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RESOURCE ALLOCATION TECHNIQUE FOR POWERLINE NETWORK USING A MODIFIED SHUFFLED FROG-LEAPING ALGORITHM

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DOCTOR OF PHILOSOPHY UNIVERSITI UTARA MALAYSIA 2018



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Abstrak

Teknik peruntukan sumber patut dijadikan lebih efisien dan dioptimakan untuk tingkatkan Kualiti Perkhidmatan (kuasa dan bit, kapasiti, keboleh-skala) bagi aplikasi jaringan data berkelajuan tinggi. Kajian ini cuba meningkatkan lagi kecekapan menuju prestasi hampir optima. Masalah peruntukan sumber merangkumi pemilihan penguntukan subpembawa, penentuan kuasa dan bit penghantaran bagi setiap subpembawa. Beberapa kajian yang dijalankan oleh Suruhanjaya Komunikasi Persekutuan telah membuktikan bahawa pendekatan peruntukan spektrum konvensional semakin tidak mencukupi dalam menangani kehendak pesat spektrum jaringan, yang mana ini menyebabkan ketidakcekapan dalam penggunaan spectrum, kapasiti dan penumpuan rendah, prestasi rendah kadar kesilapan bit, kelewatan maklumbalas saluran, keboleh-skala lemah serta kerumitan pengiraan membuat penyelesaian masa nyata sukar dikawal. Terutamanya ini adalah disebabkan oleh kekangan yang canggih, ketat, berbilang objektif, tidak adil, saluran bising, juga tidak realistik apabila menganggap saluran yang sesuai boleh didapati. Tujuan utama kajian ini adalah untuk membangunkan satu rangka kerja konseptual dan model matematik untuk peruntukan sumber menggunakan Algoritma Menyusun Semula Lompat Katak (SFLA). Justeru, satu SFLA yang diubahsuai untuk kuasa optimum, bit, dan teknik-teknik peruntukan subpembawa telah diperkenalkan dan disepadukan ke dalam sistem OFDM. Populasi enyelesaian yang dijanakan SFLA secara rawak (kuasa, bit), dimana ketepatan setiap penyelesaian dihitung dan ditingkatkan untuk setiap subpembawa dan pengguna. Kemudian, penyelesaian disahkan dan dijaminpasti secara numerik dengan menggunakan saluran jaluran kuasa berasaskan simulasi. Prestasi sistem telah dibandingkan dengan kajian yang serupanya dari segi kapasiti, keboleh-skala, kadar/kuasa yang diperuntukkan dan penumpuan sistem. Peruntukan sumber sentiasa dioptimakan and kapasiti yang diperolehi adalah lebih tinggi secara malar berbanding dengan algoritma Mencari Punca, Linear dan evolusi Hibrid. Algoritma yang dicadangkan ini mampu menjana kapasiti yang tinggi serta penumpuan yang paling cepat memandangkan jumlah lelaran yang diperlukan untuk mencapai 0.001% ralat optimum global ialah 75 berbanding dengan 92 dalam teknik konvensional. Akhir sekali, model peruntukan untuk pemilihan optima nilai sumber diperkenalkan: kuasa adaptif dan peruntukan bit dalam OFDM berasaskan sistem jaluran kuasa dan modifikasi TLBO dan PSO berasaskan SFLA dicadangkan.

Kata Kunci: Jaluran kuasa, Pemultipleksan Pembahagian Frekuensi Ortogon (OFDM), Peruntukan Sumber, Menyusun Semula Lompat Katak (SFLA).

Abstract

Resource allocation (RA) techniques should be made efficient and optimized in order to enhance the QoS (power & bit, capacity, scalability) of high-speed networking data applications. This research attempts to further increase the efficiency towards near-optimal performance. RA's problem involves assignment of subcarriers, power and bit amounts for each user efficiently. Several studies conducted by the Federal Communication Commission have proven that conventional RA approaches are becoming insufficient for rapid demand in networking resulted in spectrum underutilization, low capacity and convergence, also low performance of bit error rate, delay of channel feedback, weak scalability as well as computational complexity make real-time solutions intractable. Mainly due to sophisticated, restrictive constraints, multi-objectives, unfairness, channel noise, also unrealistic when assume perfect channel state is available. The main goal of this work is to develop a conceptual framework and mathematical model for resource allocation using Shuffled Frog-Leap Algorithm (SFLA). Thus, a modified SFLA is introduced and integrated in Orthogonal Frequency Division Multiplexing (OFDM) system. Then SFLA generated random population of solutions (power, bit), the fitness of each solution is calculated and improved for each subcarrier and user. The solution is numerically validated and verified by simulation-based powerline channel. The system performance was compared to similar research works in terms of the system's capacity, scalability, allocated rate/power, and convergence. The resources allocated are constantly optimized and the capacity obtained is constantly higher as compared to Root-finding, Linear, and Hybrid evolutionary algorithms. The proposed algorithm managed to offer fastest convergence given that the number of iterations required to get to the 0.001% error of the global optimum is 75 compared to 92 in the conventional techniques. Finally, joint allocation models for selection of optima resource values are introduced; adaptive power and bit allocators in OFDM system-based Powerline and using modified SFLA-based TLBO and PSO are proposed.

Keywords: Powerline, Orthogonal Frequency Division Multiplexing, Systems Performance, Shuffled Frog-Leap Algorithm.

Declaration

Some of the work presented in this thesis has published as listed below.

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- [3] Osman, S., Nisar, K., & Altrad, M. (2012). Initial model based Malaysia Regulations Broadband Technology over Power Line Networks. Knowledge Management International Conference (KMICe), Johor, Bahru, Malaysia, 433-436.
- [4] Osman, S., Nisar, K., & Altrad, M. (2013). Characterizing Broadband over Low Voltage Power Line Network in Malaysia. Rural ICT Development (RICTD) International Conference 2013, Melaka: MALAYSIA.
- [5] Nisar, K., Osman, S. & Altrad, M. (2014). Modelling of Broadband over Indoor Power Line Network in Malaysia. The 10th International Conference on Computing and Information Technology (IC2IT). Published in Springer. Phuket, Thailand.
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Table of Contents

Permission to Use	i
Abstrak	ii
Abstract	iii
Declaration	iv
Acknowledgement	v
Table of Contents	vi
List of Tables	ix
List of Figures	X
List of Abbreviations	xi
CHAPTER ONE INTRODUCTION	1
1.1 Background of the Study	1
1.2 Research Motivation	7
1.3 Problem Statement	9
1.4 Research Objectives	10
1.5 Research Scope	10
1.6 Research Strategy	11
1.7 Research Framework	12
1.8 Research Contributions	13
1.9 Thesis Organisation	14
CHAPTER TWO LITERATURE REVIEW	16
2.1 Power Line Communication (PLC)	16
2.1.1 PLC Channel Transfer Function	20
2.2 Orthogonal Frequency Division Multiplexing (OFDM)	24
2.3 Resource Allocation Techniques in OFDM	27
2.3.1 Water-Filling Solution	
2.3.2 Maximization and Minimum Fairness Criterion	35
2.3.3 Weighted Fairness	
2.3.4 Utility Maximization	37
2.3.5 Cross Layer Optimization	
2.3.6 Resource Allocation Based Game Theory	40
-	

2.3.7 Non-cooperative Solutions	42
2.3.8 Cooperative Solutions	43
2.4 Resource Allocation Techniques in Powerline Network	
2.5 Shuffled Frog-Leap Optimization Algorithm	
2.6 Research Gap	67
2.7 Chapter Summary	68
CHAPTER THREE RESEARCH METHODOLOGY	69
3.1 Research Methodology	69
3.1.1 Critique Phase	71
3.1.2 Design Phase	71
3.1.3 Implementation Phase	72
3.1.4 Evaluation Phase	72
3.2 Network Evaluation Techniques	73
3.2.1 Analytical Modelling	73
3.2.2 Measurement	74
3.2.3 Simulation	74
3.3 Simulation Tool	75
3.4 Performance Metrics	76
3.5 Resource Allocation	77
3.6 Powerline Channel Model	78
3.7 Chapter Summary	81
CHAPTER FOUR EFFICIENT POWER ALLOCATION TECHNIQUE	82
4.1 Allocation System Model	82
4.1.1 Number of Bit and Subcarriers per User	88
4.1.2 Power per Subcarrier	91
4.1.3 SFLA for Power per User	91
4.2 Implementation of Simulation	93
4.2.1 Comparison's Result	96
4.2.2 Simulation's Results	98
4.3 Modified SFLA Based TLBO	103
4.3.1 Analytical and Numerical Analysis	111

4.3.2 Result of the Modified SFLA Based TLBO	114
4.4 Chapter Summary	118
CHAPTER FIVE EFFICIENT RATE ALLOCATION TECHNIQUE	120
5.1 Allocation System Model	120
5.1.1 Power per User	121
5.1.2 Subcarrier Allocation	122
5.1.3 Bit Allocation	125
5.2 System's Result of the Adaptive Model	127
5.2.1 Bit Rate of each User	127
5.2.2 Channel Gain of each User	127
5.2.3 Subcarriers Allocation	128
5.2.4 Bit Loading	128
5.3 Modified Shuffled Frog Leaping Algorithm	130
5.4 Result's Comparison	136
5.5 Analytical and Numerical Benchmark Effectiveness Test	
5.6 Chapter Summary	
CHAPTER SIX CONCLUSION AND FUTURE WORK	145
6.1 Conclusion	145
6.2 Achieved Objectives	146
6.3 Summary of Contributions	147
6.4 Limitations of the Research	
6.5 Recommendations for Future Work	149

List of Tables

Table 2.1. Sources of PLC Noise 18
Table 2.2. Path variables and Attenuation of N=4 PLC Channels [65]21
Table 2.3 Resource Allocation Techniques in PLC Technology
Table 2.4 Shuffled Frog-Leaping Algorithm Applications and Comparison55
Table 3.1 Comparison of Communication System Evaluation Approaches
Table 4.1 Simulation Parameters
Table 4.2. Optimal Minimum Power Rate Values at Different Users101
Table 4.3. Optimal Maximum Bit Rate Values at Different Users 102
Table 4.4. Benchmark Optimization Test Functions 112
Table 4.5. Results of Numerical Experiment Optimization 113
Table 4.6. Analytical Result of Schwefel Function 114
Table 4.7. Optimal Maximum Bit Rate (bits/s/Hz) Values at Different Users117
Table 5.1. Bit Rate (bit/sec) per User
Table 5.2. Channel Gains (dB) for all Subcarriers of each User128
Table 5.3. Subcarriers Allocation
Table 5.4. Bit Allocation (Comparison)
Table 5.5 Number of Required Iterations for DeJong's F1 Function141
Table 5.6. Number of Required Iterations for DeJong's F2 Function141
Table 5.7. Number of Required Iterations for Extended Rosenbrock's Function 141
Table 5.8. Number of Required Iterations for Rastrigin Function
Table 5.9 A Comparison of System Capacity using a Power Allocator
Table 5.10. A Comparison of Transmitted Power of the System for Bit Allocation

List of Figures

Figure 1.1. Orthogonal Frequency Division Multiplexing System
Figure 1. 2. Adaptive Power/bit and Subcarrier Allocation in OFDM System [18]5
Figure 1.3. Subcarrier's Power Amount
Figure 1.4. Research framework
Figure 2.1. A General PLC Channel (source [58])17
Figure 2.2. Types of PLC Noise (source [3])
Figure 2.3. Effect of Noise on the PLC Channel
Figure 2.4. Periodic Synchronous Impulsive Noise
Figure 2. 5. PLC Channel Gain, N=4
Figure 2.6. Basic 2PN Model
Figure 2.7. OFDM's Spectral Form of Compared to FDM [74]24
Figure 2.8. Basic OFDM Transmitter (source [3])25
Figure 2.9. Mapping/De-mapping Scheme of 16-PSK and 16-AQM (source [3])26
Figure 2.10. Shuffled Frog-Leap Algorithm
Figure 2.11. Modification Sections in SFLA
Figure 3.1. Research Methodology (source [177])70
Figure 3.2. Network Performance Evaluation Techniques
Figure 4.1. OFDM System Block Diagram for Multiusers
Figure 4.2. Capacity Curves for 14 Users
Figure 4.3. Power Allocated Rate vs Number of Users
Figure 4.4. System's Capacity of 16 Users
Figure 4.5. System Throughput vs Number of Users101
Figure 4.6. Normalized Capacity Ratios for 16 Users
Figure 4.7 Local Search in the SFLA Scheme
Figure 4.8. Process of the Proposed Internal Shuffle in SFLA108

Figure 4.9. (a) Memeplex Process in SFLA, (b) Memeplex Arrangement in the
Modified SFLA
Figure 4.10. Capacity Comparison of SFLA and Modified SFLA_TLBO with 16
Users
Figure 4.11. Power Allocated Rate vs Number of Users
Figure 4.12. SFLA vs Modified SFLA_TLBO, 16 Users116
Figure 4.13. Improvement over Fitness Vlaues per Iteration118
Figure 5.1. Process Flow of Subcarrier Allocation Scheme
Figure 5.2. Subcarrier & Bit Allocation Model Structure126
Figure 5.3. Powers Allocated vs Bit Amounts
Figure 5.4. Improvement of SFLA based Global and Local Best Frog Using PSO 133
Figure 5.5. Modified Internal Shuffle Process in SFLA
Figure 5.6 Pseudocode of the Modified SFLA Based TLBO and PSO135
Figure 5.7. Generated Random Power Amount versus Bits137
Figure 5.8. Comparison Result of the Allocated Bits to Power137
Figure 5.9. Amount of Power Allocated to each User
Figure 5.10. Number of Required Iterations for SFLA and Modified FSLA142

List of Abbreviations

2NP	Two-port Network
ABC	Artificial Bee Colony
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ACO	Ant Colony Optimization
ADSL	Asymmetric Digital Subscriber Line
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase-Shift keying
CDMA	Code Division Multiple Access
CSI	Channel State Information
CTF	Channel Transfer Function
CTF	Channel Transfer Function
dB	Decibel
DMT	Discrete Multi-tone
E _b /N _o	Energy per Bit to Spectral Noise Density
GA	Genetic Algorithm
ICI	Inter-Carrier Interference
IDFT	Inverse Discrete Fourier Transform
IFFT	Inverse Fast Fourier Transform
ISI	Inter-Symbol Interference
KBACO	Knowledge-based Ant Colony Optimization
LV	Low Voltage
MA	Margin Adaptive
MA	Memetic Algorithm
MAC	Media Access Control
MATSLO	Multi-Agent Tabu Search Local Optimization
MCC-SFLA	Modified Chaos Clonal Shuffled Frog Leaping Algorithm
MHBMO	Modified Honey Bee Mating Optimization
MOGA	Multi-Objective Genetic Algorithm
M-PSK	M-ary Phase Shift Keying
M-PSK	M-ary Phase Shift Keying
M-QAM	M-ary Quadrature Amplitude Modulation
MSFLA MSFLA	Hybrid Shuffled Frog Leaping Algorithm
MSFLA	Modified Shuffled Frog Leaping Algorithm
	Net Applicable
IN/A	Not Applicable
INA NDS	Noch Dereggining Solution
NCSA	Non Donominated Sorting Constin Algorithm
ND	Non-Denominated Soluting Genetic Algorithm
OFDM	Arthogonal Frequency-Division Multipleying
	Orthogonal Frequency Division Multiple Access
OFDMA	Ormogonal Frequency-Division Multiple Access

PAPR	Peak-to-Average Power Ratio	
PDS	Power Density Spectrum	
PDS	Power Density Spectrum	
PHY	Physical Layer	
PLC	Power Line Communication	
PSO	Particle Swarm Optimization	
PSO	Particle Swarm Optimization	
PSO	Particle Swarm Optimization	
QoS	Quality of Service	
RA	Rate Adaptive	
SA	Simulated Annealing	
SA	Simulated Annealing	
SFLA	Shuffled Frog-Leap Algorithm	
TLBO	Teacher Learner Based Optimization	
SNR	Signal to Noise Ratio	
SPEA	Strength Pareto Evolutionary Algorithm	
SVR	Support Vector Regression	
TLBO	Teacher Learner Based Optimization	
\mathbf{Z}_L	Impedance Load	
Zs	Impedance Source	

CHAPTER ONE INTRODUCTION

1.1 Background of the Study

Power Line Communication (PLC) is a high data, video, and voice transmission network over power line grid. It utilises indoor electricity cable for sending highfrequency transmission signals [1]. It meets the Quality of Service (QoS) requirements in high data transmission applications [2]. There are several successful installed projects that made the data transmission over power lines very possible. They are namely PLC, Digital Power Line (DPL), Power Lines Transmission (PLT), and Broadband over Power Lines (BPL).

In PLC, users are able to connect the Internet power line adapters with home electrical appliances on the same grid. Users are then able to control the connected appliances over the same alternating current grid using PLC features. Given such feature, this technology could be applied into controlling building electrical system such as lights and alarms system [3]. In fact, this technology is proven cost-effective by using the existing electrical wiring.

PLC is produced for two purposes, which are recognized and classified as two systems namely, Broadband over PLC and Narrowband over PLC. While Broadband over PLC is used for high data transmission exceeding two Mbps, Narrowband is used for relatively low data transfer, such as those below a few hundred bps which are normally used in electronic systems, air conditioning, heating, and automation meter applications [4, 5].

PLC system uses Medium Voltage (MV) and Low Voltage (LV) for data communication applications. The competitive advantage of using PLC over MV lies in its ability to provide broadband at several frequencies where interference with telecommunication is not in the same range. Therefore, this enables data to be sent to the end users' home LV electrical network [6]. Important to note, MV and LV networks are able to connect last-mile users in the remote areas, and thus reduce the gap between people who have and do not have access to broadband services.

Using PLC with MV network could also close the gap between telecommunication providers and LV network, as PLC developers would focus on the electricity parts in whole. Therefore, possible new business and interest opportunities breed from the investigation and development of such PLC technology. Further, other than allowing the Internet providers to offer cost-effective broadband services with wide coverage electrical generation companies can apply it to control and manage the user's meters [7].

Various studies conducted by the federal communications commission in several cities in America [8], and others [9, 10] have demonstrated evidence of the insufficiency of the conventional resource allocation approach in addressing rapid development of networking technologies, and that there is a call for the development of a more dynamic resource access to compensate for the underutilization of transmission channels.

The technology of using power cable for sending high-frequency data transmission signals is introduced and available in several standards [11]. The best efficient

modulation model utilized in PLC networks is OFDM [12, 13], see Figure 1.1. Using only the available wideband channel, it encodes data on multiple narrower carrier frequencies. Each of these channels has its own modulated subcarrier. Users in the OFDM systems are allocated sets of non-overlapping subcarriers. Problems may arise in the assignment of subcarriers and their resources.



Figure 1.1. Orthogonal Frequency Division Multiplexing System

Therefore, an adaptive OFDM modulation mechanism is crucial to be in place to handle possible cases of hostile transmission channel such as PLC, and consequently enables high data transmission over its channel [14]. The modification needed for such mechanism could be done by improving several factors such as bit/power allocation model [15]. This modification could reduce PLC network's channel problem [16]. In adaptive resource allocation for each user, signal to noise ratio (SNR) and allocated power/bits of users may differ due to the different fading environments. In addition, different QoS requirements would also cause variation in the received power required at the receivers. Finally, considering that PLC channels are prone to changing constantly, resource allocation techniques should be fast enough to keep up with the changing real life environment should the real-time applications be made feasible. Give the alluded, the ultimate outcome of this study is to develop an efficient subcarrier and power-and-bit-resource-allocation powerline channel, which would yield better- and lesser-transmitted power as well as increased capacity, beyond the existing achievement in the field thus far.

Notably, research and development works on resource allocation issue have had a long research history, and it became common in the field of networking application design particularly after Hanly and Tse's (1998) work [17]. The vital advantage of employing OFDM modulation system in PLC, wirelesses, and wire networking applications lies in its method of reducing channel complication through the forming of broadband frequency channel in sub-channels. However, the common OFDM system uses a fix method for allocating bit and power at each sub-channel. Such way of working is not efficient for the time-variant frequency response channel, and it further causes degradation of Bit Error Rate (BER) performance.

Specifically, dynamic resource allocation technique is capable of handling major modifications on modulation system in such hostile channel as PLC. It is done by assigning different subcarrier, bit, and power rate according to the conditions of channels. Depicted in Figure 1.2 and 1.3 are the schematic illustrations of the adaptive data modulation methods, where the amount of bits and power level are allocated at each OFDM subcarrier with respect to channel characteristic.



Figure 1. 2. Adaptive Power/bit and Subcarrier Allocation in OFDM System [18]



Figure 1.3. Subcarrier's Power Amount

Practically, in order to fully exploit the transmission channel bandwidth efficiently, accurate and instantaneous information of channel status is needed [19]. For the purpose of improving the modulation system performance, there are several factors which could be modified in the modulated subcarrier's SNR [20, 21]. These factors are namely: (i) transmit power and allocated bit, (ii) instant BER, (iii) channel code or scheme, (iv) inter-symbol interference (ISI) & inter-carrier interference (ICI), and (v) constellation size. A modification may involve adjusting one or more than one factors.

It is an important to note that, the high possibility of applying BER in OFDM for fading channel is faced with the main challenge related to problem due to the probability of weak sub-channels. Countering this shortcoming, the SNR of OFDM sub-channel which control the entire system performance causes less error probability. Specifically, the coded-OFDM process uses channel interleaving and/or forward error correction to achieve communication reliability [22].

However, in non-adaptive OFDM system, the size of allocated power and bit for all sub-channels are considered same. The major problem of this method in case of noise channel such as PLC is its low performance of bit error estimation. Further, bandwidth efficiency is potentially reduced if sophisticated coding and decoding techniques are applied.

Empirical works related to adaptive data modulation systems based on various communication channels are observable in past researches [23-31], as identified in two classifications, namely the rate adaptive (RA) and margin adaptive (MA). While RA technique maximizes the data rate amount that are allocated to BER and power conditions (i.e., [28, 29]), the MA technique minimizes the allocated energy to BER and bit rate conditions at each sub-channel (i.e., [24, 27]).

To note, the adaptive power and rate allocation approaches are based on common water-filling algorithms with high computation and mathematical complex models. Given the above discussion, this thesis aims at solving the aforementioned difficulties through the use of an improved modulation approach in noisy channel. To fill in the void, novel algorithms are introduced based on the Shuffled Frog-Leap Algorithm (SFLA), and evaluated based on powerline channel. Several channel models are discussed in past literatures [32-35].

SFLA is a powerful evolutionary optimization technique used to deal with several engineering issues and application. SFLA is inspired based on the swarm intelligence due to its features of powerful optimal performance, concept, parameters, fast calculation speed, and easy realization. It has been applied in many fields including model identification problems, scheduling problems, parameter optimization problems, and the traveling salesman problem [36].

Generally, the processes of SFLA are started by initializing a random population of frogs, followed by calculating the fitness function for each frog. After that, it sorts the frogs based on their fitness values. Further, the population is partitioned into group of memeplexes by allocating the frogs to the groups according to their fitness values. Finally, all the memeplexes are shuffled and checked for the termination criteria.

