeds the total maximum generation and when the workforce used for maintaining generators exceeds the total workforce available. In order to satisfy several limitations, including the maintenance window constraint, the workforce constraint, the load power demand constraint, and the reserve constraint, the problem is then based on mathematical optimization techniques. The solution to the issue can be found in mathematical optimization techniques like metaheuristics and evolutionary algorithms, which will be covered in a later chapter.

3. THE FIRST-BIT FLIP AND SHIFT-BASED DISCRETE MAYFLY OPTIMIZATION ALGORITHM

3.1. Introduction

A bio-inspired population-based method called the Discrete Mayfly Optimization (DMFO) algorithm was recently proposed and has been effectively used to solve successfully several engineering issues, Zervoudakis and Tsafarakis first proposed the DMFO in the year of 2020. The DMFO algorithm begins by creating a population of mayflies at random, which are represented as points in the search space. A fitness function is used to evaluate each mayfly's effectiveness as a solution to the optimization problem. Any objective function that needs to be minimized or maximized can be the fitness function. The exploration phase is represented by a brief period of time during which the mayflies execute a random search of the search area. The mayflies move randomly in the search area during this phase while being directed by a random vector. As a result, the algorithm can quickly explore multiple regions of the search area.

Following the exploration phase, the mayflies converge on the best solution as of now; led by the solution that has the highest rate of success among the population. The phase of exploitation is represented by this. Then use a swarm intelligence strategy, the mayflies proceed in the direction of the right approach, with each one adjusting its location in regard to the best answer and its neighbors' positions. Up until an ending requirement is satisfied, the algorithm runs through the exploration and exploitation stages. The optimal solution generated by the algorithm during the search phase is the ultimate solution.

3.2. Motivation

As technology has advanced, there are more optimization issues than ever before, and these problems typically exhibit nonlinearity and high dimensionality. The Newton technique and gradient descent method were once thought to be efficient approaches for solving these issues since they could produce the desired outcomes in an acceptable amount of time. Moreover, the limitations of those traditional methods are that: they can only be used to solve small-scale issues and that they necessitate that the issues be differentiable. As a result, they are not the ideal option when problems get more complicated. Swarm intelligence optimization algorithms, which draw their inspiration from the behavior of naturally occurring biological groups, have gained popularity because it has been shown that they are effective at handling complex issues.

Swarm intelligence optimization methods have so far been proposed to handle a variety of optimization problems such as ABC, PSO, SOS, Grey Wolf Optimization (GWO), and Hunger Games Search (HGS), etc. They are commonly utilized in many different domains. In 2020, a fresh swarm intelligence optimization technique called the DMFO algorithm was proposed. It mixes the properties of several well-known optimization algorithms, including the Firefly Algorithm (FA), GA, and PSO.

The DMFO algorithm is an effective method for resolving optimization issues due to many advantages [47]:

- Easy implementation: DMFO algorithm is a workable option for resolving optimization issues in a variety of fields because it is simple to use and doesn't demand a lot of computational capabilities [47].
- Effective search: DMFO algorithm effectively explores the search space and identifies the best solution by combining local search and global search methodologies [47].
- Flexibility: A wide variety of optimization issues, such as engineering design, financial optimization, and power system optimization, can be resolved with DMFO algorithm [47].
- Robustness: DMFO algorithm can handle optimization issues with many objectives and is noise-resistant [47].

Therefore, the DMFO algorithm has demonstrated beneficial result in a variety of optimization situations and can be a helpful tool for academics and industry professionals who must resolve challenging optimization issues [47].

3.3. The Discrete Mayfly Optimization Algorithm

According to [48], it has been demonstrated that certain modifications are required for the PSO algorithm in order to ensure the attainment of an optimal point in when dealing with high-dimensional spaces. The DMFO algorithm gives researchers who worked to improve the effectiveness of the PSO algorithm using methods like crossover [49] and local search [50] an effective hybrid algorithmic structure. [51] and [52] report on improved optimization techniques that take advantage of existing techniques' advantages. The algorithm draws inspiration from the mating process of mayflies, utilizing their social behavior. The assumption is made that mayflies, upon hatching from eggs, instantly reach adulthood, and the survival of the fittest mayflies is independent of their lifespan. Each mayfly's position in the search space signifies a potential solution to the problem at hand. The algorithm begins by generating two sets of mayflies randomly, one representing the male population and the other representing the female population. Every mayfly is placed randomly within the problem space, representing a potential solution denoted by a d-dimensional vector $x = (x_1, \ldots, x_d)$. The effectiveness of each mayfly's solution is assessed using a predetermined objective function f(x). The velocity of a mayfly $v = (v_1, \ldots, v_d)$ is determined by the change in its position, taking into account both individual and social flying experiences. Notably, each mayfly modifies its flight path in order to reach both its individual best position (p_{best}) and the best position reached by any mayfly within the group (g_{best}) [53].

3.4. The Discrete Mayfly Optimization Algorithm Application

The DMFO algorithm can be applied to a wide range of optimization problems across different domains. Some of the common uses of the DMFO algorithm include:

- Function Optimization: The DMFO algorithm can be used to find the optimal solution for mathematical functions. It explores the search space to locate the global or near-global optimum, making it suitable for problems with multiple local optima [47].
- Engineering Design: The DMFO algorithm can be employed in engineering design tasks, such as parameter tuning, circuit design, and structural optimization. It helps in finding optimal configurations and designs by exploring the solution space efficiently [47].
- Data Clustering: Clustering is a common task in data mining and pattern recognition. The DMFO algorithm can be utilized to partition data points into distinct clusters by optimizing a clustering objective function. It aids in discovering hidden patterns and grouping similar data points together [47].
- Image and Signal Processing: The DMFO algorithm can be used for image and signal processing tasks, such as image segmentation, feature selection, and noise

reduction. It helps in finding optimal parameters and configurations to enhance the quality and analyze the data effectively [47].

- Machine Learning: The DMFO algorithm can be integrated into machine learning algorithms to optimize hyper parameters, such as learning rates, regularization parameters, and network architectures. It aids in improving the performance and generalization capabilities of machine learning models [47].
- Portfolio Optimization: The DMFO algorithm can be applied in financial portfolio optimization, where the goal is to find the optimal allocation of assets to maximize returns or minimize risks. It helps in selecting the right combination of investments based on historical data and risk preferences [47].
- Resource Allocation: The DMFO algorithm can be used to optimize the allocation of limited resources, such as workforce, energy, or transportation, to maximize efficiency and minimize costs. It aids in finding optimal schedules or configurations for resource utilization [47].
- Neural Network Training: The DMFO algorithm can be utilized in training neural networks by optimizing the weights and biases. It helps in improving the convergence speed and finding better network architectures for various applications [47].

These are just a few examples of the potential applications of the DMFO algorithm. Its versatility and ability to handle complex optimization problems make it a useful tool across various domains where finding optimal solutions is crucial.

3.5. Movement of Mayflies

3.5.1. Movement of Male Mayflies

Males tend to congregate in swarms; this suggests that each male mayfly adjusts its position based on its own experience and that of its neighbors. Let suppose the actual position of the male mayfly i is x_i^tat time step t in the search area. A velocity v_i^{t+1} is added to modify the position [53]. This could be expressed as follow:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{3.1}$$

With $x_i^0 \sim U(\mathrm{x}_{\min}, \mathrm{x}_{\max})$

Assuming that male mayflies cannot achieve enormous speeds and that they move constantly since they are often a few meters above water when doing the nuptial dance [53]. Consequently, the velocity is then developed as follow:

$$v_{ij}^{t+1} = v_{ij}^{t} + a_1 e^{-\beta r_p^2}\left(p_{best_{ij}} - x_{ij}^{t}\right) + a_2 e^{-\beta r_g^2}\left(g_{best_j} - x_{ij}^{t}\right) \tag{3.2}$$

Where, v_{ij}^t is the mayfly i velocity at time step t in dimension j where $j = 1, \dots, n$, x_{ij}^t is the male mayfly i position at time step t in dimension j, $a_1$and a_2 stand for the positive attraction constants for the social role used to scale the contribution of the cognitive and social component respectively while β is the mayflies' visibility coefficient, it controls the visibility range of each one. Moreover, $p_{best_{ij}}$ is the best position has been visited by mayfly i and g_{best_j}stands for global best position for mayflies.

According to [53], at next time step t + 1 the $p_{best_{ij}}$ is determined as follow:

$$p_{best_i} = \begin{cases} x_i^{t+1}, & if\ f(x_i^{t+1}) < f\left(p_{best_i}\right) \\ remains\ unchanged, & otherwise \end{cases} \tag{3.3}$$

Where, f that goes from $\mathbb{R}^n$ to $\mathbb{R}$, is the objective function that evaluates the effectiveness of a solution [53]. Then, at the time step t the $g_{best}$is determined as follow:

$$g_{best} \in \left\{p_{best_1}, p_{best_2}, \dots, p_{best_N} \middle| f(c_{best})\right\} = \left\{\min f\left(p_{best_1}\right), f\left(p_{best_2}\right), \dots, f\left(p_{best_N}\right)\right\} \tag{3.4}$$

Where, N is the total number of males in the mayfly swarm. Furthermore, r_p is the distance in Cartesian terms between the actual position x_i and the individual best position p_{best} and r_g is the distance in Cartesian terms between the actual position x_i and the global best position g_{best} [53]. These tow distances in Cartesian terms is determined as follow:

$$\|x_i - X_i\| = \sqrt{\sum_{j=1}^{n}\left(x_{ij} - X_{ij}\right)^2} \tag{3.5}$$

Where, x_{ij} is the j^{th} element of mayfly i and X_i stands to p_{best_i} or g_{best}.

The best mayflies in the swarm must continue to dance their up-and-down nuptial dance in order to make the algorithm execute properly [53]. The best mayflies therefore need to change constantly their velocities. As a result and according to [53], the velocity of a male mayfly i is determined as follow:

$$v_{ij}^{t+1} = v_{ij}^{t} + dr \tag{3.6}$$

Where, r is a random number, providing a mayfly's flight a random element ranges in $[-1, 1]$, $r \in [-1, 1]$, and d stands for the nuptial dance coefficient [53].