1.2 Research Motivation

PLC technology has proven to be cost-effective by using the existing electrical wiring [37]. Users are able to connect the internet power line adapters with home electrical appliances on the same grid. Moreover, users can control the connected appliances over the same alternating current grid using PLC features. Thus, this technology can be used to control building electrical system such as lights and alarms system [3], smart house network, traffic light control, street lighting control, advanced control metering infrastructure, and in-vehicle data communications [38].

Despite the fact that power line has been used in several data communication applications and has demonstrated advantages in terms of cost-effective installation, this cable was not produced as data carrier. Therefore, adaptive efficient techniques in medium access control (MAC) and allocation at the physical (PHY) layer are required. High spectral productivity, less complexity design, link adaptation flexibility are some of OFDM advantages, while ISI, ICI, and Bit/Power allocation to subcarriers are the most severe problems [39, 40].

Broadband technology requires efficient subcarrier resource allocation technique for maximizing bit and minimizing power rate under BER constraint in OFDM system [41]. OFDM applies allocation mechanisms for data bit and power rate of each individual subcarrier based on SNR and BER model to achieve subcarrier fairness and ensure QoS. In technology such as PLC network, the transmission channel displays multipath channel fading due to noise and interference sources. Thus, in the current research, the problem of power and bit allocation is closely investigated, and new algorithms are introduced.

To note, in non-adaptive OFDM system, the size of allocated power and bit for all sub-channel are considered same. The major problem of this method in case of noise channel such as PLC is its low performance of bit error estimation. Moreover, bandwidth efficiency is reduced in cases where sophisticated coding and decoding techniques are applied. To address this, power and rate resource allocation algorithms are introduced based on powerline application, whereby analytical and simulation analyses are used to show the improvement and efficiency. By applying an adaptive power and bit allocation techniques, the networks could be improved in term of capacity and BER performance [42].

1.3 Problem Statement

Resource allocation techniques should be made efficient and optimized in order to enhanced the QoS requirements (power & bit rate, delay, BER, etc.) of data network's applications [43, 44]. Recently, several optimal algorithms have been proposed. These optimal algorithms are heightened based on the different restrictive conditions, in which the maximization of data network capacity under power spectrum density constraints is achieved. However, most of these works assume that the perfect channel state is available at the transmitter for simplifying the analysis. Unfortunately, this assumption is unrealistic due to channel estimation errors, channel feedback delay, and impulsive noise present in powerline. Powerline channel impulsive noise has a characteristic of fast variation of amplitudes in short duration [45, 46].

The most critical problem is challenges related to resource allocation that requires the sharing the resources (power, data rate, spectral) between users as dependent on the SNR gap [47-49]. In this respect, several optimization techniques are introduced in previous researches, concentrating on efficient spectrum's data rate and power adaptive formulation models [50-54]. However, these models cannot fully utilize and allocate data rate and energy over hostile network channel such as powerline. Still to date, several problems existed in resource optimization models due to weak improvement and scalability as well as computational complexity, which altogether reveal low channel bandwidth in real applications.

Obviously, the computational complexity behind the conventional optimization techniques are due to the new added constraints to the objective function; if the number of the constraints increases, then the complexity also increases. The memetic evolutionary algorithm, on the other hand, shows good performance in solving optimization problem. However, it suffers from slow convergence to a stable point, especially in the distributed scenario where users communicate with each other independently.

1.4 Research Objectives

Adaptive resources allocation techniques are important for efficient performance of data networks application. In this study, techniques that are aimed at maximizing the system capacity and improving the convergence are introduced. In order to achieve the research goals, the following objectives are formulated.

- To design and implement efficient technique for power allocation in OFDM by modifying SFLA-based TLBO.
- 2. To design and implement efficient technique for rate and subcarrier allocation in OFDM by modifying SFLA-based TLBO and PSO.
- 3. To evaluate the proposed techniques based on OFDM and powerline channel in terms of the capacity, power and bit rate, and convergence.

1.5 Research Scope

This study focuses on the important factors that could influence data network performance such as capacity, reliability, and scalability among several other factors. Thus, it is bounded for only allocation process of subcarrier, power, and bit techniques based on powerline channel for high data transmission for better performance of networks's applications. The purpose is to allot optimezed power amount for each user and subcarriers and to allocate subcarriers and bits efficiently. The attained improvements in resource allocation techniques are guided for better performance in data link layer and the entire network performance. Powerline channel model are used based OFDM for simulation of complete transmission network system.

1.6 Research Strategy

This study is conducted step-wise, started from the review of the state-of-the-art literature of PLC channel models, data modulation, and resource allocation techniques. Specifically, the strategy embeds several crucial steps and requirements.

- The study investigates the powerline technology and its channel function models, the digital data modulation techniques' characteristics and further introduces their main components. After that, the researcher models the proposed new resource allocation techniques, which is then integrated and evaluated in OFDM system-based powerline channel.
- OFDM system's design is needed to evaluate the proposed techniques and their components according to the research objectives set forth.
- Next, the simulation processes are constructed to analyse the introduced system's performance. Simulation verification and evaluation were conducted using MATLAB tool. The reasons of opting for this tool are

discussed in Chapter Three. Several scenarios and configurations of networks are later conducted, as are detailed in Chapter Four and Chapter Five.

• Further, validation of the proposed system's simulation is carried out to ensure and verify the results' validity. Verification is ensured during code constructing, while the validation process is executed after each different scenarios of evaluation on the proposed system. The obtained results shows the system improvement.

1.7 Research Framework

The research framework comprises seven phases as shown in Figure 1.4.



Figure 1.4. Research framework

The first phase is literature review; it includes reviewing the technology of powerline communication and channel data transmission models, as well as data modulation

and resource allocation techniques in OFDM and PLC. It flows from the main matters, to the concepts and basics of various resource mechanisms, and then further tunneled down to highlight the main problems of resource allocation and its solutions.

1.8 Research Contributions

The followings are the contributions of this research.

- 1. A joint allocation model for selection of optima power values introduced by efficient allocation techniques: Near-optimal technique, non-iteration proportional low-complexity technique, SFLA, and water-filling algorithm.
- Optimal power allocator in OFDM system-based powerline channel using modified SFLA-based TLBO technique.
- Bit, subcarrier, and power allocation mechanisms-based Min-Max improved dynamic solution, adaptive proportional fairness technique and Greedy algorithm.
- Modified SFLA-based PSO for allocation of subcarrier and bit for OFDMbased powerline network.
- 5. Integration of the proposed models with OFDM according to the research's aims, as well as the validation and evaluation of system performance over powerline channel.

- 6. Integration, validation, and evaluation of the proposed modified algorithms with OFDM over powerline channel.
- Comparing the performance evaluation with existing competiting (and similar) research works in term of the system's capacity, allocated bit/power, and convergence.

1.9 Thesis Organisation

The organization of this thesis formed as follows.

Chapter One reviews the issue to highlight the research void under investigation. This is followed by discussion of research motivation, and crystallization of problem statement. This chapter also includes sections on research objectives, research scope, research strategy, research framework and contribution of the study.

Chapter Two comprises literature review of relevant empirical and theoretical evidence. Specifically, it provides understanding for resource allocation techniques and their applications in various networking systems, powerline communication technology and its network architecture, PLC noise, data modulation techniques, and PLC channel transfer function modelling techniques.

Chapter Three discusses all the methodologies and techniques applied in the study. The chapter resides discussions of the research methodology phases (namely, critique, design, implementation, and evaluation), and network evaluation techniques (Analytical modelling, measurement, and simulation) for describing and solving the research problems. Further, performance metric and resource allocation are briefed, followed by powerline channel (impulsive noise model).

Chapter Four introduces the modified SFLA. Power allocator is introduced and explained in details, as well as the corresponding appropriate simulation tool for evaluation. After that, a novel modified SFLA power allocation is presented and explained mathematically in several notations, and followed by the codification in Matlab simulation tool, which is crucial for displaying the system's improvement.

In Chapter Five, further novel modification over SFLA is introduced and detailed up to the evaluation of SFLA as a bit and subcarrier allocation technique. The modified SFLA has never been utilized as bit allocator. The chapter also includes explanation of Mathematic models in various equation, and its codification in Matlab. Results of convergence comparison of both proposed algorithms are discussed, and the outcomes of the results are presented. Some significant findings are highlighted.

Finally, the research summary, conclusions, and future work are discussed in Chapter Six.

CHAPTER TWO LITERATURE REVIEW

Powerline Communication technology is investigated and explained with brief description of noise models and architecture of system, and then modelling techniques of PLC channel transfer function are classified, as well as digital modulation techniques. These are followed by resource allocation approaches. Finally, in the last part of this chapter, the most-relevant literatures and research gaps are presented.

2.1 Power Line Communication (PLC)

Electricity was deregulated in telecom markets in the early 90's; whilst, the old plan of using the existing power network wiring for broadband data transmission got a new chance to be explored as a potential medium for providing telecom services to end users [55]. Using the utility infrastructure for data networking is almost century old. It is used essentially for control and monitoring purposes [5].

Generally, a wide area is covered by the communication system to provide Internet applications and radio systems. In the radio system, the data modulates in analog form between users in a certain coverage area. Whilst in normal Internet applications, data is modulated in a digital pulse form to be transmitted between users [56].

However, in case of a PLC system, a coupling circuit on both sides of the transmission channel is required as shown in Figure 2.1. It also shows an example of

cascade networks connected by two-ports. Z_s is the transmitter has output Impedance, and Z_L is the receiver has input impedance; both are important factors for PLC implementation. Mean whilst, the coupling circuit is installed for two reasons. First, it protects the equipment from damage. Second, it ensures that the information signal is within the frequency band allowed for communication on both sides of the channel [57, 58].



Figure 2.1. A General PLC Channel (source [58])

Indoor power grid is connected to a variety of electrical appliances, which introduce time variant impedance sources. Thus, a PLC system faces noise in different forms subjected to the medium appearing in multipath propagation [59, 60]. Consequently, the error rate increases and makes data correction process more difficult. Figure 2.2 shows the collective noise in the PLC environment.



Figure 2.2. Types of PLC Noise (source [3])

Table 2.1. Sources of PLC Noise

Noise Type	Cause
Colored Background Noise	Sum of many low-power noise sources
Narrowband Noise	Stations' broadcast
Periodic Impulsive Noise (asynchronous to the transmission frequency)	Switching power supplies
Periodic Impulsive Noise (synchronous to the transmission frequency)	Appliances
Asynchronous Impulsive Noise	Switching within the network

Tremendous research effort has been spent to model and characterize noise types and sources in the PLC environment. Author in [61] has categorized PLC noise regarding the spectrum used, strength and time duration into five types. Table 2.1 above consists of a brief explanation of these types of noise. Figure 2.3 shows the obvious effect of White Gaussian Noise (WGN) and random noise on power line carriers;



Figure 2.3. Effect of Noise on the PLC Channel

Background noise is defined as the remaining noise at a certain channel part after removing all types of distortion; it can be identified by the Power Density Spectrum (PDS). Basically, its power density starts from -120 dB up to -140 dB particularly at low frequencies less than 1 MHz [57]. Background noise is changeable over time and its level depends on the frequency used [3]. Its simple model is formed by OPERA association [62] as follows:

$$S(f) = S_{\infty} + S_0 \cdot e^{-f/f_0}$$
(2.1)

Where S_{∞} is the PSD when *f* goes to ∞ . Whilst S₀ represents the variance between S_{∞} and *S*(*0*).

Narrowband noise is a sinusoid form and modulated amplitude over time and location produced by wireless and radio networks that run high frequencies in the same range with the PLC network [57, 63]. While, synchronous impulsive noise (harmonic noise) appears in the frequency of voltage from 50 Hz to 100 Hz caused by the rectifier diodes of electrical devices that are connected to a network. It comes in the time domain measurement and is converted with data input to the frequency domain [64]. Electrical power sources that use the main signal frequency are generators of Synchronous noise; see Figure 2.4 below.



Figure 2.4. Periodic Synchronous Impulsive Noise

2.1.1 PLC Channel Transfer Function

PLC channel functions are constructed by either top-down or by bottom-up, Modelling of a power line channel in a time domain approach is achieved by several studies [32-35] based on real experimental results, conducted on various electrical networks and in different countries using a very widely accepted model which formed as follows:

$$H(f) = \sum_{i=1}^{N} g_i \cdot e^{(a_0 + a_1 \cdot f^k) \cdot l_i} \cdot e^{-j2\pi f \tau_i}$$
(2.2)
Where:

 $\sum_{i=1}^{N} g_{i}$: Weighting term $e^{(a_{0}+a_{1}.f^{k}).l_{i}}$: Attenuation term $e^{-j2\pi f\tau_{i}}$: Delay term

 a_0 , a_1 , C_i , and k are the attenuation factors based on the characteristics' cable.

- *t* : Transmission factor
- g_i : Path gain, l_i Channel length
- v_p : Phase velocity
- τ_i : Delay duration time .
- *N* : Number of propagation paths.
- e^{-} : Cable attenuation.

Table 2.2 shows the measured parameters that are injected into the time domain model for describing the channel function gains of 15 different communication paths. It is very clear in Figure 2.5 below that the channel suffers from deep notches and unstable movement.

Attenuation Parameters and Path Parameters							
<i>K</i> =1		$a_0 = 0$		$a_1 = 7.8 *$	10^{-10} s/m		
Ι	$g_{ m i}$	di/m	Ι	d_i	di/m		
1	0.64	200	3	-0.15	244.8		
2	0.38	222.4	4	0.05	267.5		

Table 2.2. Path variables and Attenuation of N=4 PLC Channels [65]

However, the drawback of the time domain channel modelling approach is that it is based on an experimental test-bed. This approach needs an accurate measurement process to be used over each single part of the electricity network, for which it seems difficult to consider all the measured results in an echo model. Since the factors are based on the measurement, the model is prone to measurement errors [66].



Figure 2. 5. PLC Channel Gain, N=4

On the other side, modelling PLC channel transfer in a frequency domain approach using a general Transmission Line Model (Two-port Network) which is the most popular modelling approach followed by many researchers, such as in [58, 67-71]. The model's basic parameters are as depicted in Figure 2.6. The derivation of the two-port network model represents the relationship of the transmission amount between the sender and the receiver.

$$\begin{bmatrix} V(x) \\ I(x) \end{bmatrix} = \begin{bmatrix} A(x) & B(x) \\ C(x) & D(x) \end{bmatrix} \begin{bmatrix} V_R \\ I_R \end{bmatrix}$$
(2.3)

Is + Vs	Two Port Network		

Figure 2.6. Basic 2PN Model

$$\begin{bmatrix} V_s \\ I_s \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} = \begin{bmatrix} V_R \\ I_R \end{bmatrix}$$
(2.4)

Where:

$$V_s = AV_R + BI_R \tag{2.5}$$

And

$$I_s = CV_R + DI_R \tag{2.6}$$

Where:

Ι	: Current
V	: Voltage
R	: Resistance
L	: Inductance
С	: Capacitance
G	: Conductance
$A = V_S / V_R$: Voltage Ratio
$B = V_S / I_R$: Short Circuit Resistance
$C = I_S / V_R$: Open Circuit Conductance
$D = I_S / I_R$: Current Ratio

The primary line parameter values are R, L, C, and G. while x is the line's longitudinal direction. Based on the transmission scheme, channel of electricity cable represent as number of cascaded *2PNs*. A similar channel model was proposed by [72] for broadband transmission.

The main drawback of the Bottom-up approach is that it is quite computationally expensive if applied to real power line communication networks [73]. A comprehensive channel status should be provided as we as cable's characteristics, network topology, and network's impedance.

2.2 Orthogonal Frequency Division Multiplexing (OFDM)

Most of powerline trails utilized an OFDM modulation system; whilst, others are constructed by the Direct Sequence Spread Spectrum (DSSS). In fact, the most suggested modulation scheme for PLC is OFDM, it also reduces the amount of bandwidth required to transport information [74]. Figure 2.7 shows the OFDM's bandwidth proficiency compared to the normal FDM. In other words, The orthogonality of OFDM is the mechanism of dividing broadband data bandwidth into several sub-streams and transfer them parallels and concurrently.



Figure 2.7. OFDM's Spectral Form of Compared to FDM [74]

The orthogonality of the sub-channels guarantees less interference; but if the symbol period is not greater than the delay time, that will cause ISI. When that occurs, sub-ICI will be generated. In order to remove ISI entirely, time guard is extended cyclically and added into the each symbol in OFDM system. There is a necessity to understand the OFDM mathematical model, which shows how to modulate and

demodulate the digital bits. Figure 2.8 depicts the basics of the OFDM transmitter by separating the sub-channel frequencies orthogonally through multiples of 1/T. T is the interval of the OFDM symbol.



Figure 2.8. Basic OFDM Transmitter (source [3])

Based on the OFDM investigation [3], the transmitted signal s (t) is expressed as:

$$s(t) = \sum_{k=0}^{N-1} \sum_{l=-\infty}^{\infty} b_l[k] \psi_k(t - lT)$$
(2.7)

The orthogonal is $(\psi_0, \psi_1, \psi_{N-1})$, thus

$$\int_{0}^{T} \Psi k(t) \Psi i^{*}(t) dt = \begin{cases} 1, & \text{if } i = k \\ 0, & \text{if } i \neq k \end{cases}$$
(2.8)

Then, the transmitted signal can be formed as:

$$s(t) = \sum_{k=0}^{N-1} \sum_{l=-\infty}^{\infty} b_l[k] p(t-lT) \cdot e^{j2\pi f_{k'}}$$
(2.9)

Sampling at the rate of $T_s = T/N$

$$x[n] = \sum_{k=0}^{N-1} \sum_{l=-\infty}^{\infty} b_l[k] \prod_{N} [nT_s - lNT_s] \cdot e^{j2\pi k nT_s/(NT_s)}$$
(2.10)

$$x[n] = \sum_{k=0}^{N-1} \sum_{l=-\infty}^{\infty} b_l[k] \prod_{N} [n-lN] \cdot e^{j2\pi kn/NT}$$
(2.11)

$$\prod_{N} [n - lN] = \begin{cases} 1, & \text{for } (lN < n \le (l+1)N) \\ 0, & \text{otherwise} \end{cases}$$
(2.12)

The signal can be expressed as:

$$x[n] = \sum_{l=-\infty}^{\infty} \prod_{N} [n-lN] \cdot \sum_{k=0}^{N-l} b_{l}[k] e^{j2\pi k n T_{s}/(NT_{s})} (2.13)$$
$$x[n] = \sum_{l=-\infty}^{\infty} \prod_{N} [n-lN] \cdot IDFT(bl.n)$$
(2.14)

Where IDFT is the Inverse Discrete Fourier Transform. Mapping bits to be transferred is achieved using IDFT based on a mapping mechanism by either M-ary Quadrature Amplitude Modulation (M-QAM) or M-ary Phase Shift Keying (M-PSK). See Figure 2.9 below. For reliable feedback over the modified OFDM model, the PLC channel's state and BER calculation are estimated using pilot symbols' value per time known for the transmitter and receiver inserted into the transmitted data [75].



Figure 2.9. Mapping/De-mapping Scheme of 16-PSK and 16-AQM (source [3]) 26

2.3 Resource Allocation Techniques in OFDM

The successful expansion of ADSL services in the 1990s has sparked interest among scholars to investigate on allocation techniques in multicarrier technology [76]. In order to cater the need of high-speed wireline data transmissions, this technology thrives on a digital multitoned (DMT) modulation. DMT is type of frequency Multitone (FMT) technology comprising of a technique of a frequency-division-based transmission.

Since crosstalk occurs from the twisted pairs of adjacent copper, the ADSL carrier is typified via strong noise in form of fading frequency. The occurrence similar to what is faced in data transfer system of OFDM, which is sufficiently elastic in allocating the power and data rate on differing subchannel. With respect to OFDM, differing criteria for the allocation of the obtainable resources are possible but it relies on what the system seeks to achieve; maximization on total bit compare to power limitation or minimization of total allocated power for certain fixed bit or BER.

In relation to this, the water-Filling criterion [77] which is the optimal OFDM adaptation algorithm initially derived for DMT systems has to allocate data to the subcarriers with maximum SNRs. constellation size is dictated by the number of bits as detailed as:

- One bit represents a binary phase-shift keying (BPSK),
- Two bits represents quadrature phase-shift keying (QPSK),
- Four bits represents 16-quadrature amplitude modulation (16-QAM).

While some case, certain subchannels with low SNR probably stay unallocated in generating dependable transmission of data.

As demonstrated in several relevant state of art, effective bit allocation technique at the existing sub-channels and effective modulation model (to all subcarriers) consider bit allocation, as well as adaptive modulation. Within the system of OFDM, the allocated power $p_n \leq \overline{p_n}$ into n^{th} subchannel, at $\overline{p_n}$ as the extreme power limitation at subchannel *n*, bits amount b_n computed with the Shannon channel capacity formula can be employed, and this is demonstrated in [23]:

$$b_n = \left\lfloor \log_2 \left(1 + \frac{h_n + p_n}{(\xi + \Gamma) \cdot \sigma_w^2} \right) \right\rfloor$$
(2.15)

Here, $\lfloor . \rfloor$ represents the floor operator, amplitude is formed as h_n shows subcarrier n frequency form, σ_w^2 represents the power of noise at subchannel. While ξ represents the added noise tolerable by system in attaining the minimum sought after condition of BER [23], when level of noise amplifies by ξ , while Γ represents the difference of SNR (it called as well as normalized SNR) for evaluating the modulation scheme's performance of a as opposed to channel's capacity.

As such, when increase the amount of ξ the system's robustness will be improved facing the noise, and thus, the new constellations process $10\log_{10} (\xi + \Gamma)$ dB at the Shannon level. Numerous theoretical works have focused on the regulation of the transmit powers $\{p_n\}$ for the performance of the adaptive bit loading. Several revolutionary and familiar bit-loading algorithms for OFDM systems are highlighted below:

- Hughes-Hartogs in 1987 [78] introduced a greedy algorithm that could generate approximation of the water-Filling (see [77] as example) for twisted-pair cable over an additive white Gaussian noise (AWGN) channel with ISI. This is a discrete bit loading algorithm that is used for minimizing the transmit power under a BER and data rate constraints for all tones. This is done by allocating bits to carriers sequentially and every time, the carrier that needs the least incremental power is selected until target rate is attained. In [76], Bingham suggested the use of sin functions for every spectra rather than employing the quadrature amplitude shift keying (QASK) as demonstrated in [78]. The technique that [76] proposed enables the separation of signals at the receiver by way of the techniques of computationally efficient FFT. However, it the improved algorithm has high complexity burden. As such, it is not fitting real-time broadband wireless application.
- Kalet [79] highlighted the power allocation and modulation's fundamental of OFDM in 1989. The author simulated an OFDM using channel of twisted-pair cable. In this simulation, subchannel employs QAM for maximization of bit rate. For a given BER, the distribution of power among subchannels and optimized the bits amount at each symbol per subchannels. This demonstrates the similar outcomes achieved by the proposed power allocation to the water-Filling solution. In addition, the performance of QAM's multiuser is poorer than capacity of channel reach approximately to 9 dB, regardless reaction produced by the channel. As shown by the quantitative outcomes for a twisted pair cable, the performance of the multitoned QAM transmission

supersedes that of the single-tone QAM by more than 40%. Within the domain of frequency, the Kalet's algorithm is often termed WF. Compared to the technique that Cimini in [80] had proposed for mobile communication channels, this version is simpler.

- In [23] Chow et al. introduced an iterative bit loading algorithm. This algorithm appears to be better in comparison to the Hughes-Hartogs algorithm [78] and the water-Filling method [79, 80]. As shown by the authors, the outcomes of the simulation carried on ADSL channel attached to 10⁻⁷ of BER demonstrate 1.3 dB as regression with respect to signal noise rate as compare to [79]. The introduced technique has more speed in comparison to the Hughes-Hartogs. However, with respect to the number of iterations and computational load, it is not optimal. Meanwhile, the work of Czylwik [81] Based on the simulation results, the introduced subchannel modulation necessitates an overall consumption of power of 5 dB nonadoptive OFDM. The placement of a condition of BER of 10⁻³ different modulation formats can be chosen. Under a continuous constraint of data rate, this will minimize the BER.
- To minimize complexity of Hughes-Hartogs and Chow algorithms, a bit loading algorithm was introduced by Fischer and Huber in 1996 [82]. Using this algorithm, the authors distributed power and bits to achieve SNR over each carrier. In order to evaluate OFDM performance over broadband wireless by sending 100 Mb/s and 6 dB SNR, Van-der Perre et al. based on the simulation outcomes, the introduced modified bit allocation technique

considerably enhances the performance, with BER equal to 10^{-2} and constant modulations.

In reality, it is possible for a frequency-selective radio channel to seriously weaken the data symbols conveyed over a number of subcarriers, and this contributes to BERs. However, distributing the bits on the assigned frequency data carrier allows the system coded to rectify the error bits and in doing so, the diversity of wideband channel frequency is exploited.

In order to decrease computational complexity associated with the decoding, the work in [83] comprises the division of the subcarriers into several separate groups grounded on the criteria obtained in [84, 85]. This respectively decreases the multiuser interference and PAPR. The authors in [75, 86] also adopted the concept of grouping the subcarriers in smaller groups. The aim was to minimize the BER in a single-user and a multi-user scenario, correspondingly. However, problems relating to linear pre-coding methods remain the difference between the bit amount attained and the capacity of external area.

In OFDMA system, the bus station point should assign bit & power to diverse subchannel in an optimal manner, according to instantaneous channel settings of differing active wireless terminals. The one condition to be satisfied is that bit amount of fading is not rapid compare to OFDMA's symbol interval.

This is because when there are rapidly varying transmission channels of mobile terminals, the instantaneous resource allocation becomes unfeasible. There are also other deficiencies. These include interference management and restricted resources, such as transmit power and bandwidth. This causes the task of link adaptation to be much more challenging in comparison to that in single-user systems.

However, for OFDMA systems, this system is not the most important interest. This is because as the next subsection will be highlighting, in nearly all resource allotment models of OFDMA, each subchannel appointed for only a user. In other words, an efficient constructed technique for maximization of the total data rate also leads to the minimization of BER of each user.

The first strategy of resource allocation shown here comprises the minimization of the power expenditure of OFDMA system for a specified target data rate for the resolution of the problem of margin adaptive optimization as shown below:

$$\min_{p,N} \sum_{k=1}^{K} \sum_{n \in N_k} P_{kn} \qquad (2.16)$$

s.t $\sum_{n \in N_k} r_{kn} \ge r_k \quad \forall k \in K \quad (2.17)$
And $\sum_{n \in N_k} P_{kn} \le \overline{p_k} \quad \forall k \in K \quad (2.18)$
And $N_k \cap N_j = \emptyset \quad \forall K, j \in K \quad k \neq j, (2.19)$

Where $k \in K = [1,...,K]$ signifies the wireless terminal index that transmits with powers $p_k = [p_{k1},...,p_{kn},...,p_{kN}]$ over *N* subscribers denoted by the set N= [1, n, N], while $p = [p_1,...,p_k,...,p_K]$. Let $N_k \subset N$ be the set of subcarriers assigned to user *k*, while r_{kn} , be the capacity of channel attainable by user *k* over the *n*th subcarrier. As clearly indicated by Equation (2.19) the blocks of appointed subchannels are separate where each subchannel will be used by user only. While, a user k attempts to achieve its amount level r_k , as presented in Equation (2.17), at the condition of $\overline{p_k}$ on its overall assigned energy, as expressed in Equation (2.18). For every n does not belong to N_k and user k, clearly there is P_{kn} equal to 0, thus consequently, r_{kn} equal to zero. For each user, the entire bit amount is attained by the formula of Shannon shown below:

$$r_k = \sum_{n \in N_k} r_{kn} = \sum_{n \in N_k} \log_2 \left(1 + \frac{h_{kn} p_{kn}}{\sigma_w^2} \right)$$
 (2.20)

Referring to the above, h_{kn} signifies the of the Gaussian compound channel's amplitude gain that *k* experiences at subchannel *n*. While σ_w^2 entails the energy of the additive Gaussian noise zero and the noise exist at each subchannel. This design is also expandable for multiple input system multiple output OFDMA technique employing the approach that [51] has proposed.

2.3.1 Water-Filling Solution

The use of the Water-Filling in an uplink OFDMA network setting was introduced by Cheng and Verdú in [87]. In this work, power and capacity are formulated and derived for each user. While the optimization of bit rate and system's capacity are expressed in comes in Equation (2.20) in terms of Equation (2.21), exemplified by:

$$\max_{p,N} \left\{ \sum_{k=1}^{K} \sum_{n \in N_k} \log_2 \left(1 + \frac{h_{kn} p_{kn}}{\sigma_w^2} \right) \right\} \quad (2.21)$$

In the variables $\{p_k\}$, the objective function in Equation (2.21) is convex. Thus, the optimum power allocation under the constraints of convex of the whole transmit power is discoverable with Lagrangian methods [88]. The best strategy for fulfilling Equation (2.21), each subchannel *n* belongs to *N* is centrally allocated to biggest channel gain user. This can be referred below:

$$k \leftarrow \arg \max_{\ell \in K} h_{en}$$
 (2.22)

For user (*k*), resultant optimal energy allocation is formed as:

$$p_{kn} = \left[\frac{1}{\lambda_k} - \frac{\sigma_w^2}{h_{kn}}\right]^+ (2.23)$$

Where $[x]^+ = \max$ [89], and λ_k denotes the Lagrangian function for water rate selected where the assigned powers amount's summation fulfils overall power limitation $\overline{p_k}$:

$$\lambda_{k} = \left| N_{k} \right| \left(\frac{\overline{p_{k}}}{p_{k}} + \sum_{n \in Nk} \frac{\sigma_{w}^{2}}{h_{kn}} \right)^{-1} (2.24)$$

In short, the Water-Filling can be referred as a greedy (centralized) power allocation system. It causes the channel capacity to increase through allocating each subcarrier to the user with the optimal path gain, and via power distribution based on Equation (2.23). In essence, the Water-Filling solution is very unfair. This is because k gain optimal channel obtain satisfactory size, although those possessing severe medium situations such as those in far locations obtain very low data rates. In order to obtain systems of fair resource allocation, other techniques have been chosen. This can be referred in the next subsections.

2.3.2 Maximization and Minimum Fairness Criterion

With respect to the network of OFDMA; presents one conceivable approach for resolving the issue of unfairness associated [90] with water-Filling. The aim of this alternative formulation is to maximize rate of data across users. This enforces the conception of rate fairness of maximaization and minimization which prevents the occurrence of users starvation.

Definition 1:- Feasible rate vector $r = [r_1, ..., r_k, ..., r_k]$ is deemed as maximum and minimum fair in case of r_k is not increasable and no reduction at further rate r_j , $j \neq k$ which smalls than or equivalent to r_k .

In essence, within the maximum and minimum power monitoring, its optimization aim is the system's performance of the weakest path between all users in case of fixed QoS-based energy monitoring. The fair of max&min technique is underpinned by the notion of fair treatment to all users as much as possible, by enlarging all rates as much as possible. Rhee and Cioffi [90] extended the work of [91] which comprises twofold minimizing hurdle of assigned power amount at a certain capacity necessity.

That usually due to, the amount of assigned data amount could not match with any real time modulation system as shown in [92]. The results also demonstrate that under the solution of max–min fair, it is possible that certain users are using significantly more bandwidth in comparison to others [93], at the cost of a decrease in the total network throughput.

2.3.3 Weighted Fairness

The main goals are to keep power and data rate amounts efficiently which that contradict with one another. As such, the radio resource usage optimization has a tendency to penalize terminals with low SINRs, notwithstanding the performance of their traffic level. The mechanism of max–min fairness (see Section 2.3.2) is indeed unsuitable in a situation where users appear with various needs. Main issue is usually in the process of adjusting the allocated resources and achieving fairness.

Therefore, the authors in [94] introduced the idea of fairness through proportional weight objectivity. Grounded by a relative maximization amount limitation, where k's rate must follow prearranged relatively set of amounts, which manages the resource assignment process by the following:

$$r_1:\ldots:r_k:\ldots:r_k = \phi_1:\ldots:\phi_k:\ldots:\phi_k(2.25)$$

Here, $\{\phi_k\}$ represents the proportion constants; ϕ_k denotes total of *k* users per period. Finally, in return, *k* obtains an assigned bit amount r_k closed to ϕ_k .

Definition 2:- Bit factor $r = [r_1, ..., r_k]$ is fair proportionally when it has feasibility. Further, other practicable bit factor $r' = [r'_1, ..., r'_k]$, collective of relative variations is not positive, as shown below:

$$\sum_{k=1}^{K} \phi_k \, \frac{r'_k - r_k}{r_k} \le 0 \quad (2.26)$$

Here exists a key drawback with respect to the proportionally fair rate allocation, that is, there is a common assumption that utility (maximization) functions are typically concave. As stated by Lee et al. [95], using the algorithms created for concave utility functions on the non-concave utility functions will cause instability to the system and unwarranted crowding in the network. Considering that the rate adaptive functions of certain real-time applications are not concave, such as, multimedia communication, this type of systems is not feasible.

2.3.4 Utility Maximization

The max–min fairness and weighted proportional fairness take into account the exact QoS requirements among users of network with a strictly concave rate adaptive function. Within some systems such as multimedia applications, the rate maximization functions are not concave. In addition, in this situation, the formulation of real-time constraints, for instance, with respect to delay, is not possible.

In relation to that, Cao and Zegura [96], dealt with these drawbacks using the notion of utility maximization with respect to the performance of application-layer with the aim of offering individual QoS requirements for every user with a (not necessarily concave) function for rate maximization. Further, a utility function mathematically describes an application in terms of its QoS characteristics. The approach of utility maximization can assure demand that is application-specific characterized by bandwidth, delay, delay jitter, or time spent in the completion of data deliveries, etc.

Simply illustrated, using this framework enables more problems of general resource allocation creatable in diverse ways based on the system's goal. As example, a system of power control for optimal uplink SNR assignment is centrally expressible as follows:

$$\max_{p,N} \sum_{k=1}^{K} \sum_{n \in N_{k}} u_{k} (\gamma_{kn})$$
(2.27)
s.t
$$\sum_{n \in N_{k}} p_{kn} \leq \overline{p_{k}} \quad \forall k \in K$$

and $N_{k} \cap N_{j} \phi \quad \forall k, j \in K, \ k \neq j$

Where

$$\gamma_{kn} = \frac{h_{kn} p_{kn}}{\sigma_w^2} \tag{2.28}$$

Represents user k's SNR on the *n*th carrier (employed exclusively by user k) as assessed at the BS, while u_k (.) denotes user k's individual maximization function that comprises a function of relevant parameters of every user. In addition, the maximization function is representable as a greedy function for all users.

The works of [97-99] highlighted the energy efficiency maximization issue bound by constraints of power based on the expended circuit power. Meanwhile in [99], Xiong et al. constructed a joint uplink/downlink water-Filled energy efficient resource allocation under the constraints of users' priority. Meanwhile, the water-Filling based iterative algorithm that proposed shows faster convergence in comparison to that proposed by [98], whereas the spectral efficiency of the algorithm that proposed by [99].

Briefly, it can consider that the approach of utility maximization has made process in handling the issues of heterogeneous resource allocation. Nonetheless, it also shows significant limitations. There appears tradeoff between average throughput and fairness in the system and at times, conflict between the QoS balance and the utility maximization can be detected. Should users choose utility functions according to their real QoS requirements, then the optimal obtained data rate may lead to completely imbalanced resource allocation inside the network.

2.3.5 Cross Layer Optimization

Numerous joint scheduling-routing-flow control algorithms have been proposed in the design of cross-layer. These include the techniques of multiuser which include: maximization of the rate transported on the radio channel [100], a fair resource distribution amongst users in the same class of traffic [101], construction of the dynamics of traffic sources via the limitation of the data packets delay in the queues [102], and the QoS maximization at the application layer [103].

From time to time, the dissimilarity between the systems of cross-layer and utility maximization becomes insignificant because systems of cross-layer may necessitate performance improvement through the application of a non-concave utility function. This utility function may contain parameters from diverse layers. The systems of cross-layer are usually underpinned by the idea of proper maintenance of packet queues to dynamically acclimatize the packet transmission alongside the rate allocation. Several works in the resource allocation domain in OFDMA as in [104-106] employed the cross-layer design.

A more wide-ranging framework of cross-layer OFDMA resource allocation can be seen in the work of Jiang et al. in [107] employing [108, 109] as special cases (highlighted in Section 4.4). Several feasible solutions for the maximization of the throughput for the downlink of an OFDMA system under the constraints of QoS can be referred in [110-112].

The proposed method also decreases the complexity of computation, with the method of Lagrangian relaxation [88]. This method is effective in offering users with very low SINRs with sound performance. Somehow, in the situation where channel conditions and the QoS requirements considerably vary between succeeding frames, it is important that a new set of Lagrangian multipliers is uncovered in each frame. This may show impracticability of the method.

2.3.6 Resource Allocation Based Game Theory

In the systems of utility maximization and cross-layer, differing users require different utility functions. Occasionally the interests of wireless terminals are misaligned in order that they fight for the wireless resources that are scarce which are power and bandwidth. The interest of every user could also contradict with that of other users. If this happens, the wireless terminals can opt to behave altruistically or selfishly.

In both situations, the associated problems are expressible using the theory of Game [113] that regards users as players in a game. In an OFDMA network particularly, multiple interacting users fill a fraction of the entire bandwidth, employing a portion of their accessible transmit power on each subcarrier according to their decisions and the interests of any other mobile terminal within the network. Such interactions type is just the game theory's primary field of application; it signifies an effective

analytical tool for expanding the methods of optimization illustrated and addressed the Pareto optimality issue.

In the problems of resource allocation, achieving a Pareto-optimal rate vector, that is rate allocation, is among the key challenges. Here, each user is given certain performance, and allocation that is other than that will cause the performance to degrade at least for one user in the network. Pareto-optimal solutions are examinable by game-theoretic formulations.

Dictated by the rules of interaction, there are many types of games in game theory. As example, if users could exchange their proper interests and information prior to the game for forming coalitions and coordinating their actions, the game is regarded as cooperative (such game is explored by the theory of cooperative game). If there is no coordination among users, the game is regarded as non-cooperative, and is constructed based on the non-cooperative Game theory.

In these two frameworks, the actions of the players are dictated by their strategies. During the game, the player's strategy can be of a single move or a set of moves. For wireless communications' games, every transmitter symbolizes a player whose space of strategy comprises the selections of modulation level, rate of coding, transmit power, frequency of transmission and so forth. The frequency of user interaction is one more factor that recognizes different game types. A game that is played over multiple rounds is called a repeated game. Games in which users interact only once are called static games [114].

2.3.7 Non-cooperative Solutions

The application of non-cooperative game theory is common for resolving the problems of wireless communication. In relation to this, there has been progress on distributed power control in Gaussian interference channels. Wu et al. in [115] looked into the system of joint power and (exclusive) subcarrier assignment in the systems of single-cell uplink OFDMA grounded on non-cooperative game theory.

In their work, the authors employed the sum-capacity as the utility function for maximization. This game has a distinct Nash equilibrium (NE). NE is a steady game outcome; it is a stable resource apportionment across users where no player is inclined to unilaterally. Meanwhile, Yu et al. [115] used another convex utility function to the similar scenario. The authors' aim was to maximize the network's power efficiency. Within the utility function, [116] proposed a (transmit) power pricing factor for overcoming the near-far effect, reaching a (nearly) Pareto-optimal NE point. A small number of users have experimentally demonstrated the fairness of both approaches [115, 117].

The work of Kwon and Lee in [118] attempted to maximize the users' weighted sum-rate within the uplink of a multicellular OFDMA scenario. Alongside the power and rate constraints, the objectives define the non-cooperative game. As demonstrated by the results of the simulation, the performance of the proposed algorithm is stringently dictated by the coefficient of power pricing, which denotes the cost levied on every BS for the co-channel interference that it produces and also that its power consumption generates.

The authors in [119] constructed a non-cooperative potential game. The aim was to maximize the energy efficiency of users. As shown, the method generated sounder performance with respect to good put (error-free delivery) for every energy unit. The similar purpose is achieved in [120] using the procedure of centralized subcarrier allocation and a distributed non-cooperative power control game.

The simulation generated a realistic multicarrier network scenario which demonstrates that the algorithm proposed attains a satisfactory performance and computational complexity problem. Non-cooperative game theory also has sufficient flexibility to scrutinize resource allocation problems for situation that differs from that of the phase of data detection; this has been frequently addressed in the literature. Bacci et al. [121] for instance, formulated a non-cooperative game for regulating the transmit powers in an uplink of OFDMA during the starting of contention-based network association.

2.3.8 Cooperative Solutions

Methods that employ many heuristics grounded on cooperative game theory [114] have recently been proposed. The purpose was to address the issue of fair resource allocation for OFDMA systems by way of either centralized or distributed algorithms. In relation to this, the Nash Bargaining Solution (NBS) appears to be [113] the most sophisticated technique employed on wireless resource allocation problems in the network of OFDMA. The NBS shows the presence and distinctiveness of an NE point of the convex utility function as shown below:

$$\max_{p,N} \prod_{k=1}^{k} \left(r_k - \underline{r}_k \right) \quad (2.29)$$

s.t
$$r_k = \sum_{n \in Nk} r_{kn} \ge \underline{r}_k \quad \forall k \in K$$

and $\sum_{n \in Nk} pkn \le \overline{p}k \quad \forall k \in K$
and $N_k \cap N_j = \phi \quad \forall k, \ j \in K, \ k \neq j$

As such, the goal is for the maximization of the output of the transmitters' rates' excesses over their own minimum demands r_k . With NBS, each user is guaranteed to accomplish its own demand. This offers an individual rationality to the allocation of resource. Importantly, using NBS generates Pareto optimal as the final rate allocation vector. With strictly concave increasing parameters of the logarithm function in consideration, Equation (2.29) can be changed into the following:

$$\max_{p, N} \sum_{k=1}^{K} \log_2(r_k - \underline{r}_k)$$
 (2.30)

Note that $\underline{r}_k = 0$ reduces the NBS fairness system to the weighted proportional one, with $\phi_k = 1$ [122].

Chee et al. in [123] introduced a centralized algorithm for the downlink scenario of OFDMA according to Resource Blocks. The outcomes demonstrate a sound performance only when there is a very big gap between the maximum and the minimum rate. Although the subcarriers are completely assigned, this algorithm's computational complexity of $O(KN+K^2)$.

The authors obtained a coalition-based algorithm [114] to give each terminal precisely the sought after rate. This will fulfil the demand of both wireless terminals and the network service provider. As demonstrated by the numerical results, the computational complexity of the proposed centralized algorithm is lower than *K.N.*

Thus, to the best of the researcher's knowledge, this represents the cheapest one found in the literature.

2.4 Resource Allocation Techniques in Powerline Network

There has been rapid growth in various powerline networks in recent years, along with the demand for Smart Housing applications, channel model standards and modulation schemes. In order to provide better service to meet QoS requirements, much research has been carried out in the field of QoS in PLC networks.

Considering the development of PLC systems, its resource utilizing efficiency must be improved effectively with the users' QoS requirements ensuring by applying the robust and efficient allocation techniques. In resource allocation models, power and margin are correlative; if two of them are restricted, the third one will be optimized, which produces the three types of optimization problems - maximization of rate, minimization of power and maximization of margin [124].

Among the said three types of issues, the minimization of power is equivalent to the maximization of margin so the optimal resource allocation falls into two types of optimization problems, namely, the Rate Adaptive (RA) optimization and Power Adaptive (PA) optimization [125].

The proposal of authors in [20], resource allocation problem with peak BER constraint has been investigated for PLC then introduced a new proportional fairness resource allocation algorithm. It showed better performances than classical

proportional fairness algorithm. However, it does not precisely guaranteed performance at several users to achieve the targeted bit rate.

While the study of [43], has introduced optimal multilayer, multiobjective resource allocation model for multiuser, multiserver OFDM based systems with the various restrictions. Bit loading lookup table algorithm was designed to decrease the greedy algorithm's complexity. However, its solution exists only if the requested target rates can be supported, that is, the requested user rates cannot be set too high.

In [126] Propose resource allocation algorithm based on the Linear precoding technique to increase the multicast OFDM systems bit rate. The conventional multicast capacity is limited by the user that experiences the worst channel conditions. Simulations are run over powerline and it is shown that the proposed solutions offer a bit rate gain up to 37% compared to the conventional multicast bit rate.

Resource allocation and scheduling schemes based on utility theory in a multiuser OFDM home PLC network was investigated in [19]. The proposed cross-layer scheme consists of two phases: subcarrier allocation at the physical (PHY) layer and scheduling scheme at the medium access control (MAC) layer. Simulation results demonstrate that the proposed scheme can greatly improve system performance based on satisfying the QoS requirements of delay-sensitive services.

Sheng-qing et al. [127] introduced an OFDM modulation scheme based on the narrowband PLC channel of a low power network. The developed model showed that the rate of transferring data over a narrowband PLC network improved using

OFDM. Noreen and Baig [128] introduced an adaptive bit allocation in Discrete Multi-tone (DMT) based on an indoor power line network. The result showed an increase in the data rate using the proposed incremental bit allocation scheme.

A study on the coded OFDM-based power line channel was proposed by M. Bogdanovic [70]. The PLC channel was generated using a simulation environment based on a transmission line model. This work showed that the PLC network had a burst error channel; whereas, the evaluations carried out several scenarios based on coder/decoder, Reed-Solomon and different modulation schemes. The modulated processes were 4-QAM and 8-QAM without coder, 4-QAM with Reed-Solomon (15, 11) and (15, 9), and 8-QAM (63, 47).

Shongwe et al. [129] addressed a narrowband PLC interference model in the presence of using the OFDM modulation scheme. This model gave information about the noise probability rate, which could affect the data stream. In the same context of using a modified OFDM-based PLC, the work of Ur Rehman et al. [130] introduced a demonstration model to evaluate the feasibility of utilizing the Multiband-OFDM Ultra-Wideband over a PLC network by using a model of a couple of signal circuit converters.