3.5.2. Movement of Female Mayflies

Female mayflies do not form swarms as males do. Instead, they fly in the direction of males to breed. Let suppose the actual position of the female mayfly i is y_i^t at time step t in the search area [53]. A velocity v_{ij}^{t+1} is added to modify the position. This could be expressed as follow:

$$y_i^{t+1} = y_i^t + v_i^{t+1} \tag{3.7}$$

With $y_i^0 \sim U(\mathrm{y_{min}}, \mathrm{y_{max}})$

The attraction process is modeled as a deterministic one even though it could be random. The best male should be attracted to the best female, the second best male should be attracted to the second best female and so on [53]. The female mayfly velocity is determined as follow:

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^t + a_2 e^{-\beta r_{\mathrm{mf}}^2}\left(x_{ij}^t - y_{ij}^t\right) & if\ f\left(y_i\right) > f(x_i) \\ v_{ij}^t + f_l r, & if\ f(y_i) \leq f(x_i) \end{cases} \tag{3.8}$$

Where v_{ij}^t is the mayfly i velocity at time step t in dimension j where $j = 1, \dots, n$, y_{ij}^t is the female mayfly i position at time step t in dimension j, a_2 stand for the positive attraction coefficients, β is the mayflies' visibility coefficient, r_{mf} is the Cartesian distance between male and females mayflies calculated using equation number3.5 [53]. Moreover, f_l is a random walk coefficient used in the case when a male does not attract a female that flies randomly and r is an random number ranges in$[-1, 1]$ [53].

3.5.3. Mating of Mayflies

According to the crossover operator, two mayflies mate in the manner described here: One parent is chosen from among the male and female populations. The process of choosing parents is similar to how females are attracted to males. This selection process can be random or based on their fitness function. At the end, the best female mates with the best male, the second-best female pairs with the second-best male, and so on [53].

After individual sorting using mutations and crossovers [53], the next generation of two offspring comes as follow:

$$\begin{cases} offspring_1 = L * x_{ij}^t + (1-L) * y_{ij}^t \\ offspring_2 = L * y_{ij}^t + (1-L) * x_{ij}^t \end{cases} \tag{3.9}$$

Where, x_{ij}^t and y_{ij}^t here are the male parent and the female parent respectively, L is a random value with a certain range and the initially set velocities of the offspring are zero [53].

3.6. Improvement of Basic Discrete Mayfly Optimization Algorithm

During the exploration of the fundamental algorithm, we discovered problems regarding the stability caused by velocity-induced perturbations in the existing solutions. Additionally, we observed premature convergence of the algorithm due to an inadequate balance between exploitation and exploration. To address these limitations, several modifications to the algorithm have been devised and are outlined below [53].

3.6.1. Velocity Limits

When evaluating the performance of our algorithm, it was discovered that the velocity can rapidly escalate to extremely large values, especially when updating the velocity of a distant mayfly from the global best or personal best position. This situation can result in mayflies flying outside the boundaries of the problem space [53]. It is important to note that addressing this issue can be achieved by assigning a zero initial velocity to offspring [53]. This allows for the presence of mayflies with small velocity values that can still contribute to convergence. Drawing inspiration from real mayflies, which do not achieve high speeds to remain above water, it is proposed in [53] propose that each mayfly has a specified maximum velocity, denoted as V_{max}. In these cases, the velocity is then determined as follow:

$$v_{ij}^t = \begin{cases} V_{max} \ if \ v_{ij}^{t+1} > V_{max} \\ -V_{max} if \ v_{ij}^{t+1} < -V_{max} \end{cases} \tag{3.10}$$

The important aspect to consider is that while V_{max} controls the extent of exploration within the search space, excessively small values may hinder exploitation beyond local optima [53]. The V_{max} values can be selected as follow:

$$V_{max} = rand \ \times (x_{max} - x_{min}) \tag{3.11}$$

Where, $rand \in (0, 1]$.

3.6.2. Gravity Coefficient

While imposing a velocity limit can restrict the mayflies from attaining high speeds, there are instances where it becomes necessary to decrease velocities in order to regulate effectively the balance between exploration and exploitation capabilities of the mayflies. The gravity coefficient$g$, functioning similarly to the inertia weight in PSO [54], helps achieve an optimal equilibrium between exploration and exploitation [53]. Consequently, the updated velocity of male mayfly i is determined as follow:

$$v_{ij}^{t+1} = g\, v_{ij}^{t} + a_1 e^{-\beta r_{\mathrm{p}}^2}\left(p_{best_{ij}} - x_{ij}^{t}\right) + a_2 e^{-\beta r_{\mathrm{g}}^2}\left(g_{best_j} - x_{ij}^{t}\right) \tag{3.12}$$

Then updated velocity of female mayfly i is determined as follow:

$$v_{ij}^{t+1} = \begin{cases} g\, v_{ij}^{t} + a_2 e^{-\beta r_{\mathrm{mf}}^2}\left(x_{ij}^{t} - y_{ij}^{t}\right) & if\ f(y_i) > f(x_i) \\ g\, v_{ij}^{t} + f_l r, & if\ f(y_i) \le f(x_i) \end{cases} \tag{3.13}$$

The gravity coefficient g can either be a constant value ranges in $(0, 1]$ or it can be gradually decreased during the iterations, enabling the algorithm to to avail some specific areas [53], by being updated using the equation as follow:

$$g = g_{max} - \frac{g_{max} - g_{min}}{n_{max}} \times n \tag{3.14}$$

Where, g_{max} and g_{min} are the maximum and minimum values that the gravity coefficientcan take, n is the actual iteration of the algorithm and n_{max} is the maximum number of iteration.

3.6.3. Reduction of Nuptial Dance and Random Walk

The female mayflies' random walking and the male mayflies' nuptial dance are two highly effective local search methods that can aid the algorithm in escaping local optima [53]. However, engaging in a random walk may inadvertently lead a mayfly to a significantly worse search area. The problem is that nuptial dance d or randomwalk f_l often takes large initial values. To mitigate this, a gradual reduction of both d and f_l over iterations is implemented [53]. As a result, both values can be updated using a geometric progression formula, as follow:

$$d_t = d_0 \delta^n \tag{3.15}$$

$$f_{l_t} = f_{l_0} \delta^n \tag{3.16}$$

Where δ is a constant value ranges in $(0,1)$, $0 < \delta < 1$ and t is the number of iteration.

3.6.4. Mutate the Genes of Offspring

In order to address the issue of premature convergence, which can result in the algorithm converging to a local minimum instead of a global minimum, a modified version of the original algorithm incorporates a random mutation into a subset of the population. This modification allows the algorithm to explore uncharted regions of the search space that might otherwise remain unvisited [53]. Specifically, a normally distributed random number is added to the selected offspring's variable for the purpose of mutation [53]. This alteration modifies the offspring as follow:

$$offspring'_n = offspring_n + \sigma N_n(0,1) \tag{3.17}$$

Where, σ is the standard deviation of the normal distribution and N_n is the standard normal distribution with $mean = 0$ and $variance = 1$.

3.7. The First Bit-Flip and Shift Local Search Strategy

Binary vector First-Bit Flip and Shift (FBFS) is a process of manipulating binary vectors, which have elements of numbers in binary form with values of sequences of 0's and 1's, by flipping and shifting their first bits. Bit flipping refers to changing the value of a single bit from 0 to 1 or vice versa, while bit shifting involves moving the flipping process of bits to the left or right. These operations can be useful in a variety of contexts, such as in computer programming, where binary vectors are often used to represent data or instructions. For example, bit flipping and bit shifting can be used to change specific values in a data structure. For that reason, binary vector bit flip shift provides a flexible and powerful tool for manipulating binary data. In our study, if the better solution vector is, for example, x_n= [4 28 25 15 46 1 21 39 11 23 14 50 12 17 7 10 45 37 27 33 16] in iteration$n$, then the solution would be improved by the FBFS strategy. The first element is 4=100 is becoming then equal to 101=5, the maintenance of generator number 1 starts then from week number 5 instead of week number 4. The new solution in iteration$n$ becomes, x'_n = [**5** 28 25 15 46 1 21 39 11 23 14 50 12 17 7 10 45 37 27 33 16]. This solution is evaluated in the evaluation function. If the new SSR of generation in iteration n provide by $x'_n$is less than the previous SSR of generation provided by x_n in iteration n, then, the new solution $x'_n$of iteration n will be considered as a new better solution. Otherwise, the previous better solution x_n in iteration n is kept and the solution x'_n provided by the FBFS strategyin iteration$n$will be rejected and will be used again for the evolutionary for the next iteration $n+1$ to prevent themetaheuristic algorithm from getting fall in local optima and keeping them in continuous search without undesired fails and stops. Another new solution will be generated in iteration $n+1$ by the evolutionary algorithm. If, for example and not necessarily, the solution provided the evolutionary algorithm in iteration $i+1$ is x_{n+1}= [5 28 25 15 46 1 21 39 11 23 14 50 12 17 7 10 45 37 27 33 16], then the value 28=11100 will be converted to 11101=29. The flipping process is then shifted to the second element of the full binary vector. The new solution x'_{n+1}in iteration $n+1$ becomes x'_{n+1}= [529 25 15 46 1 21 39 11 23 14 50 12 17 7 10 45 37 27 33 16]. This solution is tested again if it is a better solution or not, if not, the previous better solution, which is found previously and not necessarily in the previous iteration, is kept and the current solution x'_{n+1} in iteration $n+1$ is used in the evolutionary algorithm to update the new solution x_{n+2} in iteration $n+2$. In iteration $n+2$, if the evolutionary algorithm generates a solution which is, as an example and not necessarily, x_{n+2}= [529 25 15 46 1 21 39 11 23 14 50 12 17 7 10 45 37 27 33 16], then the value 25=11001 will be converted to 11000=24 and the same process will be performed in next iteration.