OFDM is the most decisive mechanism in burst error channels, such as power line networks. Therefore, PLC needs an adaptive digital modulation scheme to achieve the required transmission throughput. The modification can be achieved by changing one of several modulation factors which are Bit/Power allocation rate, Constellation size, BER constraint and Channel coding scheme or any combination, according to Chung and Goldsmith [131]. Liu et al. [27] designed an Unequal Bit Error Rate (UBER) algorithm-based modified power allocation scheme and uniform bit allocation system in OFDM in order to minimize the transmitted power and control the BER limit. Table 2.3 summarized some of techniques used for resource allocation system in PLC technology.

#	Approach	Application	Outcome	Rate Adaptive (RA) & Margin Adaptive (MA)	Drawbacks
1.	Proportional Fairness Maiga et al, (2009)	PLC based linear precoded OFDM (LP- OFDM)	A peak BER constraint method combined with linear precoding technique offers better performances	MA	lack of subcarrier pairing criterion
2.	Multiobjective Optimization Zhiqiang et al, (2010)	OFDM- based PLC systems	optimal multilayer, multiobjective resource allocation model for multiuser, multiserver OFDM-based PLC systems with the various restrictions	RA MA	High complexity
3.	Linear precoding Maiga et al, (2009)	PLC based multicast OFDM	Bit rate gain up to 37% compared to conventional multicast resource allocation method	RA	Run with limited bit amount per symbols
4.	Utility theory Cross-layer scheme Dong, Ouzzif, Saoudi (2010)	Multiuser OFDM home PLC network	A cross-layer joint resource allocation and scheduling scheme for indoor PLC networks	RA MA	Optimal rate may lead to imbalanced resource allocation inside the network
5.	Water-Filling Zhou He, Mingyue Zhai (2010)	PLC	Bit and power allocation model with power self adaptation and speed rate self adaptation	RA MA	Solution is very unfair

Table 2.3 Resource Allocation Techniques in PLC Technology

6.	greedy approach	PLC	New robust algorithms for	MA	Conflict between
	Nhan Vo, Amis,		the problem of achievable		the QoS balance
	Chonavel (2014)		throughput maximization		and the utility
			in PLC systems		maximization can
					be detected

Recently, various approaches are introduced (Table 2.3) as efficient recource allocators based on several QoS contraints and objectives. Therefore, in order to improve the effectiveness of resource allocations schemes in PLC systems, efforts are needed to reduce the following difficulties:

- In case of Max-Min approach, network capacity does not meet users's need. As well as decrease in the total network throughput.
- In case Proportional Fairness, it stills in lack of quality fairness assurance with hostile PLC frequency channel changeable over time.
- While in case of Multiuser Margin Adoptive, it limits the amount of bit rate at each users which means no fully exploit network bandwidth.
- Many techniques introduced considered on BER as QoS requirement.
- On the other hand some are not applicable and do not function in case of shortage resources.
- The existing techniques do not perform the resource allocation, in a realistic manner and in the presence of implusive noise.
- In essence, the Water-Filling solution is very unfair. This is because k gain optimal channel obtain satisfactory size.

- Weighted Fairness, causes instability to the system and unwarranted crowding in the network.
- Utility Maximization, conflicts between the QoS balances.

2.5 Shuffled Frog-Leap Optimization Algorithm

Various powerful evolutionary optimization algorithms have been designed to handle various complex engineering problems such as Genetic algorithm (GA), Memetic algorithm (MA), Simulated annealing (SA), Ant colony optimization (ACO), Particle swarm optimization (PSO), Shuffled frog leaping algorithm (SFLA) [132], and Artificial Bee Colony (ABC).

The SFLA is one of a number of nature inspired algorithms based on the swarm intelligence [133]. Because of its characteristics which that firstly, a simple concept, reduced parameters, powerful optimal performance, fast calculation speed, and easy realization, it has been applied in many fields including model identification problems, scheduling problems, parameter optimization problems, and the traveling salesman problem [36].

In other words, SFLA is characterized by simple process and construction as well as simple realizing and a smaller amount of parameters compare to most of Water-Filling, max-min fairness, utility max, cross-layer, cooperative and non-corporative algorithms [134]. Moreover, it has the advantages of being easy to implement and having fast speed and global optimization capability and has been widely used in many areas. Additionally, high precision and fast restraint speed [135].

Consequently, SFLA is developed based on four key parameters: the number of memeplexes (m), the number of frogs in each memeplex (n), the number of frogs in population (p), the number of evolution or iterations between two consecutive shuffling (s), and the number of maximum iteration (N).

The population of frogs is shown as:

$$X = \{x_1, x_2, \ldots, x_p\}, (2.31)$$

In addition, the frog *i* is presented as:

$$x_i = \{x_i^1, x_i^2, \dots, x \le i^h\}, \quad (2.32)$$

Where h indicates the number of decision variables (parameters) in a frog (solution). To handle multi-objective optimization problems with several conflicting objectives which have to be considered simultaneously, the main objective function should be defined as follows [136]:

$$(\min, \max) F = [f_1(x), f_2(x), \dots, f_k(x)]^T \quad (2.33)$$

While quality constraint gi(x) and inequality constraint hi(x) are satisfied:

$$g_i(x) < 0$$
 $i = 1, 2, ..., N_1$
 $h_i(x) = 0, i = 1, 2, ..., N_2$

Where k shows the number of objective functions, $f_i(x)$ is *i*th objective function, and



 N_1 and N_2 are the number of equality and inequality constraints respectively.

Figure 2.10. Shuffled Frog-Leap Algorithm

In the main, the steps of SFLA are given in Figure 2.10 explained below as follows:

- 1. Initialize a random population of *p* solution (frogs).
- Calculate the fitness function (position) for each frog (solution's fitness value).
- 3. Sort the frogs based on their fitness values (in descending order).
- 4. Partition the population into *m* groups (memeplexes) as follows: allocate the frogs to the groups according to the fitness values. The first frog with the highest value moves to the first group, the second highest frog moves to the second group, the *m*th highest frog moves to the last group. Then, *m* plus the first frog moves to the first group again. These operations continue until the last frog is allocated to a group. Finally, each group contains *n* frogs, thus, $p = n \times m$.
- 5. For each group (memeplex), the following steps:
 - 5.1. Select the frogs with the worst position x_w and best position x_b .
 - 5.2. For a predefined number of times (*s*), improve the worst position by the following steps:
 - 5.2.1. Perform a local search for each group (memeplex) using the following equation:

$$x_i = x_i + r(x_b - x_w)$$
 $i = 1, 2, ..., m, (2.34)$

- Where x_i indicates a new position in the next iteration and r is a random number between 0 and 1.
- 5.2.2. If $x_i > x_i$, then go to step 5.2.7.
- 5.2.3. Select the global best frog position x_g .
- 5.2.4. Apply global search using the following equation:

$$\dot{x_i} = x_i + r(x_g - x_w)$$
 (2.35)

5.2.5. If $x_i > x_i$, then go to step 5.2.7.

- 5.2.6. Generate a new frog x_i randomly.
- 5.2.7. Replace frog x_i with x_i
- 6. Shuffle all the memeplexes.
- Check the termination criteria. If it has happened, then stop; else, continue from step 2.

The termination criteria for the algorithm could be satisfied by one of the following three conditions:

- 1. The value of the main objective function F reaches an acceptable and optimum value.
- 2. The number of iterations gains to a predefined value (*N*); it varies for different number of dimensions in a problem.
- 3. During several consecutive iterations, no progress could be seen in the value of the main objective function *F*.

After predefined number of developmental steps, the solutions for developed groups are replaced into new population. The process is known as shuffling process. These steps are repeated until and unless the required criterion for global maxima is obtained. In short: this analogy of Shuffled Frog-Leap Algorithm is this:

• Each frog represents a possible solution which means a combination set of power amount allocation for all users.

• Frog leaping gives us a specific combination of user allocated power maximized system capacity.

The control parameters in SFLA have to be initialized for optimization. These parameters are the total number of frogs or population size (p), number of memeplexes (m), number of frogs in each memeplex (n), and maximum number of evolution or iteration (N). In Table 2.4, review various literatures about Shuffled Frog-Leap Algorithm and its applications as well as a comparision provided in term of convergence, rate, processing, time, and performance.

#	SFLA & Modified SFLA	Converg -ence rate	Processin g time	Generally Performanc e	Application	Modified Part	Remark
1.	Eusuff and Lansey (2003) [132]	N/A	SFLA > GA, SA	SFLA > GA, SA	Water Distribution Network Optimization Problems	Shuffle Frog (slow convergence)	p = 510, m = 30, n = 17 N = 100
2.	Eusuff and et al (2006) [137]	SFLA > GA	SFLA > GA	SFLA > GA	Water Distribution Network Optimization Problems	Frog Position (worst frog is always omitted)	p= N/A, 100 < m < 150, 30 < n < 100 N = N/A
3.	Elbeltagi et al. (2007) [138]	N/A	MSFLA > SFLA, GA	N/A	Project Scheduling Problem	Local Search (Increased search time)	p = 200,m = 20, n = 10, N = N/A
4.	Vahed and Mirzaei (2007) [139]	HSFLA > MOGA	HSFLA < MOGA	HSFLA > MOGA	Assembly Line Sequencing Problem	Use exist SFLA	p = 15, m = 5, n = 3, N = N/A
5.	Rahimi- Vahed et al. (2009) [140]	N/A	N/A	HSFLA > NSGA-II, SPEA-II	Flexible Job/Flow Shop Scheduling Problem	Search Process (low solution quality) extra critera &	p = 200, m = 4, n = 50, N = 500

Table 2.4 Shuffled Frog-Leaping Algorithm Applications and Comparison

6.	Shayanfar et al. (2010) [141]	MSFLA > SFLA, PSO	N/A	MSFLA > SFLA, PSO	Electrical Power System Optimization	Frog Position (Trapped, Premature Convergenc)	p = N/A, m = N/A, $n =$ N/A N = N/A
7.	Li et al. (2010) [142]	N/A	N/A	MSFLA > NGSA-II, SPEA-II, Dynamic Programmin g	Reservoir Flood Control Problem	Use exist SFLA	p = 200, m = 20, $n = 10, N$ = N/A
8.	Teekeng and Thamman o (2011) [143]	N/A	N/A	N/A	Flexible Job/Flow Shop Scheduling Problem	Selection Frog (falls to achieve near optimal solution)	p = 50, m = 5, n = 10, N = 100
9.	Li and Wang (2011) [144]	MSFLA > SFLA, PSO, GA	MSFLA > SFLA, PSO, GA	N/A	Traveling Salesman	Extend Step- Leaping (Increased Optimization Criteria, trap)	p = 100, m = 5, n = 20, N = N/A
10.	Pu et al. (2011) [145]	MSFLA > SFLA, PSO	MSFLA > SFLA, PSO	MSFLA > SFLA, PSO	Autonomous Flight Control Optimization	Use exist SFLA	p = 20, m = 4, n = 5, N = 30
11.	Chittineni et al. (2011) [146]	MSFLA > SFLA	N/A	MSFLA > SFLA	Classification Problems	Combine SFLA with Clonal Selection Algorithm (Premature Convergence)	p = 20, m = 5, n = 4, N = N/A
12.	Wang et al. (2011) [147]	MSFLA > PSO	N/A	MSFLA > PSO	No_Idle Permutation Flow Shop Scheduling Problems	Local Search using Roulette Wheel Operator (No suboptimal best frog)	p = 100, m = 20, $n = 5, N = N/A$
13.	Niknam et al. (2011) [148]	MSFLA > GA, PSO, SFLA	MSFLA > GA, PSO, SFLA	MSFLA > GA, PSO, SFLA	Feeder Reconfiguratio n Problem in Distribution Networks	Combine Self- Adaptive Optimization with SFLA (Trapped Local Search for optimal frog and reduce convergence speed)	p = 10, m = 10, $n = 1, N =$ 100
14.	Niknam et al. (2011) [149]	N/A	N/A	MSFLA > PSO_HBMO , PSO-ACO,	Feeder Reconfiguratio n Problem in Distribution Networks	Evaluation Part (generate optimal solution from only small population size)	= N/A, <i>m</i> = N/A, <i>n</i> = N/A, <i>N</i> = N/A
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15.	Malekpour et al. (2012) [150]	N/A	N/A	N/A	Volt/Var Control Of Distribution System	Evaluation Part (Waek of determination of worst frog position)	p = N/A, m = N/A, $n =$ N/A, N = N/A
16.	Banati and Mehta (2012) [151]	MA > GA; PSO > MA; SFLA > PSO	N/A	SFLA > PSO, MA, GA	N/A	Use exist SFLA	p = N/A, m = N/A, $n =$ N/A N = N/A
17.	Tavakolan and Ashuri (2012) [152]	SFLA > GA, PSO, ACO	SFLA > GA, PSO, ACO	SFLA > GA, PSO, ACO	Time-Cost Trade-Off Construction Management	Use exist SFLA	p = N/A, m = N/A, $n =$ N/A N = N/A
18.	Yammani et al. (2012) [153]	N/A	N/A	SFLA > GA	Optimization of Placement in Distribution Network	Local Search (unable to identify best optimal in memeplex)	p = 32, m = 4, $n = 8$ N = 100
19.	Li et al. (2012b) [154]	N/A	N/A	MSFLA > GA, PSO-SA, GA, MATSLO, PSO-TS, MOGA, KBACO	Flexible Job Shop Scheduling Problems	Leaping part & Local Exploration (added extra optimization objectives, reduce convergence)	p = 100, m = 20, n = 5, N = N/A
20.	Shirvani et al. (2012a) [155]	N/A	N/A	N/A	Optimization of PID Power System Stabilizer	Use exist SFLA	p = N/A, m = N/A, n = N/A, N = N/A
21.	Kimiyagha lam (2012) [156]	MSFLA > SFLA, GA	N/A	N/A	Detection of Fault Location in Distribution Networks	Population Division And Evaluation (inefficient velocity)	p = N/A, m = N/A, n = N/A, N = N/A
22.	Gomez- Gonzalez (2013)	N/A	N/A	N/A	Optimization of Parameters of Induction	Local Search (complicated process reduce	p = 60, m = 10, $n = 6, N$ = 50

	[157]				Machines	convergence)	
23.	Srinivasa Reddy and Vaisakh (2013) [158]	N/A	HSFLA > GA, PSO, TS	N/A	Large Scale Non-Convex Economic Dispatch Problem	Optimal Solution Selection (Small Population and Iteration Number)	p = 200, m = 20, $n = 10, N$ = 300
24.	Fallah- Mehdipour 2014 et al [159]	SFLA > SA, GA	SFLA > GA	SFLA > SA, GA	Finance-Based Scheduling	Use exist SFLA, Combine SFLA with a differential mutation operator (exand search range)	P = 500, m =10, $n =$ N/A, N = 50
25.	Zhou Jie, et al 2015 [160]	MCC- SFLA > GA, Quantum Evolutio nary Algorith m (QEA)	MCC- SFLA > QEA	MCC-SFLA > GA, (QEA)	PAPR Reduction in OFDM System	Combine SLAF with Clonal Selection (complicated modification by extra criteria)	$p = \{F_1 F_2 \cdot \cdot F_M \}$ $m \in [1,M],$ $n = 40$ $N = 10$
26.	Hu Bin, et al 2016 [36]	SFLA > MA PSO, GA	SFLA > GA	SFLA > GA, PSO	Optimized High Dimensional Biomedical Data	Convergence Criteria (early premature Convergence and less optimal option accuracy)	P = N/A, n = N/A m = N/A N = 50
27.	Mahmoudi , Orouji, and Fallah- Mehdipour 2016 [161]	SFLA > GP	N/A	SFLA > GP	Prediction of Water Quality Parameters	Use exist SFLA, combine SFLA with Support vector Regression	p = N/A $m = 50$ $n = 20$ $N = 50$
28.	Kaur, Parmeet, and Shikha Mehta. 2017 [162]	SFLA > GA, ACO, PSO	SFLA > PSO	SFLA > GA, ACO, PSO	Provisioning and Resource Availability in Scientific Workflow Applications	Frog Improvement Part (SFLA Resource Provisioning and Workflow Scheduling) Incorporation in process of best and worst frog and memeplex integeration	p = 100 m = 4 n = 50 N = 250

Generally, local search, evaluation, and shuffled phases in SFLA and MSFLA required most modifications as shown in Figure 2.11. For example, the worst frog's position never jumps over the best frog's position. This limitation decreases the convergence speed, causes premature convergence and reduces local search space in each memeplex and convergence probability. Most of the review papers showed weakness were they suffer from the problem of being trapped in local optima.



Figure 2.11. Modification Sections in SFLA

In addition, the basic SFLA tries to balance between a deep and wide exploration of the search space that are close to a local optima [163]. It is clear that if the worst and best frog's positions are close to each other, the change of leaping is also small. Thus, it causes to being trapped in the local optimum, and premature convergence reported by several researchers such as [138] is a concern in basic SFLA.

In this section, modified SFLA proposed by previous researchers are considered separately. In addition, the goal of the modifications and their compensation are highlighted. Additionally, the results of comparisons between the proposed MSFL with other evolutionary algorithms on different features are located in Table 2.4. Shayanfar et al. (2010) [141] utilized a modified SFLA to enhance local search. The modified SFLA presented in that paper applied a new equation for updating the worst frog's position.

The researchers [143] have considered one more step into their proposed modified SFLA. By this step, for each memeplex, a number of frogs (usually with higher fitness values) are chosen to make a sub-memeplex, which performs the local exploration independently. Submemeplex could improve the convergence rate and processing times.

To overcome to premature convergence in SFLA, Elbeltagi [138] and Xu et al [163] proposed a new equation by applying a new factor named 'search-acceleration'. The factor as a positive constant value, linear, or nonlinear function of time, could balance local and global local exploration by considering the global exploration fundamentals and search extremely in the region of feasible solutions. However, both metgods are failed with introducing optimal solution.

To overcome the limitations of basic SFLA in the evolution phase and improving the memetic evolution process, it was recommended by Li and Wang [144] to utilize local and global best information for frog leaping and transfer them between individual frogs. To increase the optimization accuracy with minimum iteration number, Roy [164] proposed a MSFLA by using GA crossover operation in local and global search. This MSFLA was applied to solve minimum spanning tree problems.

Malekpour et al [150] and Niknam et al [165] proposed a new solution to find the position of the selected frog. They applied a Chatoic Local Search to create a new solution if the quality of the new frogs was not improved compared to the worst frog.

Furthermore, Niknam et al [149] employed a new mutation for reducing computational time, raising solutions' quality, as well as avoiding being trapped in the local optima. Moreover, Niknam et al [166] used a novel MSFLA by modifying frog leaping rule in SFLA and Tribe-MSFLA was employed to prevent the prematurity. Each memeplex is considered as a tribe in Tribe-MSFLA.

To improve the global searching capability of SFLA, Pu et al [145] employed a new MSFLA. The algorithm was proposed by modifying the division method of SFLA to balance the performance of memeplexes, and by using a new frog leaping rule and to give more chance for the best frog to be evolved. The results in that paper showed that the MSFLA is better than the basic SFLA and PSO algorithm.

To enhance the effectiveness of basic SFLA, Chittineni et al [146] applied a new MSFLA by employing the local best value of each memeplex rather than creating a

new frog. To initialize a population with high quality, search exploitation and the exploitation capability, [154, 167] developed an MSFLA.

An effective MSFLA was proposed by Wang et al [147] to improve the capability of exploitation, to solve multimode resource-constraint project scheduling problems. Population in the proposed algorithm was generated by multimode forward–backward improvement as well as a simplified two-point crossover using traditional binary encoded GA.

Consequently, Li et al [142] applied an MSFLA to solve multi-objective optimization problems. The offered algorithm applied a self-adaptive niche technique (a storing technique) to handle non-dominated solutions. Li et al [154] resented an HSFLA by modifying the frog-leaping rule and employing a hill climbing local search called extremal optimization (EO). EO has a high local search capability and could improve the effectiveness of basic SFLA in optimization.

Srinivasa Reddy and Vaisakh [158] employed differential evolution algorithm in HSFLA. In the proposed hybrid algorithm, all the solutions in each memeplex could take part in the evolution. As well, using memetic evolution process in differential evolution algorithm and a novel mutation could enhance the local and global search ability, respectively.

The victorious modifications are motivated from the theory noted by most of the researchers that SFLA needs a wide local search space at former iterations to avoid premature convergence and a narrow search space to speed up convergence rate at the next iterations.

One strategy for modifying the mutation in basic SFLA is considering a new factor in the following Equation (2.36) as explained in [138, 163, 168]:

$$x_i = x_i + r \times (x_b - x_w)$$
 $i = 1, 2, ..., m, (2.36)$

This constant factor presents the searching scale for frog-leaping step and should be assigned to a large value. Thus, the new frog-leaping equation is as follows:

$$x_i = x_i + r \times c \times (x_b - x_w), \quad (2.37)$$

Where *r* indicates a random number between 0 < r < c while 1 < c < 2. Additionally, employing one more factor in Equation (2.37) as an inertia weight could regulate the search operation and enhance local exploration. This factor is assigned to a large value at first (at the initializing phase) and is reduced regularly to find more sophisticated solutions [167, 169, 170], the new frog-leaping formula is as follows:

$$x_{i} = x_{i} + w + r \times c \times (x_{b} - x_{w}), \quad (2.38)$$

Where *r* indicates a random number between -1 and 1, also $w_{min} < w < w_{max}$, in which w_{min} and w_{max} define the minimum and maximum permitted perception, respectively. This perception weight is linearly decreased during the algorithm run. Applying the strategy of self-adaptive PSO as a local exploration and integrating the information from local searches in parallel could increase the accuracy and convergence rate [149].

Variable neighborhood descent could be utilized to raise the diversification and frogs' quality in memeplexes individually [171]. While, employing the concept of AFSA into SFLA during global information exchange and local deep search could

enhance the convergent rate and local and global exploration as well as accuracy [172].

Although using sub-memeplex recommended by some researchers enhance local exploration, it could not improve global exploration. Modifying the process of leaping frog's position in each memeplex could reduce the processing time of the optimization.

Using a heuristic or initialization rules to distinguish better situation for a solution could initialize a population with high quality and high diversification. It produces an individual or frog, while all other solutions are produced accidentally to improve the population's diversity [173].

Based on the experimental result, the performance of the SFLA is significantly enhanced by utilizing novel modification or hybridization. Nowadays, many researchers have proposed MSFLA and HSFLA on various problems. In addition, based on the literature review and as HSFL could bring the best out of basic SFLA and other evolutionary algorithms, HSFL could outperform the other algorithms in solving complex and continuous problem.

Moreover, the proposed SFLAs by previous researchers were evaluated to find their most common and valuable improvements. It is clear that there has not been enough effort to enhance the processing time and the accuracy of the result. In summary, the SFLA is a comprehensive meta-heuristic optimization algorithm and could be extended to various optimization problems.

Fallah-Mehdipour at el [159] used the SFLA to solve two large benchmark financebased problems with 120 and 210 activities, respectively. SA and SFLA employing the approaches of the repaired and penalized solutions. In addition, the performance of the SFLA was compared against two common meta-heuristic algorithms, GA and SA.

While authors [36] have improved SFLA by a new chaos memory weight factor, an absolute balance group strategy and an adaptive transfer factor. This approach explored the space of possible subsets to obtain the set of features that maximizes the predictive accuracy and minimizes irrelevant features in high-dimensional biomedical data.

The performance of the shuffled frog-leaping algorithm has extensively investigated by using large number of experimental studies in [174]. They have shown, first, that each of the three discrete SFLAs obtained good quality of solutions by utilizing both the local search procedure based on swarm intelligence and the competitiveness mixing of information of the genetic based memetic algorithms.

In [162], a new Augmented SFLA based on the meta-heuristic optimization technique, SFLA has been presented for Resource Provisioning and Work flow Scheduling in Clouds. Comparison performance with SFLA and PSO has been conducted and the experimental analysis shows that the former outperforms the other algorithms in reducing the overall execution cost of the considered workflows.

For the first time, SFLA was integrated by Support Vector Regression (SVR) model to optimize SVR model's parameters by [161]. The performance of SFLA-SVR method was investigated with respect to Genetic Programming (GP) as a capable method in water quality prediction that has been reported in former presented research. Based on obtained findings, the SFLA-SVR method resulted in less values of RMSE relative to GP, in the both training and testing data sets.

A grouped SFLA for solving continuous optimization problems combined with the excellent characteristics of cloud model transformation between qualitative and quantitative research introduced by [135]. The algorithm divides the definition domain into several groups and gives each group a set of frogs. However, the proposed integrated algorithms is complex.

Qali and Hasanien [175] has presented a multi-objective design optimization of the transverse flux linear motor with an inner mover using the SFLA. The optimization target is to reduce the transverse flux linear motor weight while maximizing its thrust force as well as minimizing its detent force. The effectiveness of the s SFLA model is compared with that of the GA and PSO models.

A novel modified chaos clonal SFLA for partial transmit sequence selection in OFDM systems introduced by Zhou at el [160] The proposed algorithm is analyzed using Markov chain theory and prove that the algorithm converges to the global optimum compare to GA and quantum evolutionary algorithm.

Robustness is the main advantage of memetic algorithms relative to traditional resolution methods of optimization problems. In other words, we can see the four major differences between the two methods:

- 1. Memetic algorithms work with a coding of the set of parameters, while the classical methods use directly the parameters.
- 2. The solution given by memetic is a set of points (frogs) and the solution for a classical methods is a single point.
- Memetic uses the objective function and the standards methods often use derivatives of function or other auxiliary knowledge.
- 4. It uses probabilistic transition rules when the traditional methods use deterministic rules.

The principle of memetics is based on the evolution of an initial population under the effect of operators such as selection, mutation and crossover. At the end of the memetics' process, the best individual in the population will be the solution of the optimization problem.

Based on the obtained results in [176], SFLAs compared to its competitor the evolutionary genetic algorithm is of a high convergence speed, with more consistency and more appropriate feature selection ability. The most unique characteristic of the SFLA is its ability in searching the locality which leads to better performance.

2.6 Research Gap

The current trends of research attempting to further increase the performance efficiency, similar techniques for OFDM still represent a hot topic of research. Many optimization methods have been proposed in the literature, focusing on power, subcarrier, and bit and allocation approaches, using the margin and the rate adaptive mechanisims. The latter optimization problem has received most attention, appearing to be the most appealing one from both the centralized and the distributed point of view, and many practical solutions have been proposed in the last two decades. Important issues such as fairness, algorithmic complexity, scalability, convergence have also been included into the loop.

Thus, to achieve targeted transmission rate over a data network several optimization techniques, have been recently adopted. Nevertheless, many drawbacks that limit the application of state-of-the-art algorithms to practical contexts still hold, mainly due to the high computational complexity, fairness, convergence and the weak scalability, that often make real-time solutions intractable problems, as they also require a considerable amount of feedback information across the network users. Thus, this research has focused on the proposal of an adaptive power, subcarrier and bit allocation OFDM-based powerline channel.

2.7 Chapter Summary

This chapter presented recapitulates of PLC technology, noise models, and its channel function. Data modulation techniques and error correction, channel coding/decoding, and channel modelling techniques were also discussed. As well as resource allocation techniques and presented open issues in this active research domain. Resource allocation models in powerline technology and the SFLA are explained. Finally, the most related literature and the research gap were presented.

CHAPTER THREE RESEARCH METHODOLOGY

This chapter establishes the research methodology through critique, design, implementation, and evaluation approaches. Data network transmission rates and QoS can be achieved using three methods, namely, analytical modelling, experimental testbed and simulation environment. Additionally, simulation tools, performance metrics, resource allocation and powerline channels are explained in this chapter.

3.1 Research Methodology

The specific methodology for this research was selected based on several factors: A methodology should be suitable to fulfilling the objectives of a study and produce a valid result. Lastly, it simplifies the method stages, from the problem statement to the analysis. Currently, validation and verification of real-time powerline applications such as a smart house system over power lines has been done by experimentation and measurements on specific platforms to adjust design parameters with the hope of achieving QoS.

The main purpose of experimental research methodology relies on its mastering and accuracy, description, and assessment or explanation of the studied issues. Therefore, the research methodology in this study is based on analytical modelling and analysis through MATLAB software. Moreover. It comprises four sequential phases to achieve the objectives and solve the problem as shown in Figure 3.1.



Figure 3.1. Research Methodology (source [177])

3.1.1 Critique Phase

The process of exploring the answers to questions in a very organized and systematic way, in which result of that process is knowledge, information and data related to any covered phenomena is called research [177]. Thus, a proper investigation places such a library or Internet database are used to conduct a literature research for materials of an OFDM system and powerline technology that currently have been done and a high consideration was given to resource allocation in OFDM modulation techniques that form the basis of this study.

The process of review and critique of data modulation techniques are archived in the first phase. Once the problem has been recognized clearly along with the factors that affect it, the next stage of this phase is concerned with exploring the current efforts of other researchers. Based on the strengths and weaknesses of the previous studies, this stage ends with the preferred conceptual properties and potential enhancement of them.

3.1.2 Design Phase

In this phase, three main issues are investigated. These include the transition from the concept of theory into mathematic form, moving to analytical models of the modulation technique based on powerline channel, which is utilized in the development of a system. In broadband telecommunication systems, such as ADSL, wireless and broadband over PLC networks, the most widely applied signal modulation method is OFDM for its effectiveness of reducing ISI and ICI, which are caused by multi-path fading channels, and its strength in coping with channel transfer attenuation. Therefore, this study proposed adaptive power, subcarrier, and bit allocation based power line channel.

3.1.3 Implementation Phase

The output of this stage is a set of data for the sake of performance evaluation. This phase is used to implement the proposed resource allocation models based on a hostile channel. The very early state of this phase is to develop the codes for the whole system, which are generated from flowchart and algorithms. Moreover, the network scenarios and their related justification are elaborated. Adding, validation, and verification of the enhanced designed algorithms are stated. The MATLAB tool is used to construct the entire system including the proposed techniques. The general outcome that derives from this software is imitating real life situation; thus, the results can be realistic. The objectives of the simulation are: to verify the proposed models and techniques in simulation environment, to validate the designed system, and to evaluate the proposed system.

3.1.4 Evaluation Phase

The fourth phase is performed to measure the success of the proposed system in meeting its performance goals. This phase shows the performance evaluation and analysis of the channel model in terms of number of users versus capacity, and normalized capacity ratios per user versus the normalized rate proportion, and the bits versus the amount of allocated power per user. The goal of this phase is accomplished through a performance comparison conducted between the proposed techniques and the latest ones. Finally, detailed information about the research overall result such as the research problem, research steps, results and evaluation are documented. In addition, this section highlights the necessary discussions for each objective followed by conclusions and need for future work.

3.2 Network Evaluation Techniques

Evaluating data network transmission rates and QoS can be achieved using three methods, namely, analytical modelling, experimental test-bed and the simulation environment [178]. Figure 3.2 shows three main techniques that can be used to evaluate network performance. The result of the evaluation is assigned for a set of network performance indices given a traffic workload and network configuration.



Figure 3.2. Network Performance Evaluation Techniques

3.2.1 Analytical Modelling

Researchers use analytical modelling for investigation and description behaviors of real situation problems, mathematically, through designing, fixing, and validating a model. This method is quite difficult in a complex system and is preferred in only a simple system. Using this method is preferred within a simple system as a tremendous number of assumptions and simplification are required in a complex system [179]. In the case of modelling the resource allocation algorithm, analytical and numerical analysis are carried out. The proposed techniques are simply described by algorithm notation and flowchart, pseudocode, and diagrams.

3.2.2 Measurement

Evaluation of a communication network performance can be carried out using the measurement approach through a testbed or a real design of a network. Actually, an experimental test-bed analysis produces an accurate result and is realistic. Thus, in developing and designing a system, many experiments are run for the proposed technology model to validate and ensure the protocols and QoS. However, it consumes more time for the device installation, money for tester devices and instruments and effort for observing over a long time [180].

3.2.3 Simulation

Evaluating a data communication system by mimicking its behavior in a simulation environment using a simulator tool is a common approach particularly for a proposed system or real situations to show them in an understandable way. Using a simulation tool gives an opportunity to represent a complex network structure and its characteristics in a simple method [179, 181].

Therefore, the MATLAB simulation tool environment was used for designing and simulating the proposed resource allocation techniques in OFDM system and then analyzed its performance in terms of the number of users versus capacity, and normalized capacity ratios per user versus normalized rate proportion, and bits versus amount of allocated power per user. Table 3.1 shows the comparison of communication system evaluation approaches [182].

Criteria	Simulation	Measurement	Analytical
			Modelling
Time Required	Medium	Various	Small
Cost	Medium	High	Small
Accuracy	Moderate	High	Small
Trade-off	Moderate	Difficult	Easy
Tools	Software	Instrumentation	Math functions and
			Equations

Table 3.1 Comparison of Communication System Evaluation Approaches

3.3 Simulation Tool

Simulation tools help to validate and verify developed projects and models. For this thesis, MATLAB R2016 was used to develop a simulation model for the proposed power and bit allocation techniques. Additionally, it was used to design the existing resource allocation techniques with an OFDM system hostile powerline channel to assess and compare the performance of the proposed system.

Many advantages have been brought by that simulation tool compared to traditional language, such as C and FORTRAN, in solving technical problems based on array elements [183]. Most studies conducted on PLC technology have used MATLAB tool for system construction and evaluation and scholars and research organisations recognize the tool.

3.4 Performance Metrics

The number of users versus channel capacity throughput, and normalized capacity ratio per user versus normalized rate proportion, and bits versus amount of allocated power per user were the parameters were used to evaluate the proposed OFDM system. In addition, Bit Error Rate (BER), Signal to Noise Ratio (SNR), Energy per Bit to the Spectral Noise Density (E_b/N_o), and Sub-Channel Index (n) were considered in the simulation.

- Overall Channel Capacity: Channel capacity is the tight upper bound of the rate at which information can be reliably transmitted over a communications channel. By the noisy-channel coding theorem, the channel capacity of a given channel is limits the information rate (in units of information per unit time) that can be achieved with an arbitrarily small error probability.
- Normalized channel capacity ratio: Normalization may cause confusion regarding what the percentage is related to. Channel utilization, channel efficiency and packet drop rate in percentage are less ambiguous terms. The channel efficiency, also known as bandwidth utilization efficiency, is the percentage of the net bit rate (in bit/s) of a digital communication channel attached goes to the actually achieved throughput. For example, if the throughput is 70 Mbit/s in a 100 Mbit/s Ethernet connection, the channel efficiency is 70%.
- **Power and Bit Amount (Allocation):** Bit and power allocation are carried out sequentially to reduce the complexity, and an optimal power allocation procedure is derived, through which proportional fairness is achieved.

- Frequency Response: This is the quantitative unit of the output spectrum of a device or system in response to a stimulus. In other words, it describes an output signal's spectrum divided by an input signal's spectrum.
- **Bit Error Rate (BER):** It is the number of bit errors divided by the total number of transferred bits during a studied time interval and often expressed as a percentage.
- Number of Users & Subcarriers: The spectrum band in OFDM-based PLC is divided into N subcarrier, denoted by N = {1,2,..., N}, with a bandwidth represented by Δf.
- **Convergence:** It is an improvement indicator of system performance-based memetic algorithms. Research has indicated that the algorithms are converged without an essential improvement in the population's fitness value.

3.5 Resource Allocation

In this study, adaptive resource allocation models are proposed based on the Shuffled Frog-Leaping Algorithm (SFLA). Generally, in adaptive OFDM, several key factors could be modified to enhance its performance over data hostile channels, such as BER feedback, power subject to each set of bits, the channel coding approach and the allocated data rate per sub-channels. Modifying one or more of these factors helps to improve OFDM performance with a provision of Channel State Information (CSI) [67].

Despite the advantages brought by OFDM, in some hostile channels it faces a high BER possibility [8]. In state-of-the-art literature, the proposed power and bit allocation schemes are classified in two groups, namely, Rate Adaptive (RA) and Margin Adaptive (MA) approaches. RA for example in [20, 70, 71, 100], is aimed at maximizing the bit rate in each sub-channel with respect to the allocated BER constraint and power. Whilst MA, for example in [19, 67], is aimed at minimizing the transmitted power in each sub-channel based on the constraints of the BER.

This study introduced a modified SFLA as a resources allocator, some of its essential benefits are based on code parameters compared to other techniques. As well as, the proposed solutions are based on a group of point, which are the so-called frogs in the technique of frog-leaping. In addition, it is based on probabilistic evolution instructions while the conventional techniques are applied deterministic instructions.

Reasons for the utilization of SFLA is its outstanding robustness compared to the state-of-the-art resolution optimization techniques. SFLA is based parametric model, while the classical methods use called parameters. Additionally, its solution(s) increases the reliability of system scalability, where a classical technique introduces a single solution. Moreover, models of objective functions simplify the complexity and reduce the convergence.

3.6 Powerline Channel Model

Power line is very difficult and noisy communications environment characterized by several unpredictable and strong types of noise and interferences. Several channel models are investigated such as a multi-conductor transmission line channel transfer channel as presented by [184]. Another study [185] has introduced the PLC channel over an LV power line network using a frequency domain method in the 9-490 KHz frequency band.

A PLC channel using the ABCD matrix of a 2PN model was introduced by [186]; the result showed that the channel amplitude and magnitude formed deep notches over different distances and frequencies. Tonello et al.[187] addressed a PLC channel model that generated its values randomly from experimental measurement results.

An analytical approach combined with Multi-Carrier Direct Sequence Code Division Multiple Access (MC-DS-CDMA) was introduced for modelling a PLC channel in the work of Rahman and Majumder [188]. A CTF model of an aircraft lighting system over LV cables was proposed in Degardin et al. [189] based on a multiconductor transmission approach. PLC has a narrow band <450 KHz and wideband/broadband ~MHz, based on various PLC channel models introduced by a noise characterization model such as [34, 190-192].

To analyze the proposed resource allocations based on a hostile channel, background noise (w_k) is modelled as an AWGN with mean zero and variance σ_w^2 as investigated in [193-195]. Impulsive noise (i_k) modelled as Poisson-Gaussian noise offers a simple and efficient representation of a power line channel and has been utilized in several studies such as [193, 196]. According to the Poisson-Gaussian model, impulsive noise is given by the following:

$$i_k = b_k \times g_k \tag{3.1}$$

where:

b_k: Arrival Impulses;

 g_k : Amplitudes of Impulses;

 $2\sigma^2$: Mean equal to zero.

The arrival of impulses (b_k) considered with respect to the Pisson process while (g_k) is a white Gaussian process representing the amplitudes of the impulses with the variance as $(2\sigma^2)$ and mean equal to zero, the total noise is:

$$n_k = w_k + i_k \tag{3.2}$$

$$n_k = +w_k + b_k \times g_k \tag{3.3}$$

where w_k is a type of White Gaussian noise. The occurrence of the impulsive noise has approximately a Poisson distribution, which means the arrival of the impulsive noise follows the Poisson process with a rate of λ units per second, so that the event of *k* arrivals in *t* seconds has the prob- ability distribution given as:

$$p_k(t) = e - \lambda t (-\lambda t) k/k \qquad (3.4)$$

In the end, the transmitted signal can be represented by:

$$r_k = a_k + n_k \tag{3.5}$$

Where signal a_k is transmitted over power lines impaired by impulsive noise, the mathematical model involved in PLC related to noise characteristics is formulated as follows:

$$r_{k} = \frac{1}{\sqrt{M}} \sum_{m=0}^{M-1} a_{m} e^{\frac{j2\pi m_{k}}{M}} + W_{k} + i_{k} \qquad k + 0, 1, 2, 3, \dots, M - 1$$
(3.6)

Where:

M: Corresponds to the number of subcarriers; a_m : is the digital modulation model of Binary Phase-shift keying (BPSK) symbol (+1,-1); i_k : is impulsive noise added to the modulation; w_k : is a form of Additive white Gaussian Noise; r_k : is the total amount of the transmitted signals; and p_k : is the subchannel power for each user.

3.7 Chapter Summary

In this chapter, the research methodology was explained through a review of stateof-art literature, design, implementation, and evaluation phases. It was important to explain the network evaluation techniques for determining the exact research method that was appropriate to achieve the study's objectives. Additionally, an explanation about the powerline channel was introduced. Finally, mathematical models of the proposed resource allocation techniques were explained.

CHAPTER FOUR EFFICIENT POWER ALLOCATION TECHNIQUE

This chapter introduced the proposed power allocation technique based on the Shuffled Frog-Leaping Algorithm (SFLA) and the modified SFLA based Teacher Learner technique. The transmission channel is a noisy wideband power line, which was built in system development. Additionality, the improved results of the adaptive technique are explained followed by the proposed modified shuffled frog-leaping algorithm. Finally, the improvement of the system performance is introduced by several results and figures.

4.1 Allocation System Model

Multiusers of OFDM system with *M* users experience different channel gains [197] are as formulated in Equation (3.6). If there are occurrences of individual fading in subcarriers the user *u* in subcarriers *n* has the channel gain $c_{u,n}$ and noise $\sigma^2 = S_0 * B/S$.

Where:

S: is defined as the noise power spectrum generated by i^{th} path; and

 S_0 : is the noise power spectral density and Bhz is the bandwidth divided into *n* orthogonal subcarrier by Bhz/n.

Therefore, the best channel gain is thus denoted as $h_{u,n} = c_{u,n}^2 / \sigma^2$ and the u^{th} is user's received SNR on subcarrier *n* which is represented as $g_{u,n} = p_{u,n}h_{u,n}$ [19, 43, 126] where $p_{u,n}$ is the optimized power amount distribution and belongs to $0 \not \vdash_{u,n}$. The transmitter is informed with the estimated channel capacity through a dedicated feedback channel as investigated in [198] where resource allocation algorithms employ these channel estimates. Additionally, SNR is adjusted to reach the required level of BER, while the BER of a square Modulation Quadrature Amplitude Modulation (M-QAM) with Gray Bit Mapping as a function of received SNR $g_{u,n}$ while the number of bits $b_{u,n}$ can be approximated to within 1dB for $b_{u,n} \ge 4$ and BER $\le 10^{-3}$ as explained (4.1) in [131]:

$$\operatorname{BER}_{\operatorname{MQAM}}\left(\tau_{u,n}\right) \approx 0.2 \, \exp\left[\frac{-1.6g_{u,n}}{2^{b_{u,n}}-1}\right] \qquad (4.2)$$

By solving $b_{u,n}$:

$$\mathbf{b}_{u,n} = \log_2\left(1 + \frac{\mathbf{g}_{u,n}}{\mathbf{r}}\right) = \log_2(1 + \mathbf{p}_{u,n}h_{u,n}) \quad (4.3)$$

Where r = -1n(5 BER)/1.6 is a constant SNR gap, and $H_{u,n} = h_{u,n} / r \frac{H_{u,n} \triangleq h_{u,n}/r}{\text{is}}$ the effective subchannel SNR.

The proposed allocation technique purposes to solve the following maximum data optimization issue with least complexity specified target BER and power supply over every subchannel. Bits are allocated equally among subcarriers in the process of resource allocation; the problem can be summarized by the following:

Maximise
$$R_{u,n} \sum_{u=1}^{U} \sum_{n=1}^{S} R_{u,n} \log_2(1 + p_{u,n} h_{u,n})$$
 (4.4)

While the constraints are:

CONST1:
$$\mathbf{R}_{u,n} \in \{0,1\} \forall u, n$$

CONST2:
$$p_{u,n} \in \{0,1\} \forall u, n$$
CONST3: $\sum_{u=1}^{U} R_{u,n} = 1 \forall n$ CONST4: $\sum_{u=1}^{U} \sum_{n=1}^{S} R_{u,n} p_{u,n} \leq P_{tot}$ CONST5: $\Gamma_i : \Gamma_j = \Phi_i : \Phi_j, \forall i, j \in \{1, 2, ..., U\}, i \neq j$

 $R_{u,n}$ is the amount of bit rate allocated at each subcarrier equal to 1 only in a condition when subcarrier *n* is assigned to user *u*, and P_{tot} is the constraint for broadcasting power. The total data rate for user *u* in constraint CONST5 is formulated as follows:

$$\Gamma_{u} = \sum_{n=1}^{S} R_{u,n} b_{u,n} = \sum_{n=1}^{S} R_{u,n} \log_{2} (1 + p_{u,n} h_{u,n}) \quad (4.5)$$

 $\phi_1: \phi_2: \ldots: \phi_U$ are the normalized proportionality constants where:

With constraints CONST1 and CONST2 in Equation (4.4) the correct values for the subcarrier allocation marker and the power are guaranteed. The constraint CONST3 makes sure that each subcarrier can only be assigned to one user, and constraints CONST4 and CONST5 are the power and proportional rate constraints respectively.

The non-linear problems are not tractable with the polynomial time algorithms. These non-deterministic polynomial problems [199] as represented in Equation (4.4) need to be illuminated. The author of [200] explains that the resources that are allocated after the amount of power consumed by each user should be estimated along with calculating the amount of subcarriers. These subcarriers are assigned to each user.

The subcarriers are allocated in repetitive cycles where each user gets a turn to select the most suitable subcarrier. The user with minimum proportional capacity is allowed first to select the most suitable subcarriers. The subcarriers estimation process simplifies the study's problem in Equation (4.4), thus maximizing the continuous variables is as:

Maximize
$$R = \sum_{u=1}^{U} \sum_{n \in \Omega_u} \log_2(1 + p_{u,n} h_{u,n})$$
 (4.6)

CONST1: $p_{u,n} \ge 0, 1 \forall u, n$

CONST2:
$$\sum_{u=1}^{U} \sum_{n \in \mathcal{Q}_{u}} p_{u,n} \leq Pow_{tot}$$

CONST3:
$$\Gamma_i : \Gamma_j = \Phi_i : \Phi_j, \forall i, j \in \{1, 2, \dots, U\}, i \neq j$$

Where \emptyset refers to the set of subcarriers assigned to user *u*, $b_{u,n}$ is as defined in Equation (4.3) while:

$$\Gamma_{\rm u} = \frac{\rm B}{\rm S} \sum_{\rm n \in \phi_{\rm u}}^{\rm S} b_{\rm u,n} \qquad (4.7)$$

Where Γ_u is the total data rate for user *u* while *B/S* represents spectral efficiency of modulation, its average data rate per unit bandwidth.