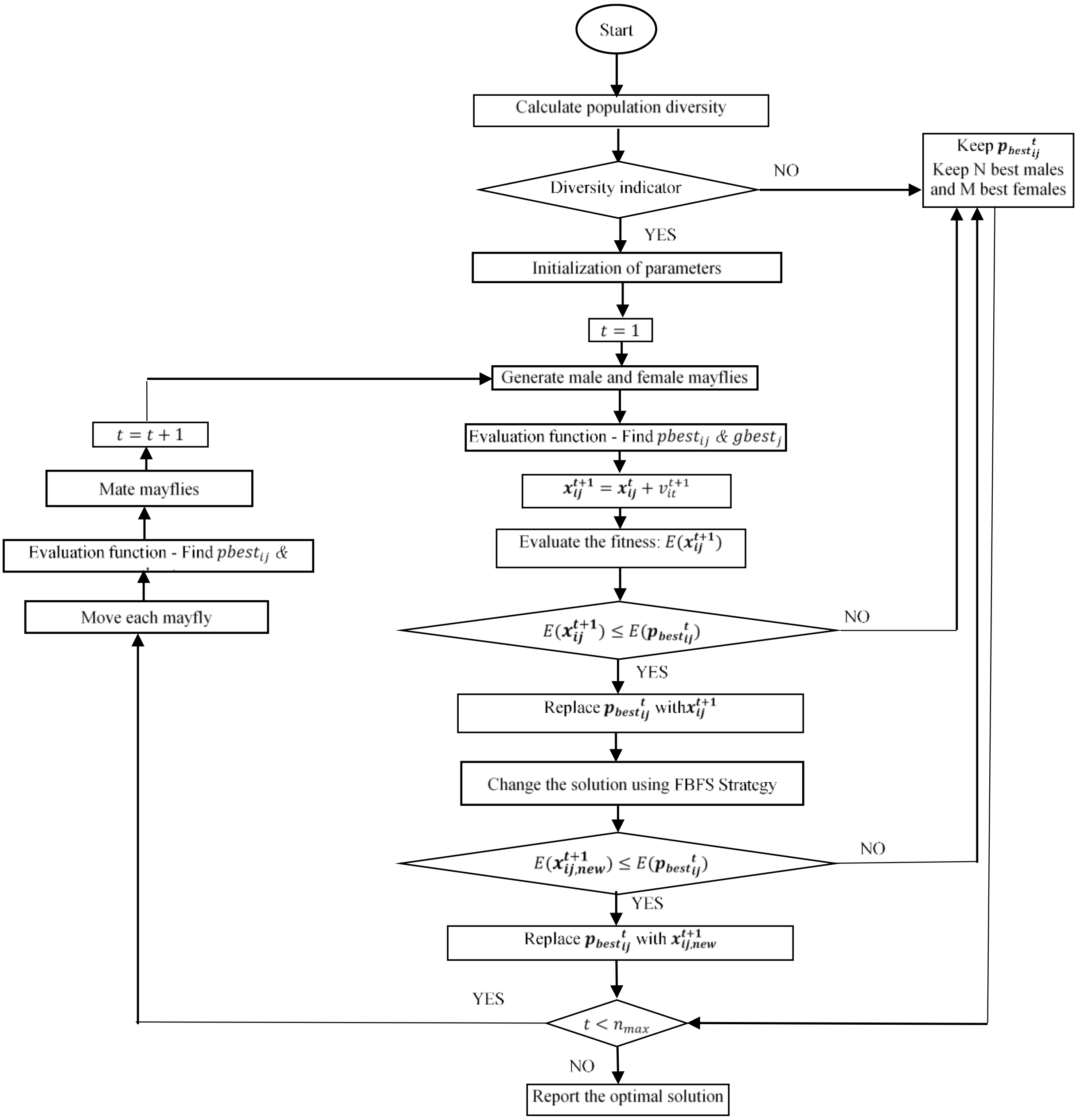

Figure 3.1: Flowchart of the FBFS-DMFO strategy search

The maintenance-starting week of a generator i, after performing the FBFS strategy and if the FBFS strategy found a new better solution may become greater or smaller than its previous maintenance-starting week, and this is according to its previous first bit value if it is 0 or 1.The FBFS strategy is a local search strategy that performs small changes to the previous solutions to help other evolutionary algorithms in local optimization and avoiding them from getting stuck in local optima. This strategy works in cooperation with algorithms. In the same iteration, the evolutionary algorithm works to find the solution, and then the FBFS strategy comes to try to improve the solution and find a new solution that is better than the previous one. If the FBFS strategy cannot find a better solution than the previous one, then the previous better solution is kept and the new worse solution provided by the FBFS strategy is used again in the evolutionary algorithm to avoid it from getting stuck in local optima and then making it in constant search without any stuck or fail. The first bit of an element is then flipped and the flip process is then shifted at each iteration by taking into account the evaluation of the new obtained solutions in the evaluation function. Two conditions should be stratified if we want to consider the solution provided by the FBFS strategy as a better solution; the SSR of generation provided by the solution made by the FBFS strategy should be less than the previous SSR of generation, and all constraints should be strictly satisfied without any kind of violations. Otherwise, the solution provided by the FBFS strategy is only used to update the new next solutions of evolutionary algorithms.

3.8. Conclusion

The First-Bit Flip and Shift-based Discrete Mayfly Optimization algorithm has been applied to various optimization problems, including function optimization, engineering design, and data clustering. Its effectiveness lies in its ability to strike a balance between exploration and exploitation, leveraging the characteristics of mayflies' short lifespan and their reproductive behavior. Overall, the DMFO algorithm is a promising optimization technique that draws inspiration from nature and the behavior of mayflies to solve efficiently complex optimization problems.

4. RESULTS AND DISCUSSION

4.1. Introduction

This chapter presents how the Discrete Mayfly Optimization (DMFO) algorithm can be used to schedule preventive maintenance for power system generators. The algorithm minimizes a discrete evaluation function that combines an objective function (which is the SSR of generation) with a penalty function for constraint violations. The algorithm ensures that several constraints (including maintenance windows, workforce, load power demand, and reserve boundaries) are satisfied and that neither load power demand nor workforce constraints are violated during maintenance time. The algorithm is tested on a 21-unit test power system and will be run for 30 times to reinforce its accuracy and robustness to reach the best solution. Then its performance (including efficacy and reliability) is compared to other recent methods using statistical metrics such as mean, standard deviation, min and max, as well as statistical tests such as the Friedman test, the Holm-Sidak test, and the Wilcoxon signed rank test.

4.2. The 21-Units Industrial Test Power System

The previously discussed GMS problem is applied to the proposed improved FBFS-DMFO algorithm in this part. A 21-unit test system shown in the Table4.1 [15] is used to evaluate the FBFS-DMFO algorithm performance. This test system is a utility that mostly burns coal. The operating characteristics of the units are provided in startup order in Table 4.1.

Table 4.1: The 21-Units Test Power System [15].

Unit	Capacity (MW)	Allowed period	Outage (Weeks)	Workforce Required for Each Week
1	555	1 – 26	7	10 + 10 + 5 + 5 + 5 + 5 + 3
2	555	27 – 52	5	10 + 10 + 10 + 5 + 5
3	180	1 – 26	2	15 + 15
4	180	1 – 26	1	20
5	640	27 – 52	5	10 + 10 + 10 + 10 + 10
6	640	1 – 26	3	15 + 15 + 15
7	640	1 – 26	3	15 + 15 + 15
8	555	27 – 52	6	10 + 10 + 10 + 5 + 5 + 5
9	276	1 – 26	10	3 + 2 + 2 + 2 + 2 + 2 + 2 + 2 + 2 + 3
10	140	1 – 26	4	10 + 10 + 5 + 5
11	90	1 – 26	1	20
12	76	27 – 52	3	10 + 15 + 15
13	76	1 – 26	2	15 + 15
14	94	1 – 26	4	10 + 10 + 10 + 10
15	39	1 – 26	2	15 + 15
16	188	1 – 26	2	15 + 15
17	58	27 – 52	1	20
18	48	27 – 52	2	15 + 15
19	137	27 – 52	1	15
20	469	27 – 52	4	10 + 10 + 10 + 10
21	52	1 – 26	3	10 + 10 + 10

The size of the units ranges from 39 MW to 640 MW. One week to ten weeks may pass without service. The system's total generating capacity is 5688 MW, while its peak load is 4739 MW. Each unit was given a 26-week window in which to begin maintenance. Units were permitted to start maintenance either between weeks 1 and 26 or between weeks 27 and 52, as stated in Table 4.1. All units required to accomplish their maintenance by week 52 in order to guarantee that similar timetables are compared. This practically forced units to start their outage before week $52 - D_i$ if they are to be maintained in the second half of the year. Where D_i represents the length of the outage. Eight outages start in the second half of the year, while thirteen units start their outages in the first half.

Table 4.2: The parameters of the applied methods.

Methods	Parameters			
GA	Population size: 200	Crossover probability: 1	Mutation probability: 0.05	-
GA/SA	Population size: 100	Tournament pool size: 10	Cooling rate: 0.95	-
SA	Initial temperature: 10	Final temperature: 0.5	Cooling rate: 0.95	-
ACO	Number of ants:10	Reward factor: 20	Initial pheromone: 0.5	Evaporation rate:0.9
SA/ACO	Number of ants: 10 Evaporation rate: 0.9	Initial temperature: 10 Reward factor: 40	Cooling rate: 0.95	Initial pheromone: 2.5
MFO	Population size: 20 Inertia weight: 0.8 Inertia weight damping ration:1	Nuptial dance: 5 Random flight: 1 Dance damping ration: 0.8 Flight damping ration: 0.9	Personal learning coefficient a_1: 1 Distance sight coefficient: 2	Global learning coefficient: $a_2 = 1.5$, $a_3 = 2$ Number of off-spring:20 Mutation rate: 0.08
LC-JAYA	Population size: 25	-	-	-
FBFS-DMFO	Population size: 20 Inertia weight: 0.8 Inertia weight damping ration: 1	Nuptial dance: 5 Random flight: 1 Dance damping ration: 0.8 Flight damping ration: 0.9	Personal learning coefficient $\boldsymbol{a_1}$: 1 Distance sight coefficient: 2	Global learning coefficient: $\boldsymbol{a_2 = 1.5}$, $\boldsymbol{a_3 = 2}$ Number of off-spring:20 Mutation rate: 0.08

The GMS problem can be formulated as an integer-programming problem by using integer variables representing the period in which maintenance of each unit starts. The variables are bounded by the maintenance window constraints. However, for clarity the problem is first formulated using binary variables, which indicate the start of maintenance of each unit at each time. Maintenance window constraints define the possible times and duration of maintenance for each unit. The relative timetabling of maintenance of certain units may be restricted. The available generation must exceed the load, and the workforce and resources available for maintenance work are limited. Further constraints may be imposed involving the reliability. The problem involves the reliability criteria of minimizing the SSR. Each unit must be maintained (without interruption) for a given duration within an allowed period and limited number of workforce.

4.3. Results and Discussion

This section compares FBFS-DMFO algorithm performance to that of other methods as GA, SA, ACO, SA combined with ACO, MFO, and Logistic Chaotic JAYA algorithm (LC-JAYA)[55]. Considering that the same objective function, the same evaluation function formula, the same evaluation function settings and the same test system were used to run each of those methods in order to make sure the comparison is adequate. In addition, those methods are applied with the same parameters listed in Table 4.2.

4.3.1. Case (a)

In this case, the load power demand is 4739 MW. The total available workforce is 25. The coefficients$C_R = 10^{-5}$, $C_M = 4$ and $C_L = 2$. For the purpose of comparison, the statistical values of the GMS problem evaluation function for 30 separate runs using the suggested FBFS-DMFO algorithm and previous techniques are all shown in Table 4.3.

Table 4.3: The statistical values of the crisp evaluation function of the GMS problem for case (a) using 30 independent runs

Method	Min	Mean	Max	SDV
GA	139.09	150.68	167.76	7.87
SA	138.26	143.83	150.36	2.93
ACO	139.99	148.63	168.95	6.82
SA/ACO	137.12	142.11	147.86	2.94
LC-JAYA	140.09	147.35	172.87	6.51
MFO	145.36	177.19	219.94	21.13
FBFS-DMFO	**136.54**	**140.49**	**146.68**	**3.37**

The numerical results in Table 4.3 have been obtained by setting the coefficients C_R, C_M and C_L to10^{-5}, 4 and 2 respectively. These results display the performance of each method by presenting their best and worst obtained values, mean values, and standard deviations. The standard deviation (SDV) measures the robustness of each method, and it indicates how the values in each series are spread out in relation to their mean. The mean value indicates the quality of the solutions provided by each method since the available solutions cluster around the mean, and the best mean value represents the best quality of solutions provided by a specific method. The lowest and highest values indicate the range limits within which the values may vary, and the best method is the one that yields the best minimum value (Min) and the lowest maximum value (Max). The obtained mean value of the solutions gained by the FBFS-DMFO algorithm is 140.49. Compared to the other mean values produced by the previous approaches, this mean is far better which can be regarded as an improvement. The obtained best solution

(Min value) by the FBFS-DMFO algorithm is 136.54 and it is better than the obtained best solutions (Min values) by other methods. The obtained worst solution (Max value) by the proposed approach is 146.68 and it is lower than the previously obtained worst solutions by the other approaches. The obtained SDV by the proposed method is 3.37 and it is much better than the other SDV values obtained by other methods.

In terms of the best reached solution and the obtained worst solution, the proposed approach performs better than the previously mentioned current methods. The main benefit is that even the worst solution found using the suggested FBFS-DMFO algorithm is superior to the best solution found using the previous methods. Additionally, as the SDV previously demonstrated, the solutions are very close to the mean value because if the SDV value is smaller, it means the solutions are closer to the average value, which suggests that the method used is more robust. As well as, the mean also demonstrated the superiority of the results produced using the suggested approach.

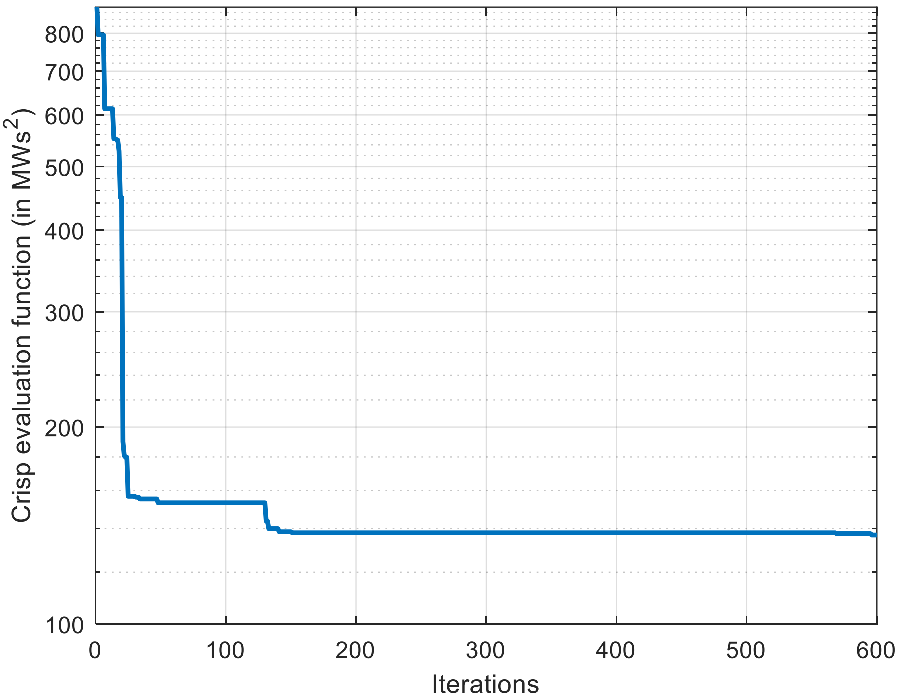

Figure 4.1: Crisp evaluation function versus iterations of FBFS-DMFO algorithm in case (a),Evaluation function = $136.76215\ MW^2$

The crisp evaluation function (E) has quick convergence during the first 150 iterations at any run as shown in Figure 4.1 then it is remarkable that this improvement starts to be slow and seems to be constant. However, the improvement is just slightly continued as the number of iterations increases.

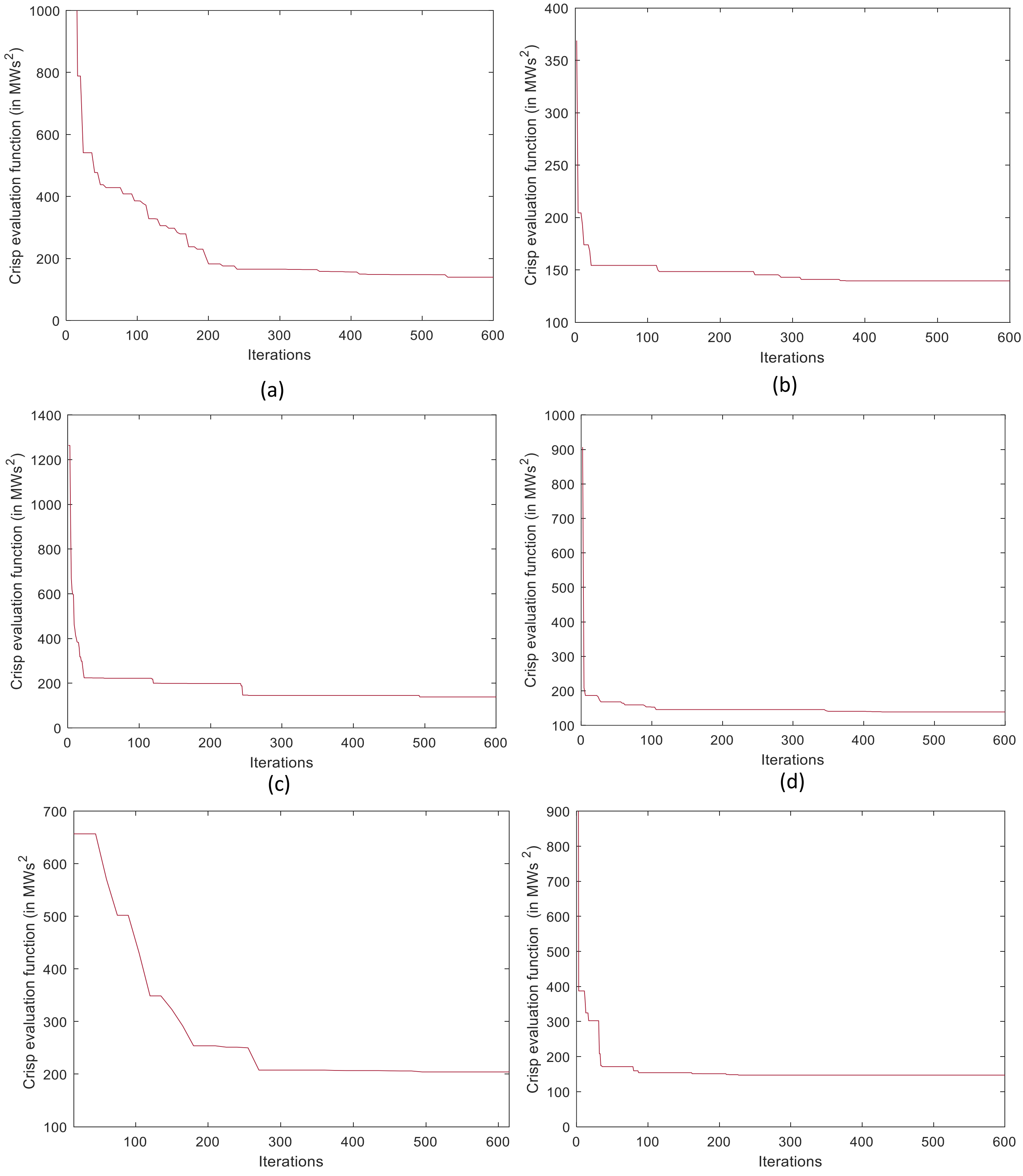

Figure 4.2: Crisp evaluation function versus iterations for case (a) using: **(a)**- GA;$E = 139.54063 MW^2$, **(b)**- SA;$E = 139.49059\ MW^2$, **(c)**-ACO;$E = 138.42575 MW^2$, **(d)**- SA/ACO;$E = 138.92987 MW^2$,**(e)**-MFO;$E = 145.47739 MW^2$,**(f)**- LC-Jaya; $E = 147.18675 MW^2$

There are four categories of optimization methods based on convergence of their evaluation function and quality of solutions. The first type achieves quick evaluation function convergence and produces the best solutions, while the second type has slow evaluation function convergence but also produces the best solutions. The third type converges quickly,but produces poor solutions, and the fourth type has slow convergence and also produces poor solutions. The last two types are not considered effective since they do not generate solutions with best quality. The first and second types are considered acceptable due to their solutions of high-quality, but the speed of convergence is crucial. The first type is preferred over the second type because it has better evaluation function convergence.

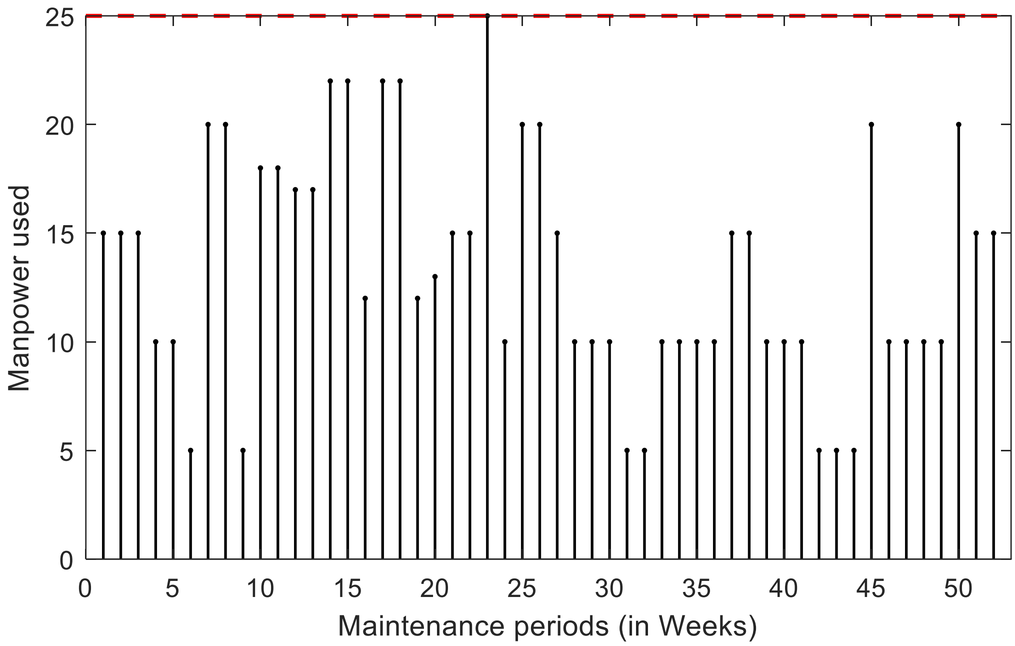

Figure 4.3: Workforce used during maintenance periods of FBFS-DMFO algorithm in case (a),Evaluation function = 136.76215 MW^2.