The set of total power assigned for each user u, denoted as Pow_u for $1 \le u \le U$, can be solved using Lagrangian multiplier technique [89] as:

$$\frac{1}{\Phi_{1}}\frac{S_{1}}{S}\left(\log_{2}\left(1+H_{1,1}\frac{Pow_{1}-V_{1}}{S_{1}}\right)+\log_{2}W_{1}\right)=\frac{1}{\Phi_{u}}\frac{S_{u}}{S}\left(\log_{2}\left(1+H_{u,1}\frac{Pow_{u}-V_{u}}{S_{u}}\right)+\log_{2}W_{u}\right)$$
(4.8)

For u = 1, 2,....U, where:

$$V_{u} = \sum_{n=2}^{S_{u}} \frac{H_{u,n} - H_{u,1}}{H_{u,n} H_{u,1}}$$
(4.9)

In addition:

$$W_{u} = \left(\prod_{n=2}^{S_{u}} \frac{H_{u,n}}{H_{u,l}}\right)^{\frac{1}{S_{u}}}$$
(4.10)

While S_u is the number of subcarriers assigned to user u. Note that the effective sub channel SNR's $H_{u,n}$ is assumed to be arranged in ascending order. Adding the total power constraint:

$$\sum_{u=1}^{U} Pow_{u} = Pow_{tot}$$
(4.11)

Thus, U nonlinear equations with U unknowns $\{Pow_u\}_{u=1}^{U}$ are obtained. To solve these equations, previous studies used the Newton-Raphson method and its variants [201-203]. These algorithms are highly complex and nonlinear, and, therefore, they are not viable for real-time environments.

Another approach [204] simplifies nonlinear equations into one variable assuming that SNR for subchannels is high. This approximation assumes $V_u = \text{zero}$ and $H_{u,1} pow_u / S_u >> 1$, then the result of nonlinear equation is:

$$\sum_{u=1}^{U} R_{u} (Pow_{1})^{d_{u}} - Pow_{total} = 0$$
 (4.12)

Where:

$$R_{u} = \begin{cases} 1 & \text{if } u = 1 \\ \frac{S_{u}}{H_{u,n} W_{u}} \left(\frac{H_{1} W_{1}}{S_{1}}\right)^{\frac{S_{1 \oplus u}}{S_{u \oplus 1}}} & \text{if } u = 2, 3, \dots, U \end{cases}$$
(4.13)

and:

$$\mathbf{d}_{u} = \begin{cases} 1 & \text{if } u = 1 \\ \frac{\mathbf{S}_{1\Phi_{u}}}{\mathbf{S}_{u\Phi_{1}}} & \text{if } u = 2, 3, \dots, U \end{cases}$$
(4.14)

These nonlinear require methods that are iterative and need less computation for resource allocation problems. Therefore, mathematical models represent the proposed techniques that has been aimed to minimize the transmit power rate per subchannel, which was given a specific target data and BER rate constraints in OFDM subchannels.

Improving of BER system keeps subchannels working at less of an error rate and in an efficient way. Therefore, this section explains four steps of the proposed subcarrier, power, and bit rate allocation model:

- 1. Find the number of subcarrier S_u for every user using [205] method;
- Assign subcarriers to each user based on maximum gain calculated using [206] method;

- Use the Shuffled Frog-Leaping Algorithm (SFLA) [137] to determine power (Pow) for users as explained in next section to maximize system capacity and;
- 4. Allocate the powers $\rho_{u,n}$ for subcarriers assigned to each user based on the total power via a waterfilling algorithm as several works have done [207, 208].

4.1.1 Number of Bit and Subcarriers per User

The first step of the proposed scheme determines the number of users in a linear state as follows:

$$S_1 : S_2 : \dots : S_U = \phi_1 : \phi_2 : \dots : \phi_U$$
 (4.15)

The equation is an assumption which utilizes the concept that the ratio of subcarriers is approximately equal to the proportion of power allocation. It simplifies how the resources are allocated in OFDM systems. Then, set the number of users to 16 for current implementation. This number can be varied, and the results show substantial and consistent improvement. This assumption is represented as $S_u = [\emptyset_u S]$.

The second step allocates the subcarrier S_u where the overall capacity sustaining the inclusive power then the users are sorted in decreasing order of S_u . Each user is allocated a subcarrier that matches its best channel state info to the subcarriers in repetitive cycles.

While the bits are allocated to each users' *K* of *N* subcarriers not shared by different users, the nth subcarrier of user *k* has power ρ (k) where *n* is $1 \le n \le N$ and $1 \le k \le K$. The bits are modulated and coded into the OFDM symbol *x* using IFFT function. When all the users have been assigned the estimated number of subcarriers, the remaining subcarriers are assigned to those users that have best channel status for these subcarriers. Thus, optimization is achieved in channel capacity as explained in the following three steps [209]:

(a) Load

$$R_{u,n} = 0, \ \forall_u \in \{1, \dots, U\} \text{ and } \forall_n \in \{1, \dots, S\}$$
 (4.16)
 $\Gamma_u = 0, \ \forall_u \in \{1, \dots, U\}$

Where the allocated power amount at each subcarrier is:

$$p = Pow_{tot} / S^2, N = \{1, 2, \dots, S\}$$

(b) Assignment

Assign unallocated subcarriers to users with maximum gain for u = 1 to U, then sort H_u in ascending order as follows:

$$n = \arg \max_{n \in \mathbb{N}} |H_{u,n}| \qquad (4.17)$$

$$R_{u,n} = 1, S_u = S_u - 1, N = N \setminus \{n\}$$

$$\Gamma_{u} = \Gamma_{u} + \frac{B}{S} \log_2(1 + pH_{u,n})$$

(c) Greedy Approach

Where:

$$||N|| > S^*, K = \{1, 2, ..., U\}$$
 (4.18)

$$u = arg \min_{u \in K} \Gamma_u / \varphi_u$$

$$n = \arg \max_{n \in \mathbb{N}} |H_{u,n}|, \text{ if } S_u > 0, R_{u,n} = 1$$

$$S_u = S_u - 1, \quad N = N \setminus \{n\}$$

$$\Gamma_{u} = \Gamma_{u} + \frac{B}{S}\log_{2}\left(1 + pH_{u,n}\right)$$

Else:

 $\mathbf{K} = K \setminus \{n\}$

(**d**) $K = \{1, 2, ..., U\}$

for
$$n = 1$$
 to S^*
 $U = \arg \max_{u \in K} |H_{u,n}|,$
 $R_{u,n} = 1$
 $\Gamma_u = \Gamma_u + \frac{B}{S} \log_2 (1 + pH_{u,n}), \quad K = K \setminus \{n\}$

The first step of the algorithm defines all the variables wherein each user's capacity is maintained by Γ_u . The subcarriers that are not allocated yet are denoted as *N*.

In the second step, these unallocated subcarriers are assigned to each user given that they have the maximum gain for that user. This assigns advantage to the users that prefer the optimum subcarrier with maximum gain.

While the third step involves greedy policy, where subcarriers are assigned based on a user's needs. The subcarriers that are not used are assigned to the optimum users in the last step. As the user can get maximum one assigned subcarrier, it is made sure that the user with best gains is not assigned to all of the remaining subcarriers, thus bringing proportional balance in the channel.

4.1.2 Power per Subcarrier

In step 3 the total power Pow_u for each user has been achieved, and this will be useful in performing waterfilling across the subcarrier for each user as introduced in [210, 211] as follows:

$$Pow_{u,n} = Pow_{u,1} + \frac{H_{u,n} - H_{u,1}}{H_{u,n}H_{u,1}}$$
(4.19)
$$Pow_{u} = \frac{Pow_{u} - V_{u}}{S_{u}}$$

4.1.3 SFLA for Power per User

This study has exploited the Shuffled Frog-Leaping Algorithm (SFLA), which [137] introduced for maximizing the capacity of channel transmission by assigning optimizing the total power consumed by each user in OFDM system. SFLA is never been proposed for that purpose as a power and bit allocator.

Generally, SFLA starts with a population 'P' that defines possible solutions, and these solutions are defined by a group of virtual frog(n) in each group. These subjects (frogs) are arranged according to their fitness function from high order to lower, and the portioning continues. Frogs are expressed as Xi = (Xi1, Xi2, ..., Xis), where S denotes the number of variables.

In each group, the frogs that have the best and worst fitness functions are filtered as X_w and X_b . The frog with overall best fitness function is known as X_g . The following equation can increase the fitness function of the frog represented by X_b with: $D_i = rand (X_b - X_w)$, $X_{newW} = X_{oldW} + D_i (-D_{max} \le D_i \le D_{max})$. Random number varies between 0 to1, and D_i is the leaping step size of *i*th frog and D_{max} is the maximum step possible in location of frog.

For example, when population size is F = 16, and memeplex number m = 4, the number of frogs in each memeplex is n = 4, the maximum search range $s_r = 6$, the maximum reference number in each memeplex $r_n = 2$, and the population P are sorted in descending order, frogs 1, 2, 3, and 4 are assigned to memeplexes 1, 2, 3, and 4, respectively.

Second, each memeplex selects one frog from the remaining frogs of the P_t , and then copies this selected frog into this memeplex. For this memeplex, the selected frog has the maximum diversity to the reference frogs among the P_t . Only one frog (frog 1) exists in memeplex 1 in this step; therefore, frog 7 is selected and moved to memeplex 1 because the diversity between frogs 1 and 7 is the largest among the P_t . Similarly, frogs 5, 6, and 10 are assigned to memeplexes 2, 3, and 4, respectively.
In steps 3 and 4, the same operations are repeated to separate the remaining frogs into the memeplexes. Two reference frogs ($r_n=2$) should be considered to calculate the diversity in each memeplex for these two steps. At the end, all the frogs are assigned to the memeplexes, while the diversity of the frogs in each memeplex has been ensured, and the local searches that follow this allocation in each memeplex have higher efficiency to evolve.

4.2 Implementation of Simulation

The power allocation scheme at each subcarrier is based on the SFLA alongside bit and subcarrier techniques. The problem of allocation is expressed as an integer programming problem. Thus, the codes simulate the performance of the proposed technique in OFDM, which allocates power to subcarrier in an improved way to reach the required data rate. Figure 4.1 provides the diagram of the allocation and channel orthogonality system.



Figure 4.1. OFDM System Block Diagram for Multiusers.

Several Matlab files are combined and written for constructing and evaluating the new proposed model based OFDM. *Main_Pallo* is the main script file, which was built to initialize the parameters required and to run the entire system by calling

various codes. The source input was for 1000000 bits, which can be less or more. A storage channel file (*chfile.mat*) is generated while running the simulation. Table 4.1 contains the main parameters involved in the simulation.

Parameters	Value
Worst power	0.01: 1.1565 mW
Population size (p)	6
No. of memeplexes (m)	4
No. of frogs in each memeplex (n_f)	16402
No. of evaluation or iteration (N _i)	5
N_0	worstpower*1e-8
Total power	1mW
BER	1e ⁻³
SNR Gap	-log(5*BER)/1.6
SNR	38dB
No. of Channel	10
No. of Sample	10
No. of user	2, 4, 8, 16 etc
No. of subcarrier (N)	8, 16, 32, 64 etc
Subcarrier modulation	BPSK
OFDM symbol	(+1,-1)µs
Frequency band (MHz)	2–30
Sub-channel frequency	41-89 Hz

Table 4.1 Simulation Parameters

The new proposed power resource allocation system is constructed based on four main processes:

- 1. Find the number of subcarrier N_k for every user.
- 2. Subcarriers are assigned to each user based on maximum gain calculated.

A) Initialization:

Set $R_k = 0$, for k=1, 2, K and A = {1, 2, ..., N}

B) for *k*=1 to *K*:

Find *n* satisfying $|H_{k,n}| \ge |H_{k,n}|$

Let $\Omega_k = \Omega_k U\{n\}$, A=A-{n} and update R_k

While:

Find *k* satisfying $R_k / \gamma_k \leq R_i / \gamma_i$

 $i, 1, \leq i \leq k$

For the found *k*, find *n* satisfying $|H_{k,n}| \ge |H_{k,i}|$ for all $i \in A$

For the found k and n, let

$$\Omega_k = \Omega_{k,u}\{n\}, A = A - \{n\}$$

3. Use SFLA to allocate set of powers (*Pow*) for users, it designed to improve metaheuristic in order solve discrete and/or combinatorial optimization problems. Implementation steps are summarized as follows [137]:

Initialize: choose m & n, where m is the number of memeplexes and n is the number of frogs in each memeplex. Therefore, the total sample size F in the swamp is given by F = mn.

Rank frogs: Sort the *F* frogs in order of decreasing decision variable value *U*. Store them in an array as follows:

 $X = \{U_i | F_i\}$ where the index i = 1, ..., F (4.20)

So that i = 1 represents the frog with the best performance value.

Partition frogs into memeplexes: Partition array *X* into *m* memeplexes Y^{l}, Y^{2} , ..., Y^{m} , each containing *n* frogs, such that:

$$Y^{k} = [U_{j}^{k}, f_{j}^{k} | U_{j}^{k} = U (k + m (j - 1)); f_{j}^{k} = f (k + m (j - 1)), j = 1, ...,$$

n]; where k = 1, ..., m (4.21)

And U is the frog index or position, for Example, for m = 3, rank 1 goes to memeplex 1, rank 2 goes to memeplex 2, rank 3 goes to memeplex 3, rank 4 goes to memeplex 1, and so on.

Memetic evolution within each memeplex: Evolve each memeplex Y^k , k = 1, ..., m.

Shuffle Memeplexes: After a defined number of memetic evolutionary steps within each memeplex, replace Y^1, \ldots, Y^m into X, such that $Y = \{Y^k, k = 1, \ldots, m\}$. Sort X in order of decreasing performance value. Update the population best frog's position P_X .

Check Convergence: If the convergence criteria are satisfied, stop. Otherwise, return to process of partition frogs into memeplexes.

 Assign power *ρ_{k,n}* for each user's subcarriers based on total power via Water-Filling Algorithm.

The existence and uniqueness of the introduced models have been verified mathematically and by simulation tools. Matlab codes constructed the assignment process for bit, power, and subcarrier for each user.

4.2.1 Comparison's Result

The obtained results of SFLA are comparatively better than those achieved by the previous researchers in a similar field. This study followed the approach of resource

allocation as Yadav [203], we have presented improved results. Gunaseelan [212] adopted a similar approach but without fully implementing a water filling algorithm.

- In both studies (Yadav and Gunaseelan), they adjusted the level of power and number of bits only.
- They tried it for a maximum of 10 users and got a maximum capacity of around 10.9 bits/second/Hertz.
- In our study for 10 users, the maximum capacity obtained was around 11.2 bits/sec/Hz.

Furthermore, [213, 214] combined the algorithm with evolutionary approach with Karush-Kahun-Tucker (KKT) parameters. The KKT parameters help to obtain power allocation corresponding to each subcarrier, and thus an optimization of subcarrier allocation is done to maximize system rate.

- They tested their system on just four (4) users, and the maximum capacity obtained was about 5.9 bits/sec/Hz.
- The method of this study had a capacity of around 10 bits/sec/Hz for four (4) users.
- Apart from these, our results are also better than those obtained by [214] and those of modified the Particle Swarm optimization algorithm [213, 215] and the Proportional Fairness algorithms of [216].

Generally, memetic algorithms are evolutionary algorithms that have been shown to be more efficient than standard genetic algorithms for many combinatorial optimization problems.

4.2.2 Simulation's Results

In this section, the simulation results are introduced, which show the system's effectiveness. Parameter settings are very important in memetic algorithm.

The simulation parameters determined the amount of the worst power, population size = 6, number of memeplexes (*m*) = 4, number of frogs in each memeplex (*n*) = 16402, while number of evaluation or iteration N_0 = 5, total power = 1mW, BER = 1e-3, and number of subcarriers (*N*) = 32.

Additionally, this current study compared two previous techniques, and the results significantly improved with the SFLA. Results are shown below in Figure 4.2, which compares the total capacity and the number of users equal to 16. While the number of assigned subcarriers is 64.



Figure 4.2. Capacity Curves for 14 Users

Figure 4.3 shows the curves of power allocated for 28 subcarriers (14 users), where power allocated at a minimum rate for error free communication in OFDM system by using SFLA based powerline channel. The power allocated is constantly optimized as compared to Root-finding [212] and Linear methodology [203] and the Hybrid evolutionary algorithm [214].

Through this method, results are significantly improved, and the capacity per user has increased. Each frog represents a possible solution, a solution here means a combination set of power allocation for all users.



Figure 4.3. Power Allocated Rate vs Number of Users

Figure 4.4 shows the capacity gain for allocated users and power at different BER. The capacity gain of optimal allocation over OFDM increases as the number of users increases. This occurrence is also known as multiuser diversity. Also, a system of 16 users with the proposed allocation solution achieves almost 13.2% and 17.4% more capacity gain than other schemes with equal power, when compared to OFDM at BER of 10^{-3} with the addition of powerline noise.



Figure 4.4. System's Capacity of 16 Users

The system capacity achievement of 16 users and optimized random power amount, achieved 800.841 (bits/s) by using SFLA, which achieves the highest level, while the root approach was 790.5394 and the linear approach was 778.1286.

Basically, the process of SFLA starts operating on each memeplex for memeplex number one for each frog in the memeplex. The process found fitness of global best frog value for frog number one, which was equal to 11.8842 and fitness number 10 was 11.7580 for the last global best frog in one iteration.

Then, the best frog by first iteration was determined. All the frogs in this memeplex get a new frog before the shuffling process ended. Then, the best solution was extracted for which the lowest cost was 0.0839.

Table 4.2 contains the optimal minimum power rate values at several allocated subcarriers where power, BER, and the total bandwidth are set as 0.1mW, 10-3, at 10^{-8} noise added to powerline subchannel, and 1MHZ, respectively over 0.8 and 0.01probability and gap probability.

Approach	oach 8 users, 1 16 subcarriers Su		32 Users, 64 Subcarriers	
SFLA (Wtt)	0.0604	0.0294	0.0197	
Root Algo (Wtt)	0.0659	0.0419	0.0258	BER = 1e ⁻³ ; Channelnum =
Linear Algo (Wtt)	0.0687	0.0401	0.0301	10

Table 4.2. Optimal Minimum Power Rate Values at Different Users

Figure 4.5 shows capacity curves for 16 users, where capacity is the maximum rate for error free communication for the number of users allocated sub channels in the OFDM system by using SFLA.



Figure 4.5. System Throughput vs Number of Users

The capacity obtained is constantly higher as compared to Root-finding [212] and Linear methodology [203] and the Hybrid evolutionary algorithm [214]. As the number of users increases capacities increases. This is the effect of multiuser diversity gain, which is outstanding in systems with the largest number of users.

- Table 4.3 contains the optimal maximum bit rate values at several allocated users where power, BER, and the total bandwidth are set as 0.1w, 10⁻³, and 1MHZ, respectively.
- The number of subcarriers was 64, and the cross-over probability and mutation probability were 0.8 and 0.01 respectivel

-3.

Number = 10

Approach	8 Users, 16 Subcarriers	16 Users, 32 Subcarriers	32 Users, 64 Subcarriers	
SFLA (bits/s/Hz)	11.07	11.16	11.14	
Root Algo (bits/s/Hz)	10.89	10.89	10.81	$BER = 1e^{-1}$ Channel

Table 4.3. Optimal Maximum Bit Rate Values at Different Users

10.84

Linear Algo

(bits/s/Hz)

Figure 4.6 represents the normalized capacity, ratios per user for 16 users averaged over 100 channels. Proportions i_k taken as input for both algorithms for each user. SFLA is the recommended solution because it has minimal deviation.

10.97

10.90



Figure 4.6. Normalized Capacity Ratios for 16 Users

The user with minimum proportional capacity are allowed to select the most suitable subcarriers first. This current study followed the approach in [8] and improved the results by exploiting the Frog-Leaping algorithm for maximizing the capacity while assigning total power to each user for appropriate resource allocation.

4.3 Modified SFLA Based TLBO

The most recent related research of SFLA models, techniques, and application were reviewed in previous sections. This review concluded that SFLA suffers from premature convergence and being trapped in the local optima search. Thus, this current study introduced an improvement in SFLA by the enhancement of frogs fitness and search process. diminishing the problem of premature convergence and trap of search. The idea behind modification is to use the best memeplex to improve the worst memeplex and then improve the memes of the frogs. This exchange of information is inspired by the metaphor of Teaching-Learning-Based Optimization Algorithm (TLBO) [217] wherein i is the best memeplex acts as a teacher to improve the results of the worst memeplex (or student).

The worst individual in memeplex will be updated by the traditional frog-leaping algorithm and the best individual by the normal cloud model algorithm. Also, the convergence of the algorithm is improved by changing the process of the worst frog from the best frog in a memeplex to the best frog in the whole population.

The goal of using SFLA is to optimize power allocation at all subcarriers. This can be written as follows [203]:

$$\max R_{k,n} \sum_{k=1}^{K} \sum_{n=1}^{N} \frac{p_{k,n}}{N} \log_2 \left[1 + \frac{p_{k,n} h_{k,n}^2}{N_{\circ} \frac{B}{N}} \right]$$
(4.22)

Where $P_{k,n}$ is the power allocated, $h_{k,n}$ is the channel gain and $\rho_{k,n}$ is the check of subcarrier assignment to kth user on nth subcarrier, P_{Tot} is the total transmission power available and N, N_o, and B denote noise power, noise power spectral density and bandwidth of the channel, respectively, subject to the following constraints:

$$\sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} \le p_{Tot}$$
$$p_{k,n} \ge 0 \forall k, n$$
$$p_{k,n} = \{0,1\} \forall k, n$$

Each frog represents a possible combination of power assigned to each subcarrier and the sum of individual powers of each frog amounts to total power. The power combination of each frog is called a memotype.



Figure 4.7 Local Search in the SFLA Scheme

In memetic evolution within each memeplex in step 4 each of the newly created memeplexes are evolved (See Figure 4.7), i.e., the frogs are evolved towards the best frog of the memeplex. This step is executed 't' times, where t is the number of

iterations for evolution in each memeplex. The original SFLA has been tested on several problems; however, the original SFLA often suffers from being trapped in local optima [218].

In this step, the internal evolution of each memeplex takes place independently 't' times. Below are the steps for internal evolution of memeplexes.

- Initialize all counters and set them to zero. For example, 'f' is the current number of memeplexes, which is being evolved; *ii* counts the iterations or evolutionary steps that have been completed so far, for each memeplex.
- For each memeplex, select the frogs with the best and worst fitness and store them in *X_b* and *X_w* respectively as follows:

$$X_{b} = (x_{b1}, x_{b2}, \dots, x_{bi}) \& X_{w} = (x_{w1}, x_{w2}, \dots, x_{wi}) (4.23)$$

• Improve the worst frog's fitness by moving it closer to the best frog. For this, calculate the step size *S* for the worst frog by equation:

$$S = min (rand * (X_b - X_w), S_{max})$$

Where S_{max} is the maximum permitted step for the frogs, it has been taken as:

$$S_{max} = P_{tot} / (K/2)$$

 P_{tot} is the total power available for assignment *K* users and *rand* generates a random number in the interval [0,1]. The worst frog's position is updated by the following equation:

$$new_{position} = X_w + S$$

If the new position's fitness is better than that of X_w , the frog is replaced with new position. Else, Step 3 is called upon.