As shown in Figure 4.2, The convergence of the GA algorithm is strong during the first 100 iteration. As well as SA is strong during the first 400 iterations while for ACO, it is strong during the first 300 iterations and for SA/ACO, it is strong during the first 400 iterations. Also for MFO, is strong during the first 300 iterations, and for LC-JAYA's strength convergence appears during the first 100 iterations. Although, both the speed of convergence and the accuracy of the optimization are still important.The next results represent the workforce used per week and the production per weeks and shown in Figure 4.3 and Figure 4.4 respectively, recorded during the obtained best solution.The results in Figure 4.3 are recorded at (Evaluation function = 136.76215 MW^2). The workforce restriction is satisfied as the total amount of workforce for maintaining units during maintenance periods should not exceed the total number of the available workforce that has been set to 25. The workforce as shown is fully used in week 23 for maintaining generators 7 and 10. The minimum workforce used is at weeks 6, 9, 31, 32, 42, 43 and 44 for maintaining generators 1, 2 and 8.

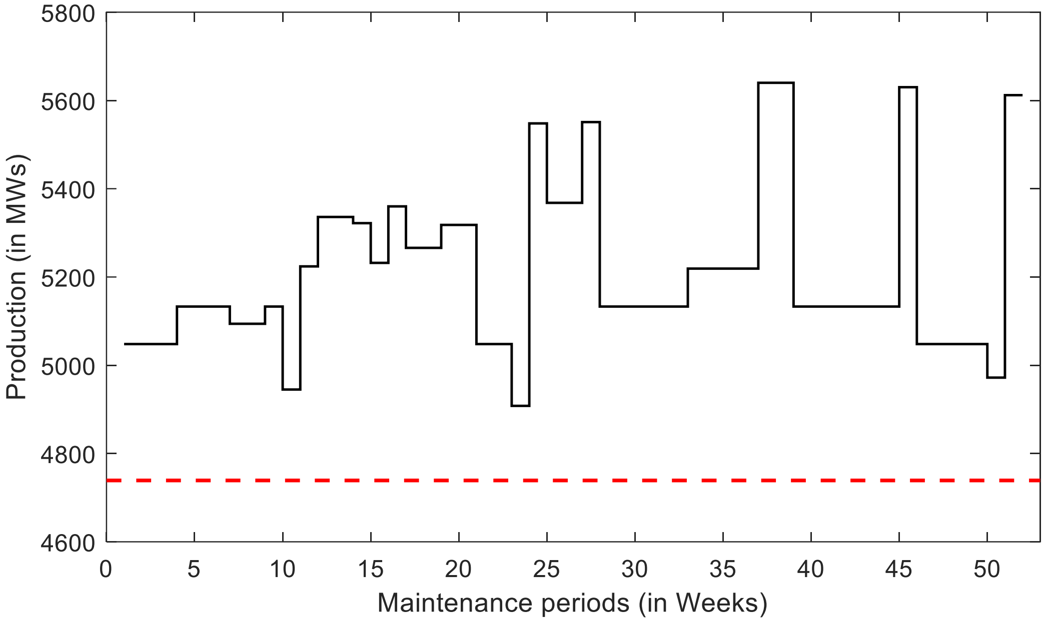

Figure 4.4: Production during maintenance periods of FBFS-DMFO algorithm in case (a), Evaluation function = $136.76215\ MW^2$.

Table 4.4: Generators maintenance planning per weeks of FBFS-DMFO algorithm, case (a), Evaluation function = $136.76215\ MW^2$.

Week no.	Generating units scheduled for maintenance	Workforce used	Production in MW	Week no.	Generating units scheduled for maintenance	Workforce used	Production in MW
1	6	15	5048	27	19	15	5551
2	6	15	5048	28	2	10	5133
3	6	15	5048	29	2	10	5133
4	1	10	5133	30	2	10	5133
5	1	10	5133	31	2	5	5133
6	1	5	5133	32	2	5	5133
7	1, 15	20	5094	33	20	10	5219
8	1, 15	20	5094	34	20	10	5219
9	1	5	5133	35	20	10	5219
10	1, 16	18	4945	36	20	10	5219
11	9, 16	18	5224	37	18	15	5640
12	9, 13	17	5336	38	18	15	5640
13	9, 13	17	5336	39	8	10	5133
14	9, 11	22	5322	40	8	10	5133
15	4, 9	22	5232	41	8	10	5133
16	9, 21	12	5360	42	8	5	5133
17	9, 14, 21	22	5266	43	8	5	5133
18	9, 14, 21	22	5266	44	8	5	5133
19	9, 14	12	5318	45	17	20	5630
20	9, 14	13	5318	46	5	10	5048
21	7	15	5048	47	5	10	5048
22	7	15	5048	48	5	10	5048
23	7, 10	25	4908	49	5	10	5048
24	10	10	5548	50	5, 12	20	4972
25	3, 10	20	5368	51	12	15	5612
26	3, 10	20	5368	52	12	15	5612

The total generation (maximum production) of the 21-unit test system under no maintenance is 5688 MW. Figure 4.4 shows that the load's power demand (in red dashed line) does not exceed the total generation, and this means that the load's power demand restriction is satisfied and the load's power demand should not exceed the maximum generation during maintenance. Under maintenance, the system achieved its minimum total generation of 4908 MW during week 23 when generators 7 and 10 are under maintenance. The maximum total generation under maintenance has achieved 5640 MW during weeks 37 and 38 when generator 18 is under maintenance. The maintenance scheduling due to the performance of FBFS-DMFO algorithm is shown in the Table 4.4 and Gantt chart represented in Figure 4.5.According to the schedule found in Table 4.4, there can be no more than three generators under maintenance each week at maximum, and there can only be one generator under maintenance at minimum. Table 4.4 has been recorded based on the results obtained from the Gantt chart in Figure 4.5 due to the optimal evaluation function value.

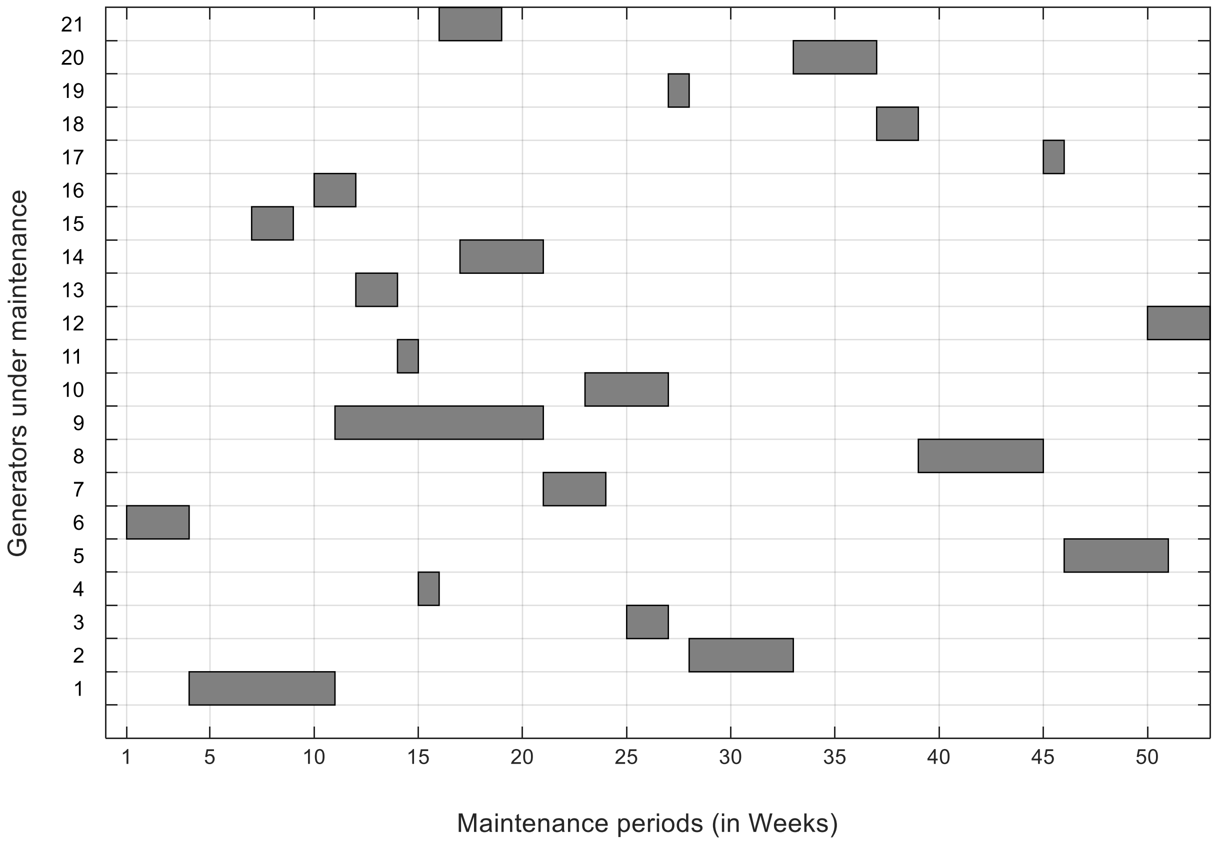

Figure 4.5: Gantt chart of maintenance planning per week of FBFS-DMFO algorithm, case (a), Evaluation function = 136.76215 MW^2

The Friedman test has been used to compare the performance of the algorithms stated in Table4.4. The Friedman test is a non-parametric statistical test used to determine if there are significant differences among multiple related groups. It is used when the data are not normally distributed, and the same subjects are measured under different conditions or at different times. The test ranks the data within each group and calculates the average rank for each subject across all groups. It then uses a chi-square distribution to determine if there is a significant difference in the ranks between groups. The Friedman test is often used in fields such as psychology, education, and medicine to analyze data from experiments where multiple treatments are applied to the same subjects[56]. Seven algorithms have been used for the comparison versus the proposed FBFS-DMFO algorithm as shown if Table 4.5.