When the second step is unable to produce a better result, this step is initiated. The following step calculates the new position of the worst frog by first calculating the step size for the frog as:

$$S = min (rand^*(X_g - X_w), S_{max})$$

Where X_g is the position of global best frog, while remaining parameters are same as previous. Once again, the new position is calculated as:

$$new_{position} = X_w + S (4.24)$$

If this new position delivers better performance, the worst frog is replaced with this position. If the fitness is still less than the worst frog, Step 4 is initiated.

If the worst frog's position is unable to be improved by Step 2 and Step 3, a new frog is generated at the index of worst frog and the previous one is discarded.

• Check the counter for iterations '*ii*'. If it is less than total iterations, then go to Step 1. Also check the counter for memeplexes '*f*', if it is less than the total number of memeplexes, then go to Step 1.



Figure 4.8. Process of the Proposed Internal Shuffle in SFLA

Shuffle each pair of memeplexes, this is the step wherein the modified algorithm distinguishes from the SFLA (See Figure 4.8). At the end of evolution process for all memeplexes, the mean fitness of each memeplex is calculated and memeplexes are arranged in descending order of their mean fitness. Then, the frogs in memeplexes

with the best and worst mean fitness are extracted and arranged in descending order of their fitness values. The best frog goes to best memeplex, the second best goes to the worst memeplex and so on.

Several modified SFLA are introduced in the literature review with their features, application and a summary of performance compared to other optimization techniques. Most of this research has shown weakness in their process of frog shuffling, search optima solution and frog step size. For example in [158, 160].

The contribution of this study is the introduction of a new shuffle process inspired by the metaphor of TLBO, where the best memeplex acts as a teacher to improve the results of the worst memeplex (or student) [217] as follows:

- 1. The mean fitness of each memeplex is calculated and denoted by mf_i .
- 2. Memeplexes are arranged in descending order of their mean fitness.

 $mf = \{mf_1, mf_2, ..., mf_m\}; mf_1 > mf_2 > ..., mf_m$ (4.25)

- 3. The frogs in memeplexes with the best and worst mean fitness (mf_1 and mf_m) are extracted and arranged in descending order of their fitness values. The best frog goes to best memeplex mf_1 , the second best goes to the worst memeplex mf_m and so on.
- 4. The process is then repeated for 2^{nd} best and 2^{nd} worst memeplex (mf_2 and mf_{m-1}) and so on for all the memeplexes. This internal shuffle is repeated a predefined number of times, i.e., if current internal shuffle 'ss' is less than the total number of shuffles defined, then go to Step 4 as shown in Figure 4.9.



Figure 4.9. (a) Memeplex Process in SFLA, (b) Memeplex Arrangement in the Modified SFLA

Shuffle memeplexes, after a predefined number of internal evolutions in each memeplex and the shuffling of each pair of memeplexes, the memeplexes are shuffled and discarded. Once again, the frogs are ranked according to their fitness values and the best frog X_g is taken. If the current number of shuffles is less than predefined number, then go to Step 3.

Criteria for the termination of algorithm process can be based on some convergence value or a predefined number of total iterations. This current study has assumed a fixed number loops after which the algorithm is terminated and the frog with the best fitness is taken as the final frog.

It is very important to mention that, several studies have showed that the section of SFLA that should be modified is the evaluation part. Because the location of the worst frog certainly not replace the location of best frog, then the entire convergence

speed performance of the local search will be decreased, and a suboptimal decision will appear due to premature convergence.

4.3.1 Analytical and Numerical Analysis

In this study, the modified SFLA is improved by using the improvement step of TLBO technique for getting Frogs' (Learners) mean closer to best globe's (Teacher) mean value. Therefore, a vector represents the extracted mean and target mean formed and added to the generated population of memeplexes mf_m when its best mean fitness is mf_1 for the process of improvement as follows:

The improvement process of population (memeplexes) is:

$$mf_{b(i)} = mf_{(i)} + rand \times (mf_{(bm)} - T_f M)$$
(4.26)

While the improvement process of frogs in the memeplexes is:

$$X_{b(i)} = X_{(i)} + rand \times (X_{(bf)} - T_f M)$$
 (4.27)

Where:

 $mf_{b(i)}$: New memeplex with improved mean value $mf_{(i)}$: Memeplexes' index $mf_{(bf)}$: Memeplex with best (Teacher) mean value $X_{b(i)}$: New frog with improved mean value $X_{(i)}$: Frogs' index $X_{(bf)}$: Frog with best (Teacher) mean value M: Mean vector $rand_i$ (1, 2) such that T_f is integer In order to evaluate the optimization improvement, there are several benchmark methods for analytical and numerical optimization experiments been used by researchers [219, 220]. The proposed algorithm is analytically tested by Sphere, Schwefel, and Rastrigin functions as listed in Table 4.4. These functions known as artificial landscapes, are useful to evaluate characteristics of optimization algorithms.

Function	Numerical Test Function	Interval of X _i	Optimum Coordination
Sphere	$f(x_i) = \sum_{i=1}^n x_i^2$	$-100 \le x_i \le 100$	(0,,0)
Schwefel	$f(x) = \sum_{i=1}^{n} x_i + \prod_{i=1}^{n} x_i $	$-10 \le x_i \le 10$	(0,,0)
Quartic function	$f(x) = \sum_{i=1}^{n} ix_i^4 + random[0,1]$	$-1.28 \le x_i \le 1.28$	(0,,0)

Table 4.4. Benchmark Optimization Test Functions

A comparison between SFLA_TLBO and SFLA showed the novelty optimization improvement have been conducted by finding minimum of global value in search space domain, average, worst values, variance, and average time. The values of common parameters of both algorithms are determined similarly in the measurement. Assume that:

> Population (P) = 50; Dimensions =30; Memeplexes (M) =10; % each have 5 frogs. No. of local iterations = 5; No. of global iteration = 200; Total iteration No. = 1000 (5*200); Maximum Iterative Algebra = 6000; Search scale (c) = 2.0;

Error Precision = 10^{-10} ; No. of offspring = 3.

Standard deviation of the proposed algorithm compared by exist method is analysed where in Sphere function, the modified algorithm solution achieved $4.3254 \times 10^{-57} \pm 0.9568 \times 10^{-56}$ while exist algorithm solution achieved $2.3059 \times 10^{-198} \pm 0$. In addition, standard deviation recorded by Quartic function is 0.0071 ± 0.0058 of modified technique while it was 0.0275 ± 0.0093 exist technique.

Table 4.5 shows the numerical experiment results of SFLA_TLBO and SFLA attained by three optimization evaluation methods. It is obvious synonym SFLA based Teacher Learner feature performs in efficient pattern. It showed consistency of robustness at random initializations during all of the analytical calculations, while the rate of its convergence higher than exist technique. Exist Frog Leaping showed various results over several measurements where the modified algorithm introduced similarity in evolution converge and better accuracy, speed, and produced optimal solutions.

Function	Scale(%)	SFLA	SFLA_TLBO
Sphere:	Min	3.027e-008	5.5091e-09
	Max	2.7589	5.3019
	Midian	2.0024e-03	4.3564e-014
	Mean	0.0704	6.3650e-067
Schwefel:	Min	2.3520e-021	3.0256e-305
	Max	1.0501	4.5604
	Midian	7.8546e-084	5.3621e-063
	Mean	2.1056	6.4756e029
Quartic function:	Min	0.0047	3.5647e-08
	Max	2.0125	4.2508
	Midian	0.0365	1.3654e-009
	Mean	0.0987	3.2145e-001

Table 4.5. Results of Numerical Experiment Optimization

In the analytical process, the changes over fitness values been ranked by Sphere benchmark function from 0 to $5*10^4$ to evaluate ordinate logarithm fitness form. The modified algorithm recorded 1.24 Friedman while the exist method showed 4.804 Friedman.

Table 4.6. Analytical Result of Schwefel Function

Algorithm	Optimal results	Worst result	Time/s	Variance
SFLA_TLBO	-2.065087	-2.065087	0.2083	1.72
SFLA	-1.38024	-1.38024	1.1591	2.06

In the same context, the proposed method achieved less variance and superior solutions and speed as shown in Table 4.6. It clear that SFLA_TLBO introduced close-optimal solutions ($-10 \le x_i \le 10$) from the respective analytical calculations.

4.3.2 Result of the Modified SFLA Based TLBO

Figure 4.10 depicts the capacity curves for 16 users, where capacity is the maximum rate for number of users allocated subchannels in OFDM system by using a modified SFLA. The curve shows a slight improvement compared to the original technique wherein the capacity increases when user number are increased.



Figure 4.10. Capacity Comparison of SFLA and Modified SFLA_TLBO with 16 Users

Figure 4.11 shows the curves of power (set of frogs) allocated for 16 users, where power is allocated at a minimum rate using SFLA. The power allocated is constantly optimized as compared to other techniques.



Figure 4.11. Power Allocated Rate vs Number of Users

Results are significantly improved, and the capacity per user has increased. The curve shows an improvement compared to the other technique in which the allocated power is decreased when user number are increased.



Figure 4.12. SFLA vs Modified SFLA_TLBO, 16 Users

Figure 4.12 shows that the capacity obtained is constantly higher as compared to Root-finding [212] and Linear methodology [203] and the Hybrid evolutionary algorithm [214] as the number of users increases capacities increases. This is the effect of multiuser diversity gain, which is outstanding in systems with a larger number of users.

Table 4.7 lists the capacity improvement achieved by the proposed modification compared to the exist techniques.

	4	8	16
Approach	Users	Users	Users
Modified SFLA	10.94	10.71	11.46
SFLA	10.93	10.69	11.44
Root Algo	10.87	10.65	11.14
-			
Linear Algo	10.8	10.45	11.3
-			

Table 4.7. Optimal Maximum Bit Rate (bits/s/Hz) Values at Different Users

The introduced determination fitness of best memeplex's is to improve the results of the worst memeplex. When the best frog goes to best memeplex, the second best goes to the worst memeplex and so on. The uniqueness of this study's approach is it simplicity and formed based on the effinciely of teacher learner algoritm in improving soluctions' fitness.



Figure 4.13. Improvement over Fitness Vlaues per Iteration

Figure 4.13 has depicted the achieved improvement within a number of consecutive shuffling iterations by our modified SFLA. Specifically, if the frogs' fitness improve the adapted solution is enhanced, else best frog remains in its original position. This study has taken into consideration not only frogs' fitness values but also the overall mean fitness of the entire memeplexes. The indicator of the fitness values is represented the efficiency of the new technique. Therefore, the end of shuffle process converged after enhancing frog's fitness.

4.4 Chapter Summary

In this chapter, a novel algorithm, a power allocation based SFLA, has been proposed and evaluated. The convergence of the proposed algorithm has been verified by simulation and the existence and the uniqueness of the modified SFLA_TLBO have been proven mathematically. One of the obvious advantages of the proposed power allocation algorithm is the quick convergence. Furthermore, the proposed distributed power allocation algorithm in this chapter is related to the first objective that presented in Chapter One.

CHAPTER FIVE EFFICIENT RATE ALLOCATION TECHNIQUE

In this chapter, a joint bit and subcarrier algorithms are introduced and evaluated in terms of system capacity. Another model of subcarrier and bit allocation is introduced by utilizing SFLA, which is explained mathematically and in through diagrams. Finally, the improvement of the system performance is introduced by convergence verification comparison and system capacity.

5.1 Allocation System Model

Different subcarrier and bit allocation algorithms have been published in the literature [221-224]. Based on the objective function that they try to optimize, most of those loading algorithms are rate-adaptive algorithms that strive to maximize the data rate subject to power and BER constraints.

For each user and subcarriers, separate set of bits and energy are allocated based on the channel status. Assuming that, K is number of users while N is the system's number of subcarriers and the SNR gap is equal to five, then the BER associated with SNR is represented as introduced in [225] as explained in section (4.1) as follows:

$$r = -1n (5*BER)/1.6$$
 (5.1)

The objective constraints of normalized proportionality, number of subcarriers to user, power and the proportional rate are explained in section (4.1). The following sections explain a model combined power, subcarrier, and bit allocation for efficient system capacity performance.

5.1.1 Power per User

The transmitted power of user k with the subcarrier n is represented as introduced in [225] as follows:

$$L_{k,n}(b_{n,n}) = \frac{a\sigma^2(2^{b_{k,n}-1})}{v_{k,n}^2}$$
(5.2)

Where:

- k = 1, 2..., K; n = 1, 2, N; $a\sigma^2 \ a\sigma^2 = AWGN$ power of the *n* subchannel;
- $v_{k,n}^2 v_{k,n}^2$ = User k's channel gain over *n* subcarrier *n*;

 $b_{k,n} b_{k,n}$ = Number of bits of the user 'k' assigned to 'n' subcarrier.

Meanwhile the process of controlling and minimizing the transmitted power is formulated as:

$$\min \sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} * \mathcal{L}_{k,n} \qquad \forall k \in \{1, 2, \dots, K\} \,\forall n \in \{1, 2, \dots, N\}$$
(5.3)

$$s.t \begin{cases} \sum_{k=1}^{K} p_{k,n} = 1 & \forall n \in \{1, 2 \dots N\} \\ H_k = \sum_{n=1}^{N} p_{k,n} b_{k,n} & \forall k \in \{1, 2 \dots K\} \\ BER_{k,n} \le BER_k & \forall n \in \{1, 2 \dots N\} \forall k \in \{1, 2 \dots K\} \end{cases}$$

Where $p_{k,n} = 1$ or 0, (if channel *n* is occupied by user *k*, $p_{k,n} = 1$, if otherwise $p_{k,n} = 0$), while $h_k =$ bit rate of user *k*. BER_{*k*,*n*} = bit error rate of user *k* over subchannel *n*, and BER_{*k*} is the upper limit of the bit error rate of user *k* allowed.

For same bit rate that remains, the bandwidth of the channel increases and the power becomes low. Then, an adaptive waterfilling algorithm is used as introduced in [210] for assigning the power amount for each subchannel as explained in Equation (4.19) in section 4.1.2.

5.1.2 Subcarrier Allocation

Inputs of this process are the amount of subcarriers each user is assigned and the channel state information for each user while the output is subcarriers allocation of multiuser network channel. This process is adaptive for a multiuser environment as it is based on instantaneous channel information as He-zheng et al [209] introduced as follows:

• Initialization: The system firstly initializes all the variables. *R_k* keeps track of the capacity for each user and *N* is the set of yet unallocated subcarriers.

 $\delta_{k,n,m} = 0$; For k = 1, 2, ..., K; And M = 1, 2, ..., M; $R_k = 0$; For k = 1, 2, ..., K; $P_m = p/N_m$, For m = 1, 2, ..., M

Where $\delta_{k,n,m}$ proportional fairness constants among carrier equal to zero.

 Assignment: The second step assigns the unallocated subcarrier to each user that has the maximum gain for that user. However, this bias is negligible when N >> K because the probability of that happening will be very low.

For k = 1 to K:

$$find(n,m) = \arg\max_{n \in n,m} |h_{k,n,m}|$$

let $\delta_{k,n,m} = 1, N = N \rightarrow \{n\},$
and $N_m = N_m - 1;$
 $R_k = \frac{1}{N} \log_2(1 + p_m h_{k,n,m})$

• The third step proceeds by assigning subcarriers to each user according to the ravening policy. Once the user gets his allotment of *N_k* subcarriers, it cannot longer be assigned any more subcarriers in this step.

While $||n|| > N^*$

$$find \ k = \arg \min_{k} \frac{R_{k}}{\phi_{k}};$$

$$find \ (n,m) = \arg \max_{n \in N, m \in M} \left| h_{k,n,m} \right|;$$

$$if \ N_{m} > 0$$

$$\delta_{k,n,m} = 1;$$

$$N_{m} = N_{m} - 1, \quad N = N \rightarrow \{n\};$$

$$R_{k} = R_{k} + \frac{1}{N} \log_{2} \left(1 + p_{m} h_{k,n,m}\right)$$

$$else$$

$$M = M \rightarrow \{m\}$$

• In addition, the fourth step assigns the remaining N^* subcarriers to the best users for them, wherein each user can have at most one unassigned subcarrier. This is to prevent the user with the best gains to get the rest of the subcarriers. This policy balances achieving proportional fairness while increasing overall capacity.

For n = 1 to N^* find $(k, m) = \arg \max_{k \in K, m} |H_{k, N(n), m}|;$ $\delta_{k, n, m} = 1, K = K \rightarrow \{k\}$

Notice that as a consequence of the suggested subcarrier allocation scheme is N_1 : N_2 : ...: $N_k \approx \emptyset_1 : \emptyset_2 : ...: \emptyset_k$ with the approximation getting tighter as $N \to \infty$ and N $\gg K$. This is reasonable assumption because current powerline networks utilize OFDM.



Figure 5.1. Process Flow of Subcarrier Allocation Scheme

The algorithm shown in Figure 5.1 is almost similar to the work in [226, 227] with minor differences such as the use of unallocated subcarriers and low complexity power allocation algorithm. By using the adaptive Water-Filling algorithm [210], the power of distinctive subchannel can be determined.

5.1.3 Bit Allocation

This aims to assign all the bits in such a way that the transmitted power is minimized. The inputs of this process are channel gain, bit rate constraint and subcarriers allocation. Whereas the output is, bits loaded to accomplish each user's bit rate constraint.

For the standardized allocation of bits processes as introduced by several research such as in [41, 225] :

- First, subcarriers assignment using [209], then each subcarrier is assigned just one bit (this is for the case in which the total number of bits per user is more than the total number of bits assigned to that user) [225].
- If the power that a subcarrier finds for a user is 0, then that subcarrier will not be assigned any bit for that particular user. However, it may see a good power gain for some other user, in which case it may be assigned to that user:

$$p_{k,n} = 0, \, b_{k,n} = 0 \tag{5.4}$$

• After that, a check should made to determine which subcarrier would cause a minimum power increase to the system if assigned one more bit. This is computed by implementing the following equation:

$$\Delta pow(n) = \frac{\sigma^2\left(2^{B(k,n)}\right)}{\left(h(k,n)\right)^2} \qquad (5.5)$$

Where σ^2 is the power of AWGN of the subcarrier *n*. This step is repeated for each subcarrier allocated to a particular user.

• Finally, find the subcarrier \overline{n} whose increase in power, $\Delta pow(\overline{n})$ is smallest and allocate one bit to that subcarrier. Repeating the steps (2) and (3) until all bits of user k are allocated as explained in the following bit loading technique, Figure 5.2.



Figure 5.2. Subcarrier & Bit Allocation Model Structure

The novelty of this part is a joint allocation model constructed by combining the power, subcarrier, and bit allocation techniques [209, 225] whereas these models are never been used together in combination before and prove their efficient system capacity performance.

5.2 System's Result of the Adaptive Model

This part presents the performance evaluation of the proposed adaptive joint allocation model. The system tested for total number of bits (to be transmitted) = 20, 30, 40, 50, 60, 70 and 80. As an example, consider the case when this value is kept equal to 70. To show it here, a simple example of 10 subcarriers and 5 users initialized as configured by other studies is as follows:

- N = 10 total number of subcarriers, or channels;
- K = 5 total number of users;
- Bandwidth = 30 MHz; and
- Bits per symbol = 64.

5.2.1 Bit Rate of each User

First, these 70 bits to be transmitted are to be divided among the different users. In this study's code, this division is done using the built in random function of MATLAB as shown in Table 5.1. In a real-time scenario, however, this would be based on system requirements.

Table 5.1. Bit Rate (bit/sec) per User

User No.	User 1	User 2	User 3	User 4	User 5
Bit Rate	23	6	13	8	20

5.2.2 Channel Gain of each User

After that, the channel gain of each user is computed that each subcarrier is found on it. It is shown in Table 5.2.

Subcarrier No.	1	2	3	4	5	6	7	8	9	10
U.	0.0265	0.0207	0 2242	1 5601	0.1910	0.2040	0.0552	0.2059	1 1542	1 7095
User_1	0.0303	0.0297	0.2245	1.3001	0.1810	0.2049	0.0332	0.5058	1.1342	1.7985
User_2	0.0048	0.0241	0.0910	0.1861	0.2466	0.2526	0.1982	0.1224	0.0529	0.0239
User_3	1.3024	0.9814	0.7457	0.9110	1.0737	0.8981	0.6193	0.7055	1.1454	1.3506
User_4	0.1737	0.1249	0.1184	0.1610	0.3256	0.5354	0.6180	0.6831	0.5131	0.2390
User_5	0.3103	0.2941	0.1931	0.0459	0.0484	0.1273	0.2396	0.3297	0.4365	0.4290

Table 5.2. Channel Gains (dB) for all Subcarriers of each User

5.2.3 Subcarriers Allocation

Next, a specific number of subcarriers are assigned to each user shown in Table 5.3. Note that this subcarrier assignment is done because of channel gain - not because of bit assignment.

Subcarrier No.	1	2	3	4	5	6	7	8	9	10
User_1	0	1	0	0	0	0	0	0	0	0
User_2	0	0	0	1	0	1	0	0	0	0
User_3	0	0	1	0	0	0	0	0	0	1
User_4	0	0	0	0	1	0	0	1	0	0
User 5	0	0	0	0	0	0	1	0	1	0

Table 5.3. Subcarriers Allocation

5.2.4 Bit Loading

In this part, the inputs are channel gain, bit rate constraint and subcarriers allocation while the output is bits loaded to accomplish each user's bit rate constraint. The constraint is the bits are allotted next. If the number of bits assigned to a specific user is greater than the number of subcarriers assigned to it, then:

1. First one bit is allotted to each subcarrier.
- 2. After that, check how much increase in power it would take if one more bit were added to each one of the assigned subcarriers.
- The subcarrier that would take the least increase of power is given one more bit to carry.
- 4. Steps 2 and 3 are repeated until all assigned bits are allotted to the assigned subcarriers.

This is a simple bit allocation algorithm and does not require any complex equations (except for that to find power increase). Applying it for 70 total bits to be transmitted, the bit allocation as shown in Table 5.4 below is achieved.

Table 5.4. Bit Allocation (Comparison)

Subcarrier No.	1	2	3	4	5	6	7	8	9	10
User_1	11	12	0	0	0	0	0	0	0	0
User_2	0	0	0	3	0	3	0	0	0	0
User_3	0	0	6	0	0	0	0	0	0	7
User_4	0	0	0	0	3	0	0	5	0	0
User_5	0	0	0	0	0	0	9	0	11	0

For the example explained above, the following curve compares the transmitted bits to the powers in the joint algorithms with two previous studies namely Guo 2015 [225] (IDRA) and Vu and Kong 2012 [228] (OFDM-FDMA) as shown in Figure 5.3 below.