Table 4.5: The Friedman test ranks

IBM SPSS 26.0 Mean ranks		
Algorithm	**Friedman Rank**	**Rank**
ACO	4.53	5
ACO-SA	2.53	2
FBFS-DMFO	**1.90**	**1**
GA	4.83	6
SA	3.23	3
LC-JAYA	4.37	4
MFO	6.60	7

The proposed FBFS-DMFO algorithm ranked first and ACO-SA ranked second, SA ranked third LC-JAYA fourth, ACO, GA and Mayfly Optimization (MFO) algorithms ranked fifth, sixth and seventh respectively. Friedman rank test has been performed to rank the methods according to the results acquired by these methods. However, this test does not show any statistical difference in the results [57]. Thus, the Holm-Sidak test has been performed to specify the statistical differences between the methods [57]. Table 4.6 shows the Holm-Sidak test results. The statistical differences between the proposed FBFS-DMFO algorithm and the other algorithms are presented by the acquired pairwise p-values from the Holm-Sidak test for all the algorithms. It ranks the p-values from smallest to largest and adjusts the significance level for each comparison based on the number of remaining comparisons. This allows amore accurate control of the error rate. If the p-value is high, it indicates that there is less statistical difference and less significant outperformance[45].

Table 4.6: The p-values of the Holm-Sidak test

Algorithm [a]	p-value
1-2	0.1746
1-3	0.0054938
1-4	0.50835
1-5	0.0010269
1-6	4.4942×10^{-5}
1-7	8.3075×10^{-35}

1-FBFS-DMFO, **2**-SA, **3**-LC-JAYA, **4**-ACO/SA Hybrid, **5**- ACO, **6**-GA, **7**-MFO

The Wilcoxon signed-rank test sown in Table 4.7 has been used to compare the performance of the proposed FBFS-DMFO algorithm against other algorithms. The symbols R+ or R- presents that the FBFS-DMFO method has better or worse performances than the control one. The meaning of ‘‘Better’’, ‘‘Equal’’ and ‘Worse’’ is the numbers of the test cases where the FBFS-DMFO method is better, equal or worse than the control one. The P-value indicates the significance level, when the P-value is less than 0.05, then the two methods have obvious differences. The symbol ‘‘+’’means that the FBFS-DMFO performance is better than the control method. The Z-value indicates which algorithm is close in performance to the performance of the proposed algorithm based on negative ranks, as Z-value increases as the rank of the algorithm towards to the proposed algorithm rank increases.

Table 4.7: The Wilcoxon signed rank test for 30 runs, alpha=0.05

Item	Better	Equal	Worse	R^+	R^-	P-value	Z-value	Symbol
FBFS-DMFO vs ACO	27	0	3	448.00	17.00	0.000	-4.4324	+
FBFS-DMFO vs ACO-SA	20	0	10	317.00	148.00	0.082	-1.7380	+
FBFS-DMFO vs GA	28	0	2	445.00	20.00	0.000	-4.3707	+
FBFS-DMFO vs LC-JAYA	26	0	4	442.00	23.00	0.000	-4.3090	+
FBFS-DMFO vs MFO	30	0	0	465.00	0.00	0.000	-4.7821	+
FBFS-DMFO vs SA	22	0	8	370.00	95.00	0.005	-2.8281	+

4.3.2. Case (b)

In this case, the load power demand is 4739 MW. The total available workforce is 35. The coefficients $C_R = 1$, $C_M = 0$ and $C_L = 0$. The proposed FBFS-DMFO has been compared with two recent techniques MDPSO and MS-MDPSO algorithms presented in [5], [34] as shown in the comparison of statistical results of table 4.8 in which only SSR of generation is considered and there is no total workforce and total load violation. At the same number of evaluation, the mean value of the proposed method is 13,732,895.11MW^2; which is better than 13,984,883.84MW^2 of MDPSO method and 13,870,778.81MW^2 of MS-MDPSO method. The minimum value of the proposed method is 13,687,592.01MW^2; which is better than 13,863,021.02MW^2 of MDPSO method and 13,749,264.32MW^2 of MS-MDPSO method. The maximum value of the proposed method is 13,967,735.97MW^2; which is better than 14,132,336.49MW^2 of MDPSO method and 14,015,289.69MW^2 of MS-MDPSO method.

Table 4.8: The SSR statistical results for case (b) of FBFS-DMFO algorithm compared with MDPSO and MS-MDPSO using 30 independent runs

Method	SSR ($in\ MWs^2$)			Total workforce violation	Total load violation
	MIN	MEAN	MAX		
MDPSO	13, 863, 021.02	13, 984, 883.84	14, 132, 336.49	No violation	No violation
MS-MDPSO	13, 749, 264.32	13, 870, 778.81	14, 015, 289.69	No violation	No violation
FBFS-DMFO	**13, 687, 592.01**	**13, 732, 895.11**	**13, 967, 735.97**	**No violation**	**No violation**

Figure 4.6 represents the convergence curve of the evaluation function versus the number of evaluation function value of $13{,}751{,}664.53 MW^2$. The convergence of this function is fast during the 600 iterations begins from the value $2.1 \times 10^7 MW^2$. The evaluation function,

in a short period of iterations, nearly achieves an optimal value better than the outcomes of the preceding two methods.

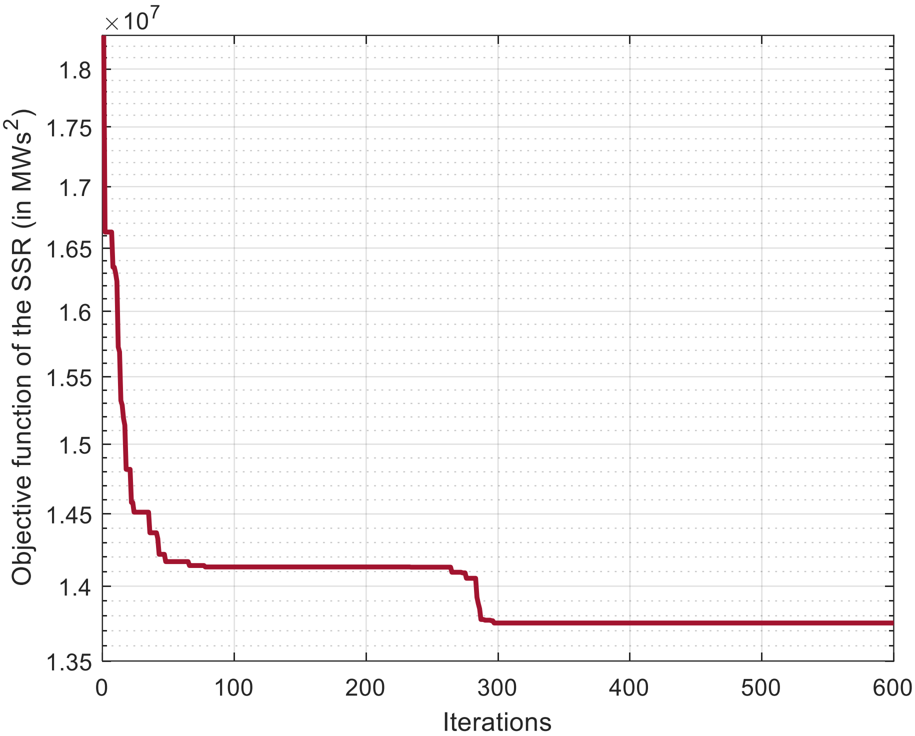

Figure4.6: The SSR objective function versus iterations of FBFS-DMFO algorithm in case (b), SSR value = $13,751,664.53MW^2$

4.3.3. Case (c)

In this case, the load power demand is 4739 MWs and 6.5% spinning reserve, i.e. load power demand is 5047 MWs, Total available workforce is 40. The coefficients $C_R = 1$, $C_M = 0$ and $C_L = 0$. Table 4.9 shows an additional comparison that has been made between the best results obtained from the proposed method and other recent methods; GAIR presented in [58], GABR presented in [34], DPSO presented in [34] and MDPSO presented in[34]. The comparison made with the same number of iterations and no total workforce and total load violation.

Table 4.9: The SSR comparison results for case (c) of FBFS-DMFO algorithm against other recent methods

Algorithm	Best Sum of the Squares of the Reserves (SSR) ($in\ MWs^2$)	Total load demand violation	Total Labour force violation
GAIR	3, 425, 971.00	Violated in weeks 6, 7, 8	No violation
GABR	8, 691, 137.00	Violated in weeks 1, 2, 3, 4, 14, 15, 16, 17, 31	Violated in weeks 15,16, 24
DPSO	3, 090, 335.00	No violation	No violation
MDPSO	3, 073, 911.00	No violation	No violation

FBFS-DMFO	**3, 008, 179.05**	**No violation**	**No violation**

The above table showed that the proposed method reaches a value of 3,008,179.05MW^2 as a best evaluation function. This value is better compared to the best values obtained using other methods where the GAIR algorithm reached$3,425,971.00MW^2$, GABR algorithm reached$8,691,137.00MW^2$, DPSO algorithm reached$3,090,335.00MW^2$ and MDPSO algorithm reached$3,073,911.00MW^2$. It is clear that the solution of the proposed approach is better the best solutions given by the previous methods.The statistical results for the proposed algorithm using 30 independent runs are presented in table4.10 compared with the previous methods GAIR, GABR, DPSO and MDPSO to show the effectiveness of the proposed method.

Table 4.10: The SSR statistical results of case (c) for FBFS-DMFO algorithm using 30 independent runs.

Method	Best objective function value SSR ($in\ MWs^2$)				Total workforce violation	Total load violation
	MIN	MEAN	MAX	SDV		
FBFS-DMFO	3, 008, 179.05	3, 069, 261.47	3, 294, 666.69	76, 005.33	No violation	No violation

The proposed FBFS-DMFO algorithm has then excelled all the GAIR, GABR, DPSO and MDPSO methods in all the 30 runs. Figure 4.7 represents the performance of the objective function during the 600 iterations of proposed algorithm. The convergence of this function is fast during the first period of the iterations and its convergence begins from a value of $8.1 \times 10^6 MW^2$ then it barely progresses up to achieve an optimal value of $3,009,696.05MW^2$.