Where the following configurations are used by other studies as follows:

- N = 256; total number of subcarriers, or channels;
- K = 16; % total number of users;
- Bandwidth = 100; % in MHz;
- Bits per symbol = 64;



Figure 5.3. Powers Allocated vs Bit Amounts

The drawbacks of several previous works that, when the total number of transmitted bits in a symbol increases from 16 bits to 64 bits, then the system has transmitted power increases. The transmitted power in the current proposed joint algorithms is each time smaller than the one in IDRA and OFDM-FDMA algorithms, thus proving this work significantly better than the previous works so far.

5.3 Modified Shuffled Frog Leaping Algorithm

SFLA is characterized by simple process and construction realizing a smaller amount of parameters compared to most of Waterfilling, Max-min fairness, Utility max, Cross-layer, Cooperative and Non-corporative algorithms [134]. Moreover, it has the advantages of being easy to implement and having fast speed and global optimization capability and has been widely used in many areas. Additionally, it has a high precision and fast restraint speed [135]. Thus, it is worthy to use SFLA as subcarrier and bit allocator for each user is worthy. Therefore, the following section presents further modification and improvement in modified SFLA (section 4.3). Hence, this is an optimization problem within the given constraints (section 4.1).

During this optimization, the assumption is that all users of the network have identical number of bits to be transmitted and that each subcarrier is assigned to exactly one user at a time (a user can have multiple subcarriers) to simplify the calculations.

The optimization problem is defined by [225] as shown in Equation (5.3). That is one of the main goals in this study which is to minimize the power 'P' required for the transmission of the total user bits, where P is given as:

$$P_{k,n}(b_{k,n}) = \frac{\Gamma \sigma^2 \left(2^{b_{k,n}} - 1\right)}{h_{k,n}^2}$$
(5.6)

Where σ^2 is the variance of noise and the value of constant Γ is calculated as shown in Equation (5.1).

While Equation (5.2) and (5.7) show that the total *K* users and *N* subcarriers, $h_{k,n}$ is the channel gain, $b_{k,n}$ is the subcarrier assignment, whereas $P_{k,n}$ is the power allocated and used as pointer check subcarrier assignment to k^{th} user on n^{th} subcarrier. Although R_k is the number of bits to be transmitted by the k^{th} user and BER is the maximum tolerable error rate. As mentioned in section 5.1.2, subcarriers are assigned randomly to each user of the network and the corresponding bit rates for each user are calculated, such that the total bits for each user are entertained by the subcarriers. It should be noted that:

- As the number of users and subcarriers increases, the complexity of this optimization problem increases;
- There is a need for an efficient and simple optimization technique; a metaheuristic technique that accounts for all the constraints that can provide an optimal solution within minimum time;
- Therefore, a slight variant of the SFLA meta-heuristic is introduced to solve this complex problem.

The first improvement on SFLA in this study is achieved by utilizing the idea of a Teacher and Learner Algorithm [217] as explained in section 4.3, and by flowchart in Figure 4.7 and a modified memeplex arrangement in Figure 4.8.

Meanwhile, the second improvement is introduced to enhance the step size of the worst frog as shown in Figure (5.4). The idea is inspired by the Particle Swarm Optimization (PSO) algorithm's step size [229]. It considers the local and global best frogs while describing the next step for the worst frog. The new step size is calculated by the following equation:

$$S = (c1 * min (Randi * (X_b - X_w), S_{max}) + c2 * min ((Randi * (X_g - X_w), S_{max}))$$
(5.7)

Where:

 S_{max} is the maximum step size;

'randi' generates a random integer;

 X_g is the global best;

 X_b and X_w are the local best and worst frogs;

and c1 and c2 are the constants called Learning Factors in PSO, whose values are taken around 2.

If these steps do not improve the cost of the frog, then this frog will be deleted, and a new frog is produced randomly.



Figure 5.4. Improvement of SFLA based Global and Local Best Frog Using PSO

The idea behind the use of both global and local optima is that the global makes the convergence faster but sometimes makes the solution prematurely converge to a local optimum. Hence, a need also exists for local information about the frogs, which is needed to exchange local memes with the frogs, although local is best when used alone advances very slowly towards the optima.

When the step size is calculated using Equation (5.7), the solution converges faster than the normal SFLA, and thus it is utilized it in the bit allocation model. The total 133

number of bits to be transmitted are equally divided among all the users in the network, i.e., an assumed setting ensures that each user is sending equal number of bits in each iteration.



Figure 5.5. Modified Internal Shuffle Process in SFLA

procedure FrogLeap	Calculate memeplexes meanFitness (mf_i) %TLBO			
Initialize parameters: $m, n, p=m*n$, etc.	procedure InternalShuffle			
Generate population(represented by P frogs)	1- for h=1 to TotalMemeplexes			
randomly;	2- meanFitness(i)=fitness(frog_members)/frogsInMe			
while (convergence criteria) do	meplex			
Populate/ShuffleMemeplexes	end-for			
while (not terminate) do	3- for it=1:MaxIt % Calculate Population Mean			
while (not terminate) do	mean = 0;			
LocalSearch	%Teaching Factor			
end-while	4- $TF = randi([1 2]);$			
InternalShuffle	5- for i=1:nPop; mean = TF*mean + pop(i).position;			
end-while	end			
UpdateStatistics	6- mean = mean/nPop;			
end-while	% Select Teacher, teacherfitness = $pop(1)$;			
end-procedure	7- tor $1=2:nPop$			
procedure initializeData	if pop(1).Cost < teacherfitness.cost			
Initialize ratafieters	teacherintness = pop(1);			
InitializeFrogs	end			
ComputeGlobalBest	; enu 9 tagabarfitnass—sort(maanFitnass_descending)			
end-procedure	9. for f=1 to TotalMemenleyes/2			
procedure Populate/ShuffleMemeplexes	10- frogsBest=fitness(f)			
1- frogs=sort(fitness, descending)	11- frogsWorst=fitness((TotalMemenlexes+1)-f)			
2- for h=1 to TotalMemeplexes	12- index=[frogsBest, frogsWorst]			
Memeplex {h} {}	$13- Memeplex(index(1))={}$			
end	14- Memeplex(index(2))= $\{\}$			
3- m=1	15- for ff=1:2: frogs			
4- for f=1 to TotalFrogs	16- Memeplex $\{index(1)\}=$			
5- if m>TotalMemeplexes	append(Memeplex{index(1)},frog_member{ff})			
m=m-TotalMemeplexes	17- Memeplex {index(2)}=			
end-if	append(Memeplex{index(2)},frog_member{ff+1}			
6- Memeplex $\{m\}$ = append(Memeplex $\{m\}$, frogs $\{f\}$)	18- arrange memeplex fitness			
7- m=m+1	meanFitness={Memeplex ₁ ,			
end-for	Memeplex ₂ ,Memeplex _m };			
end-procedure	$Memeplex_1 > Memeplex_2 > Memeplex_m;$			
procedure LocalSearch	19- Extract best&worst frog			
1- for h=1 to 1 otal Memeplexes	best frog goes to best memeplex ₁ , the 2^{nu} best goes			
2- 10r 1=1 to 1 otaliterations from member=frogs(i)	to the worst memeplex memeplex _m ,			
4. Xh=max(fitness(frog_member))	end-tor			
 Xw= min(fitness(frog_member)) 	end-ior & Improvement step size of the worst from (PSO)			
6- Step=min((rand)*(Xh - Xw) Smax)	$20_{-} S = (c_1 * min((randi([0 K] 1 1))*(xh - xw) Smax) + c_1 + c_2 +$			
7- new position=Xw+Step:	$c^{2*\min((randi([0 K], 1, 1))}(Xg - xw) Smax))$			
8- if (fitness(new position)>fitness(Xw))	21- new position=round($xw+S$):			
9- frog member=new position	22- new cost=cost function(new position)			
10- else Step=min((rand)*(Xg - Xw),Smax)	end			
11- new_position=Xw+Step;	23- if			
<pre>12- if (fitness(new_position)>fitness(Xw))</pre>	new_cost <old_costfrog_member{xw_ind}=new_posi< td=""></old_costfrog_member{xw_ind}=new_posi<>			
13- frog_member=new_position	on; mem{1, f}{1, xw_ind}=frog_member{xw_ind};			
14- else GenerateNewFrog	24- cost_local(xw_ind)=new_cost			
end-if	else			
end-if	25- new_cost=nan;			
end-for	26- while(isnan(new_cost));			
end-tor	27- S=min(randi($[0 K], 1, 1$)*(Xg - xw),Smax);			
ena- procedure	$23-5=(c1^{min}((randi([U K], 1, 1))^{*}(xb - xw), Smax)$			
	c2 ^{-min} ((randi([0 K],1,1))*(Xg - xw),Smax));			
	new_position=round(xw+S);			
	new_cost-cost_function(new_position);			
	end			
	VIII			

Figure 5.6 Pseudocode of the Modified SFLA Based TLBO and PSO

In this setting, the combination of subcarriers assigned to all users represents one virtual frog. A specific number of random frogs is generated, and the required transmission power of each frog is calculated, which represents the cost of each frog.

Then, the algorithm continues with its routine iterations and shuffles, updating the worst frogs and replacing them with newer frogs when required as depicted in Figure 5.5. In this meta-heuristic optimization, the frog's leaping tends to move towards the combination of subcarriers, which incurs minimum costs or transmission power; at the end of the algorithm, the frog that offers minimum cost is finalized. A brief description of the original and modified algorithm is presented with a pseudocode to facilitate its implementation in Figure 5.6.

5.4 Result's Comparison

We have compared the results of the proposed modification with those of a few previous methods such as IDRA and ODFM-FDMA and the results show that modified SFLA_PSO has surpassed these algorithms in bit allocation. The power required for the bits transmission is much lower than the case for the other techniques previously mentioned.

The system improvement of both modified SFLA_PSO is depicted in Figure 5.7, which shows the allocated power rate compare to the bit rate for 7 user and 30Mhz bandwidth at a caused noise density equals to 10^{-8} as introduced in the previous studies. Additionally, *BER* = 10^{-3} and total of the bits reached 1000000 while the total power is 1. Moreover, impulse noise is being added (this represents PLC channel) where $i_1 = 3$ as SNR and addition of PLC noise in transmitted signal is added.



Figure 5.7. Generated Random Power Amount versus Bits



Figure 5.8. Comparison Result of the Allocated Bits to Power

Meanwhile, Figure 5.8 combines and compares the results of the system improvement of both first and second modified algorithms. The results show significant improvement compared to the IDRA and the ODFM-FDMA approaches.

At each iteration of the main bit allocation process, the total number of bits is increased and the corresponding subcarrier combinations (or frogs) are once again calculated using shuffled frog's leaping algorithm. The number of frogs and memeplexes should vary with the number of users and subcarriers in the system. In the case of 5 users and 10 subcarriers, 20 to 30 frogs and 5 memeplexes are enough to converge to the best solution within 5 shuffles and an equal number of iterations.

However, an increase in these parameters should be commensurate with the number of users and subcarriers. It's important to note that the number of subcarriers should not be less than the number of users because each subcarrier can entertain only one user at a time in the current supposition.



Figure 5.9. Amount of Power Allocated to each User

Figure 3.9 illustrates the amount of power allocated to each user by different techniques at different data rates. Obviously, the optimized minimum optimal power values are found and identified by the proposed modified techniques based on SFLA. The main objective is to achieve the highest sum capacity under the optimum power constraint.

5.5 Analytical and Numerical Benchmark Effectiveness Test

In both the power and bit allocation models, the performance of the original SFLA was compared with the modified SFLA. To get a fair picture of the convergence and efficiency of both algorithms, as well as proving the supremacy of this study contribution in the original algorithm, DeJong's standard functions are used.

DeJong's functions are a set of functions that have been used for benchmarking with other algorithms [230]. The main feature of the DeJong's functions is the presence of several local optima along with a global optimum. Thus, all local search methods are likely to get stuck in a local optima, while only global search methods can reach the global optima [231]. DeJong's functions are given as follows:

• DeJong's F1 Function (Three-dimensional Paraboloid):

$$F_1(x)\sum_{i=1}^3 \chi_i^2$$
 s.t - 512 $\leq x_i \leq 512$ (5.8)

Where $x_i = 0$, i = 1:n,

E.g:
$$F_1(x) = \text{sum } (i * x (i) ^2), i = 1:n, -5.12 \le x(i) \le 5.12$$

• DeJong's F2 Function (Rosenbrock's Saddle):

$$F_2(x) = 100(x_1^2 - x_2)^2 + (1 - x_1)^2; \quad s.t - 2018 \le x_1, x_2 \le 2018$$
 (5.9)

Where $x_i = 0$, i = 1:n,

E.g:
$$F_2(x) = (100 \cdot (x(i+1)-x(i)^2)^2 + (1-x(i))^2);$$

i=1:n-1; -2.048<=x(i)<=2.048.

And the global minimum is f(x)=0; x(i)=1, i=1:n.

• Extended Rosenbrock's Function:

$$F_{R}(x) = \sum_{i=1}^{9} 100(x_{i}^{2} - x_{i+1})^{2} + (1 - x_{i})^{2}; \quad s.t - 2018 \le x_{1}, x_{2} \le 2018 \quad (5.10)$$

E.g: $F_{2}(x) = \text{sum} (100 \cdot (x(i+1) - x(i)^{2})^{2} + (1 - x(i))^{2});$
 $i=1:n-1; -2.048 \le x(i) \le 2.048.$

• Schaffer's F6 Function (Rastrigin):

$$F_6(x) = F(x) = 0.5 - \frac{\sin^2(x_1^2 + x_2^2)^{0.5} - 0.5}{1.0 + 0.001(x_1^2 + x_2^2)^2} \quad s.t - 100 \le x_1, x_2 \le 100 \quad (5.11)$$

E.g:
$$F_6(x)=10*n+sum(x(i)^2-10\cdot sin(2\cdot pi\cdot x(i))), i=1:n; -5.12 \le x(i) \le 5.12.$$

In each case, different parameters of both the algorithms were changed, and the results were averaged over 10 simulations. The stopping criteria for the algorithms was that the solutions are converged to a 0.001 percent error in all the cases of the above-mentioned problems, although the iterations for each algorithm varied between different cases.

For comparison with the SFLA, this study used its proposed modified algorithm for both power allocation part as well as bit allocation. The conditions were kept similar as of the original SFLA, and with each case, the simulations were run for 10 times while varying different parameters such as memeplexes, total frogs, iterations and shuffle.

For example, the total memeplexes was changed from 5 to 20, with step 5, and the number of frogs ranging from 10 to 30 in each of the memeplexes. The following tables, (Tables 5.6 - 5.9) summarize the number of iterations required to get to the 0.001% error of the global optimum through several functions.

Table 5.5 Number of Required Iterations for DeJong's F1 Function

Algorithm	Iterations
SFLA	92
SFLA_TLBO	81
SFLA_PSO	75

Table 5.6. Number of Required Iterations for DeJong's F2 Function

Algorithm	Iterations
SFLA	750
SFLA_TLBO	670
SFLA_PSO	643

Table 5.7. Number of Required Iterations for Extended Rosenbrock's Function

Algorithm	Iterations
SFLA	1220
SFLA_TLBO	970
SFLA_PSO	856

Table 5.8. Number of Required Iterations for Rastrigin Function

Algorithm	Iterations
SFLA	550
SFLA_TLBO	485
SFLA_PSO	462

While Figure 5.10 below shows the results of Delong's Function in the above tables.



Figure 5.10. Number of Required Iterations for SFLA and Modified FSLA

Now, this section turns to the problem at hand; that is the optimization of power, subcarrier and bit allocation systems. As a first case, the performance of SFLA with the modified SFLA power allocator is compared. The performance can be visualized by the capacity of the system for different number of users. The comparison is given in Table 5.9 below for a constant value of 20 total iterations.

Algorithm	Users	Capacity (Bits/sec/Hz)
	1	10.8915
SFLA	5	10.7580
	8	11.1547
	1	11.4960
SFLA_TLBO	5	11.1857
	8	11.1887

Table 5.9 A Comparison of System Capacity using a Power Allocator

In the case of bit allocation, the concern was to minimize the total transmitted power against the total number of bits transmitted including all the users in the system. The total number of bits were varied from 10 to 70 for 5 users in the system.

The comparison for SFLA with the modified one for constant 20 iterations is given in Table 5.10 below.

Algorithm	Bits	Transmitted Power (mW)
	20	0.0069
SET A	30	0.0383
SFLA	50	0.5700
	70	1.7418
	20	0.0064
SELA DOO	30	0.0180
SFLA_PSO	50	0.1000
	70	0.4095

Table 5.10. A Comparison of Transmitted Power of the System for Bit Allocation

As can be seen from the tables above, the modifications in the SFLA have produced superior results when the number of iterations were held constant at 20. Thus, modifications have increased the computational time and efficiency of the SFLA. When the total number of iterations are made, this amounts to converging to a better solution within lesser iterations than the original algorithm.

Finally, a shortage of time and resources limited this study in conducting a realworld testbed based on simulation and emulation. At the same time, it is very important to highlight that the outcomes of this study were achieved and evaluated based on the simulation models of resource allocation, modulation, and data transmission channel. Furthermore, simulators do not always reflect real-world scenarios.

However, simulators are still very useful due to their simplicity, flexibility, and result repeatability in studying network behaviors. Therefore, a comparison of the current study's result with the real powerline data network is inconsequential. In each of the PHY, MAC and IP layers, researchers found several discrepancies and differences between the simulations and the testbeds and the way these differences affect the network traffic flow behaviour.

Moreover, simulations can still have a good match with experiments in simple environments like outdoor with line-of-sight transmissions, even if multiple different bit rates are used. In the same context, if we adapted and utilized our modified algorithms in the commercial technology, their system performance will most probably improved since these technology do not use adaptive techniques such as PLC Standard (IEEE 1901).

5.6 Chapter Summary

In this Chapter, a novel algorithm, subchannel and bit allocation based SFLA has been proposed and tested. The convergence of the proposed algorithm has been verified by simulation and the existence and uniqueness of the modified SFLA have been proven mathematically. One obvious advantages of the proposed bit allocation algorithm is the quick convergence. Furthermore, the proposed distributed power allocation algorithm in this chapter is related to the second objective presented in Chapter One.

CHAPTER SIX CONCLUSION AND FUTURE WORK

6.1 Conclusion

The issue of assigning power, bit, and subcarriers to the different users in an OFDM system has been an area of active research recently. An iterative subcarrier and power allocation algorithm is proposed to minimize the total transmit power given a set of fixed user data rates and bit error rate (BER) requirements.

In the rate-adaptive problem, in which the objective was to maximize the total data rate over all users subject to power and BER constraints, the results showed that each subcarrier should be allocated to the user with the best gain to maximize the total capacity

However, no fairness among the users was considered in this problem. This was partially addressed by ensuring that each user would be able to transmit at a minimum rate and incorporating a notion of fairness in resource allocation through maximizing the minimum user's data rate. The OFDM modulation system is the system most recommended for use because of its bandwidth efficiency.

The findings of this thesis are summarized below in several main topics with respect to its research's objectives. These topics are powerline technology, noise models, channel transfer function models, OFDM modulation, resource allocation techniques in OFDM, resource allocation in powerline network, and the shuffled frog leaping optimization algorithm. The main contribution of this study, which is efficient techniques for power and bit allocation models, is introduced and evaluated based on an OFDM system and a powerline channel.

6.2 Achieved Objectives

The main objective was optimizing the performance of data transmission over powerline technology in terms of capacity, scalability, and convergence. The study achieved its objective though the several models proposed in Chapter Four, in which a modified SFLA technique (SFLA_TLBO) for power allocation purposes was proposed and evaluated.

Simulation verified the convergence of the proposed algorithm simulation, and the uniqueness of the modified SFLA was proven mathematically. One obvious advantage of the proposed power algorithm was its quick convergence. The evaluation showed improvement in terms of the number of user versus capacity.

In Chapter Five, a novel algorithm (SFLA_PSO), subcarrier and bit allocation-based SFLA was proposed and tested. An improvement for scalability, capacity, and convergence of the proposed algorithm was evaluated mathematically by simulation. Results showed quick convergence and proved the uniqueness of the modified SFLA.

The third objective was achieved by developing a system of transmission networkbased OFDM, powerline channel, and proposed algorithms for purpose of performance evaluation. The capacity of the system was measured as well as power and the bit rate. Finally, the improvement of the proposed algorithms was investigated by measuring the convergence rate. It offered fastest convergence since the number of iterations required to get to the 0.001% error of the global optimum is 75 compare to 92 in conventional algorithm.

Answers to the research questions in this thesis have been attained by using simulation. The concept in the proposed model improved the system's performance over the earlier model in terms of bit and power allocated to the sub-channels based powerline.

6.3 Summary of Contributions

This study offers several contributions for the benefits of data transmission networks (Powerline, Wireless, Ethernet Cable) in terms of scalability, reliability, and capacity. Efficient network performance and throughput in real network applications are essential.

The first contribution is a joint allocation model for the selection of an optimal power amount introduced by efficient allocation techniques. This was constructed by an allocator of bit and subcarrier based near-optimal technique and non-iteration proportional low complexity technique and SFLA for allocation of power per user with water-filling algorithm used for the allocation of power per subcarrier.

The second contribution was the optimal power allocator based on a modified SFLA. The modification part was inspired by the TLBO technique, and one of its features was adding SFLA for improving the worst solutions. The overall performance of both contributions showed improvement in terms of capacity and scalability. In the third contribution, a power allocation mechanism of user and subcarrier userbased Min-Max improved the dynamic solution. In addition, the allocation of the subcarrier was based on an adaptive proportional fairness technique while the bit allocation technique was based on a greedy algorithm. The uniqueness of the joint model presented superior results compared to other models.

The last contribution was based on a further modification added to SFLA using an optimization feature of PSO. The proposed improvement was achieved by enhancement factors of PSO in the process of shuffling step size in global and local best Frog.

6.4 Limitations of the Research

The existence of certain assumptions and limitations in this study restricted the outcome and contributions of this work from providing a more accurate comparison of resource allocation techniques and modulation approaches on the one hand, and a precise estimation of the errors in real power line systems on the other. An unequipped lab did not permit the actual measurement of powerline network performance.

Highlighting and suggesting some areas in which, if the necessary time and facilities were provided, further investigation would result in improvements that would be worthwhile. Powerline was not designed to convey communications because of electromagnetic and radiation limitations. To have an ideal channel and perfect timing, synchronization between the transmitter and receiver must be achieved as is the case in most real communication systems. Therefore, investigating a reasonable channel model is essential.

With the scope of this study, the research was only interested in the effects of one modulation technique. Therefore, the scope of this thesis was limited to the basic resource allocation technique based OFDM. Additional investigation and research would be worthwhile using various modulation and channel models.

6.5 Recommendations for Future Work

The proposed power and bit allocation techniques were evaluated only for a powerline channel. Thus, in the future, researchers should investigate other communication channels such as wireless and fibre optics and investigate the potential of using several network channels for wireless technology would be worthwhile.

This research concentrated on the utilization of the OFDM modulation technique in a powerline system. However, other modulation techniques should be used to investigate the possibilities for greater enhancement of system performance.

The proposed power, bit and subcarrier allocation algorithms in the OFDM system were evaluated based on powerline channels analyzed in the frequency domain approach. Evaluate it using the time domain channel transfer function of the powerline system with different types of noise is important.

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