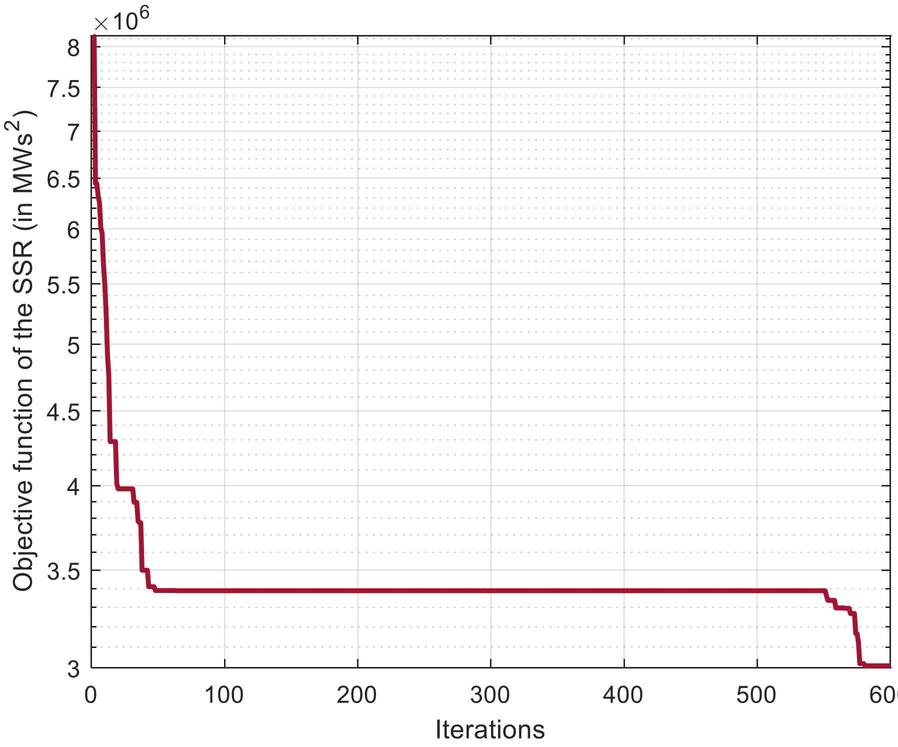

Figure 4.7: The SSR objective functionversus iterations of FBFS-DMFO algorithm in case (c), SSR value = $3,009,696.05\ MW^2$

4.4. Conclusion

This section presents the findings of the suggested FBFS-DMFO algorithm, which was employed to address the problem of scheduling preventive maintenance for generators in the 21-unit test power system. The effectiveness of the proposed algorithm was assessed by comparing it to various metaheuristic algorithms using different statistical measures, including standard deviation, mean, maximum, and minimum values. Additionally, statistical tests such as the Friedman rank test, the Holm-Sidak test, and the Wilcoxon signed rank test were conducted. The results demonstrated that the proposed method outperformed all other metaheuristic algorithms. The Friedman test ranked it as the best algorithm compared to the others, and the Wilcoxon signed rank test confirmed its superiority in all pair wise comparisons against the alternative algorithms. Notably, the developed algorithm exhibited fast convergence, high reliability, and required minimal computational efforts.

GENERAL CONCLUSION

In order to find the best way to schedule the preventive maintenance of generators in power systems, this thesis studied the Generator preventive Maintenance Scheduling (GMS) problem which is described as an optimization problem in terms of dependability criteria, where a number of constraints have been validated and satisfied with the outcome. The GMS problem has been resolved using an improved Discrete Mayfly Optimization (DMFO) metaheuristic algorithm with First-Bit Flip and Shift search strategy. The evaluation function of a weighted sum of the objective function of the Sum Squares of the Reserves of generation (SSR) and the penalty function for violations of the restrictions has been optimized using the algorithm. A week-long maintenance starting duration has been determined optimally for each generator unit using the proposed DMFO algorithm. The vector for the best maintenance starting period produces the lowest evaluation function value and the lowest reserve. This best case solution offers an optimum maintenance schedule with maintenance starting period and maintenance duration for each unit.

The proposed approach First-Bit Flip and Shift-based Discrete Mayfly Optimization (FBFS-DMFO) finds an optimal solution by using the best results from the optimization process, which are updated from the current solutions in the search area. For comparing present study against previous recent works for solving the Generator preventive Maintenance Scheduling problem in electric power systems, the performance of the suggested algorithm has been examined using conventional and advanced renowned tests. The FBFS-DMFO algorithm proved its efficacy comparing to other approaches. It also yields significantly better results, achieving very high-quality optimal solutions in a brief period of time, with high reliability and constant closeness of solutions to each other when contrasted with new and traditional methods.

Finally, the proposed FBFS-DMFO algorithm succeeds to find better results to solve the GMS problem and achieve optimal maintenance schedule. As prospective work, this proposed approach will be applied to achieve better results for scheduling the power system maintenance and solving other optimization problems in power systems.

BIBLIOGRAPHY

[1] E. Reihani, A. Sarikhani, M. Davodi, and M. Davodi, “Reliability based generator maintenance scheduling using hybrid evolutionary approach,” *Int. J. Electr. Power Energy Syst.*, vol. 42, no. 1, pp. 434–439, 2012, doi: 10.1016/j.ijepes.2012.04.018.

[2] G. Giftson Samuel and C. Christober Asir Rajan, “Hybrid: Particle Swarm Optimization-Genetic Algorithm and Particle Swarm Optimization-Shuffled Frog Leaping Algorithm for long-term generator maintenance scheduling,” *Int. J. Electr. Power Energy Syst.*, vol. 65, pp. 432–442, 2015, doi: 10.1016/j.ijepes.2014.10.042.

[3] K. Dahal, K. Al-Arfaj, and K. Paudyal, “Modelling generator maintenance scheduling costs in deregulated power markets,” *Eur. J. Oper. Res.*, vol. 240, no. 2, pp. 551–561, 2015, doi: 10.1016/j.ejor.2014.07.008.

[4] P. Mazidi, Y. Tohidi, A. Ramos, and M. A. Sanz-Bobi, “Profit-maximization generation maintenance scheduling through bi-level programming,” *Eur. J. Oper. Res.*, vol. 264, no. 3, pp. 1045–1057, 2018, doi: 10.1016/j.ejor.2017.07.008.

[5] Y. Yare and G. K. Venayagamoorthy, “Optimal maintenance scheduling of generators using multiple swarms-MDPSO framework,” *Eng. Appl. Artif. Intell.*, vol. 23, no. 6, pp. 895–910, 2010, doi: 10.1016/j.engappai.2010.05.006.

[6] S. Belagoune, N. Bali, K. Atif, and H. Labdelaoui, “A Discrete Chaotic Jaya algorithm for optimal preventive maintenance scheduling of power systems generators,” *Appl. Soft Comput.*, vol. 119, p. 108608, Apr. 2022, doi: 10.1016/J.ASOC.2022.108608.

[7] E. K. Doyle, “On the application of stochastic models in nuclear power plant maintenance,” *Eur. J. Oper. Res.*, vol. 154, no. 3, pp. 673–690, 2004, doi: 10.1016/S0377-2217(02)00805-6.

[8] E. L. Silva, M. Morozowski, L. G. S. Fonseca, A. C. G. Melo, J. C. O. Mello, and G. C. Oliveira, “Transmission constrained maintenance scheduling of generating units: A stochastic programming approach,” *IEEE Trans. Power Syst.*, vol. 10, no. 2, pp. 695–701, 1995, doi: 10.1109/59.387905.

[9] D. Chattopadhyay, “Life-cycle maintenance management of generating units in a competitive environment,” *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 1181–1189, 2004, doi: 10.1109/TPWRS.2003.821616.

[10] J. Yellen, T. M. Al-Khamis, S. Vemuri, and L. Lemonidis, “A decomposition approach to unit maintenance scheduling,” *IEEE Trans. Power Syst.*, vol. 7, no. 2, pp. 726–733, 1992, doi: 10.1109/59.141779.

[11] M. K. C. Marwali and S. M. Shahidehpour, “Integrated generation and transmission maintenance scheduling with network constraints,” *IEEE Power Eng. Rev.*, vol. 17, no. 12, p. 65, 1997, doi: 10.1109/pica.1997.599373.

[12] J. Eygelaar, D. P. Lötter, and J. H. van Vuuren, “Generator maintenance scheduling based on the risk of power generating unit failure,” *Int. J. Electr. Power Energy Syst.*, vol. 95, pp. 83–95, 2018, doi: 10.1016/j.ijepes.2017.08.013.

[13] B. Chandra Mohan and R. Baskaran, “A survey: Ant Colony Optimization based recent research and implementation on several engineering domain,” *Expert Syst. Appl.*, vol. 39, no. 4, pp. 4618–4627, 2012, doi: 10.1016/j.eswa.2011.09.076.

[14] J. F. Dopazo and H. M. Merrill, “Optimal generator maintenance scheduling using integer programming,” *IEEE Trans. Power Appar. Syst.*, vol. 94, no. 5, pp. 1537–1545, 1975, doi: 10.1109/T-PAS.1975.31996.

[15] Z. Yamayee, K. Sidenblad, and M. Yoshimura, “A computationally efficient optimal maintenance scheduling method,” *IEEE Trans. Power Appar. Syst.*, vol. PAS-102, no. 2, pp. 330–338, 1983, doi: 10.1109/TPAS.1983.317771.

[16] H. H. Zürn and V. H. Quintana, “Generator maintenance scheduling via successive approximations dynamic programming,” *IEEE Trans. Power Appar. Syst.*, vol. 94, no. 2, pp. 665–671, Mar. 1975, doi: 10.1109/T-PAS.1975.31894.

[17] G. T. Egan, T. S. Dillon, and K. Morsztyn, “An Experimental Method of Determination of Optimal Maintenance Schedules in Power Systems Using the Branch-and-Bound Technique,” *IEEE Trans. Syst. Man Cybern.*, vol. 6, no. 8, pp. 538–547, 1976, doi: 10.1109/TSMC.1976.4309548.

[18] G. Balaji, R. Balamurugan, and L. Lakshminarasimman, “Mathematical approach assisted differential evolution for generator maintenance scheduling,” *Int. J. Electr. Power Energy Syst.*, vol. 82, pp. 508–518, 2016, doi: 10.1016/j.ijepes.2016.04.033.

[19] B. L. Kralj and R. Petrović, “Optimal preventive maintenance scheduling of thermal generating units in power systems -A survey of problem formulations and solution methods,” *Eur. J. Oper. Res.*, vol. 35, no. 1, pp. 1–15, 1988, doi: 10.1016/0377-2217(88)90374-8.

[20] P. E. Duval and R. Poilpot, “Determining maintenance schedules for thermal production units: The kapila model,” *IEEE Trans. Power Appar. Syst.*, vol. PAS-102, no. 8, pp. 2509–2520, 1983, doi: 10.1109/TPAS.1983.317751.

[21] K. P. Wong and H. N. Cheung, “Thermal generator scheduling algorithm based on heuristic-guided depth-first search,” *IEE Proc. C Gener. Transm. Distrib.*, vol. 137, no. 1, p. 33, 1990, doi: 10.1049/ip-c.1990.0006.

[22] J. F. Bard, “Short-term scheduling of thermal-electric generators using Lagrangian relaxation,” *Oper. Res.*, vol. 36, no. 5, pp. 756–766, 1988, doi: 10.1287/opre.36.5.756.

[23] J. A. Muckstadt and S. A. Koenig, “Application of Lagrangian Relaxation To Scheduling in Power-Generation Systems.,” *Oper. Res.*, vol. 25, no. 3, pp. 387–403, 1977, doi: 10.1287/opre.25.3.387.

[24] K. P. Dahal and N. Chakpitak, “Generator maintenance scheduling in power systems using metaheuristic-based hybrid approaches,” *Electr. Power Syst. Res.*, vol. 77, no. 7, pp. 771–779, 2007, doi: 10.1016/j.epsr.2006.06.012.

[25] E. B. Schlünz and J. H. Van Vuuren, “An investigation into the effectiveness of simulated annealing as a solution approach for the generator maintenance scheduling problem,” *Int. J. Electr. Power Energy Syst.*, vol. 53, no. 1, pp. 166–174, 2013, doi: 10.1016/j.ijepes.2013.04.010.

[26] S. Lakshminarayanan and D. Kaur, “Optimal maintenance scheduling of generator units using discrete integer cuckoo search optimization algorithm,” *Swarm Evol. Comput.*, vol. 42, pp. 89–98, 2018, doi: 10.1016/j.swevo.2018.02.016.

[27] A. Volkanovski, B. Mavko, T. Boševski, A. Čauševski, and M. Čepin, "Genetic algorithm optimisation of the maintenance scheduling of generating units in a power system," *Reliab. Eng. Syst. Saf.*, vol. 93, no. 6, pp. 779–789, 2008, doi: 10.1016/j.ress.2007.03.027.

[28] T. Satoh and K. Nara, "Maintenance Scheduling By Using Simulated Annealing Method," *IEEE Trans. Power Syst.*, vol. 6, no. 2, pp. 850–857, 1991, doi: 10.1109/59.76735.

[29] J. T. Saraiva, M. L. Pereira, V. T. Mendes, and J. C. Sousa, "A Simulated Annealing based approach to solve the generator maintenance scheduling problem," *Electr. Power Syst. Res.*, vol. 81, no. 7, pp. 1283–1291, 2011, doi: 10.1016/j.epsr.2011.01.013.

[30] A. Fetanat and G. Shafipour, "Generation maintenance scheduling in power systems using ant colony optimization for continuous domains based 0-1 integer programming," *Expert Syst. Appl.*, vol. 38, no. 8, pp. 9729–9735, 2011, doi: 10.1016/j.eswa.2011.02.027.

[31] R. Anandhakumar, S. Subramanian, and S. Ganesan, "Artificial Bee Colony Algorithm to Generator Maintenance Scheduling in Competitive Market," *Int. J. Comput. Appl.*, vol. 31, no. 9, pp. 44–53, 2011, [Online]. Available: https://www.semanticscholar.org/paper/Artificial-Bee-Colony-Algorithm-to-Generator-in-Anandhakumar-Subramanian/2840bd6ebfeff2260fd10c9801b26706d850cb77#paper-header

[32] I. El-Amin, S. Duffuaa, and M. Abbas, "Tabu search algorithm for maintenance scheduling of generating units," *Electr. Power Syst. Res.*, vol. 54, no. 2, pp. 91–99, 2000, doi: 10.1016/S0378-7796(99)00079-6.

[33] W. K. Foong, A. R. Simpson, H. R. Maier, and S. Stolp, "Ant colony optimization for power plant maintenance scheduling optimization-a five-station hydropower system," *Ann. Oper. Res.*, vol. 159, no. 1, pp. 433–450, 2008, doi: 10.1007/s10479-007-0277-y.

[34] Y. Yare, G. K. Venayagamoorthy, and U. O. Aliyu, "Optimal generator maintenance scheduling using a modified discrete PSO," *IET Gener. Transm. Distrib.*, vol. 2, no. 6, pp. 834–846, 2008, doi: 10.1049/iet-gtd:20080030.

[35] S. Kumhar and M. Kumar, "Generator maintenance scheduling of power system using hybrid technique," *Int. Res. J. Eng. Technol.*, vol. 3, no. 2, pp. 418–423, 2016, [Online]. Available: www.irjet.net

[36] R. Anandhakumar, S. Subramanian, and S. Ganesan, "Modified ABC Algorithm for Generator Maintenance Scheduling," *Int. J. Comput. Electr. Eng.*, vol. 3, no. 6, pp. 812–819, 2011, doi: 10.7763/ijcee.2011.v3.425.

[37] K. Suresh and N. Kumarappan, "Hybrid improved binary particle swarm optimization approach for generation maintenance scheduling problem," *Swarm Evol. Comput.*, vol. 9, pp. 69–89, 2013, doi: 10.1016/j.swevo.2012.11.003.

[38] J. Kim and Z. W. Geem, "Optimal scheduling for maintenance period of generating units using a hybrid scatter-genetic algorithm," *IET Gener. Transm. Distrib.*, vol. 9, no. 1, pp. 22–30, 2015, doi: 10.1049/iet-gtd.2013.0924.

[39] M. Y. El-Sharkh and A. A. El-Keib, "An evolutionary programming-based solution methodology for power generation and transmission maintenance scheduling," *Electr. Power Syst. Res.*, vol. 65, no. 1, pp. 35–40, 2003, doi: 10.1016/S0378-7796(02)00215-8.

[40] N. Bali and H. Labdelaoui, "Optimal generator maintenance scheduling using a hybrid metaheuristic approach," *Int. J. Comput. Intell. Appl.*, vol. 14, no. 2, pp. 1–11, 2015, doi: 10.1142/S146902681550011X.

[41] K. W. Edwin and F. Curtius, "New maintenance-scheduling method with production cost minimization via integer linear programming," *Int. J. Electr. Power Energy Syst.*, vol. 12, no. 3, pp. 165–170, 1990, doi: 10.1016/0142-0615(90)90029-B.

[42] M. K. C. Marwali and S. M. Shahidehpour, "Integrated generation and transmission maintenance scheduling with network constraints," *IEEE Trans. Power Syst.*, vol. 13, no. 3, pp. 1063–1068, 1998, doi: 10.1109/59.709100.

[43] S. Subramanian, R. Anandhakumar, and S. Ganesan, "Artificial Bee Colony Based Solution Technique for Generator Maintenance Scheduling," *Aust. J. Electr. Electron. Eng.*, vol. 9, no. 2, pp. 109–126, Jan. 2012, doi: 10.1080/1448837x.2012.11464315.

[44] Y. Yare and G. K. Venayagamoorthy, "A differential evolution approach to optimal generator maintenance scheduling of the Nigerian power system," *IEEE Power Energy Soc. 2008 Gen. Meet. Convers. Deliv. Electr. Energy 21st Century, PES*, pp. 1–8, 2008, doi: 10.1109/PES.2008.4596664.

[45] K. P. Dahal, C. J. Aldridge, and J. R. McDonald, "Generator maintenance scheduling using a genetic algorithm with a fuzzy evaluation function," *Fuzzy Sets Syst.*, vol. 102, no. 1, pp. 21–29, Feb. 1999, doi: 10.1016/S0165-0114(98)00199-7.

[46] K. P. Dahal, C. J. Aldridge, and J. R. McDonald, "Generator maintenance scheduling using a genetic algorithm with a fuzzy evaluation function," *Fuzzy Sets Syst.*, vol. 102, no. 1, pp. 21–29, 1999, doi: 10.1016/S0165-0114(98)00199-7.

[47] M. Zhao, X. Yang, and X. Yin, "An improved mayfly algorithm and its application," *AIP Adv.*, vol. 12, no. 10, 2022, doi: 10.1063/5.0108278.

[48] J. Chen and J. Shi, "A multi-compartment vehicle routing problem with time windows for urban distribution – A comparison study on particle swarm optimization algorithms," *Comput. Ind. Eng.*, vol. 133, no. May, pp. 95–106, 2019, doi: 10.1016/j.cie.2019.05.008.

[49] N. Mansouri, B. Mohammad Hasani Zade, and M. M. Javidi, "Hybrid task scheduling strategy for cloud computing by modified particle swarm optimization and fuzzy theory," *Comput. Ind. Eng.*, vol. 130, no. July 2018, pp. 597–633, 2019, doi: 10.1016/j.cie.2019.03.006.

[50] H. Zhou, J. Pang, P. K. Chen, and F. Der Chou, "A modified particle swarm optimization algorithm for a batch-processing machine scheduling problem with arbitrary release times and non-identical job sizes," *Comput. Ind. Eng.*, vol. 123, no. April, pp. 67–81, 2018, doi: 10.1016/j.cie.2018.06.018.

[51] O. B. Haddad, A. Afshar, and M. A. Mariño, "Honey-bees mating optimization (HBMO) algorithm: A new heuristic approach for water resources optimization," *Water Resour. Manag.*, vol. 20, no. 5, pp. 661–680, 2006, doi: 10.1007/s11269-005-9001-3.

[52] X. S. Yang, "A new metaheuristic Bat-inspired Algorithm," *Stud. Comput. Intell.*, vol. 284, pp. 65–74, 2010, doi: 10.1007/978-3-642-12538-6_6.

[53] K. Zervoudakis and S. Tsafarakis, “A mayfly optimization algorithm,” *Comput. Ind. Eng.*, vol. 145, p. 106559, Jul. 2020, doi: 10.1016/J.CIE.2020.106559.

[54] Y. Shi and R. Eberhart, “A Modified Particle Swarm Optimizer,” pp. 69–73.

[55] X. Jian and Z. Weng, “A logistic chaotic JAYA algorithm for parameters identification of photovoltaic cell and module models,” *Optik (Stuttg).*, vol. 203, no. December 2019, p. 164041, 2020, doi: 10.1016/j.ijleo.2019.164041.

[56] “Minerva,” *BMJ*, vol. 311, no. 7006, p. 698, Sep. 1995, doi: 10.1136/BMJ.311.7006.698.

[57] S. Holm, “A simple sequentially rejective multiple test procedure,” *Scand. J. Stat.*, vol. 6, no. 2, pp. 65–70, 1979, [Online]. Available: http://www.jstor.org/stable/4615733

[58] K. P. Dahal, “Generator maintenance scheduling of electric power systems using genetic algorithms with integer representation,” no. 446, pp. 456–461, 2005, doi: 10.1049/cp:19971223.