FINITE IMPULSE RESPONSE OPTIMIZERS FOR SOLVING OPTIMIZATION PROBLEMS

TASIRANSURINI BINTI AB RAHMAN

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ABSTRAK

Masalah pengoptimuman sering ditemui dalam pelbagai bidang. Pengelasan algoritma metaheuristik berasaskan anggaran telah diperkenalkan bagi menyelesaikan masalah pengoptimuman. Algoritma Kalman Penapis Simulasi (SKF) adalah salah satu algoritma di bawah klasifikasi ini. SKF diilhami oleh rangka kerja penapis Kalman (KF) iaitu penganggar yang popular bagi menyelesaikan masalah anggaran. SKF memerlukan parameter keadaan awalan, ralat kovarian awalan, hingar pengukuran, dan hingar proses untuk beroperasi. Namun, tiada kajian penalaan parameter dijalankan bagi kesemua parameter SKF. Memilih nilai parameter optimal dapat meningkatkan prestasi algoritma. Ini boleh dilakukan melalui eksperimen penalaan parameter. Namun, penalaan beberapa parameter adalah tugas yang mencabar dan memakan masa. Oleh itu, kajian ini cuba mengguna pakai strategi pencarian baru dari penganggar popular yang lain, dinamakan Penapis sambutan dedenyut terhingga saksama lelaran muktamad (UFIR) yang bekerja dengan hanya satu parameter. Penapis UFIR adalah salah satu daripada variasi penapis sambutan dedenyut terhingga (FIR). Penapis FIR diperkenalkan untuk mengatasi had dalam penapis KF yang mempunyai beberapa parameter yang sukar ditentukan dalam aplikasi-nyata. Dalam kerja ini, tiga algoritma baru metaheuristik berasaskan anggaran diperkenalkan. Algoritma pertama adalah algoritma berasaskan ejen-tunggal, dinamakan pengoptimum FIR ejen-tunggal (SAFIRO). Algoritma kedua adalah algoritma berasaskan ejen-berbilang dengan mekanisme kemas kini segerak, dinamakan pengoptimum FIR ejen-berbilang (MAFIRO). Algoritma ketiga adalah algoritma berasaskan agen-berbilang dengan mekanisme kemas kini tak segerak, dinamakan pengoptimum FIR tak segerak (AFIRO). SAFIRO berbeza daripada MAFIRO dari segi bilangan ejen. Manakala, MAFIRO berbeza daripada AFIRO dari segi strategi pencarian lelaran. Ketiga-tiga algoritma ini dipanggil secara pendek sebagai pengoptimum-pengoptimum FIR (FIROs). Setiap ejen FIROs bertanggungjawab mencari penyelesaian dengan melakukan pengukuran dan anggaran. Semasa pengukuran, FIROs menggunakan mutasi rawak bagi penyelesaian terbaik setakat ini beserta kaedah kejiranan tempatan untuk mengimbangi antara proses penjelajahan dan eksploitasi. Nilai pengukuran ini kemudiannya digunakan dalam anggaran bagi menambah baik penyelesaian secara lelaran. Prestasi FIROs diuji dengan menyelesaikan suit tanda aras CEC 2014. Kompetensi FIROs dibandingkan secara statistik dengan empat algoritma metaheuristik sedia ada: SKF, penyelesaian-tunggal SKF (ssSKF), Pengoptimuman kerumunan zarah (PSO), dan algoritma Genetik (GA). Analisis statistik menggunakan ujian Friedman dan ujian Holm post hoc dilaksanakan untuk membariskan prestasi FIROs. Ujian Friedman menunjukkan SAFIRO mempunyai baris tertinggi, diikuti oleh MAFIRO, AFIRO, ssSKF, SKF, PSO, dan GA. Ujian Holm post hoc mendedahkan prestasi SAFIRO nyata lebih baik daripada SKF, ssSKF, PSO, dan GA. Manakala, prestasi kedua-dua MAFIRO dan AFIRO nyata lebih baik daripada PSO dan GA, tetapi setara dengan SKF dan ssSKF. SAFIRO, MAFIRO, dan AFIRO memberikan prestasi yang setara. Walau bagaimanapun, SAFIRO boleh dianggap sebagai algoritma terbaik dengan baris tertinggi Friedman dan jumlah tertinggi prestasi terbaik dalam menyelesaikan suit tanda aras CEC 2014. Penemuan menunjukkan konsep penapis UFIR adalah inspirasi yang baik bagi algoritma metaheuristik. Algoritma-algoritma metaheuristik baru berasaskan penganggaran ini boleh menawarkan hasil yang diharapkan bagi menyelesaikan masalah pengoptimuman.

ABSTRACT

Optimization problems are frequently found in various fields. The classification of estimation-based metaheuristic algorithms has been introduced for solving optimization problems. Simulated Kalman filter (SKF) algorithm is one of the algorithms under this classification. SKF is inspired by the framework of Kalman filter (KF) which is a popular estimator for solving estimation problems. SKF needs parameters of the initial error covariant, measurement noise, and process noise to operate. Nonetheless, no study on parameter tuning being carried out for all SKF's parameters. Selecting optimal parameters' values may improve an algorithm's performance. This can be done through parameter tuning experiment. However, tuning several parameters is a challenging task and time-consuming. Thus, this study attempts to adopt a new search strategy from another popular estimator, named the Ultimate iterative unbiased finite impulse response (UFIR) filter which works with only one parameter. UFIR filter is one of the variants of the finite impulse response (FIR) filter. FIR filter is introduced to overcome the limitation in KF filter which has several parameters that difficult to be determined in a real application. In this work, three new estimation-based metaheuristic algorithms are introduced. The first algorithm is a single-agent-based algorithm, named Single-agent FIR optimizer (SAFIRO). The second algorithm is a multi-agent-based algorithm with synchronous update mechanism, named Multi-agent FIR optimizer (MAFIRO). The third algorithm is a multi-agent-based algorithm with asynchronous update mechanism, named Asynchronous FIR optimizer (AFIRO). SAFIRO differs from MAFIRO in term of the number of agents. Meanwhile, MAFIRO differs from AFIRO in terms of the iteration search strategy. These three algorithms are called in short as FIR optimizers (FIROs). Each agent in FIROs responsible for searching a solution by performing the measurement and estimation. During measurement, FIROs employ a random mutation of the best-so-far solution with local neighbourhood method to balance between the exploration and exploitation process. This measurement value is then used in the estimation to improve the solution iteratively. The performances of FIROs are tested by solving the CEC 2014 benchmark suite. The competencies of FIROs are statistically compared with four existing metaheuristic algorithms: the SKF, single-solution SKF (ssSKF), Particle swarm optimization (PSO), and Genetic algorithm (GA). Statistical analysis using the Friedman test and Holm post hoc test are performed to rank the performances of FIROs. Friedman test shows that SAFIRO has the highest rank, followed by MAFIRO, AFIRO, ssSKF, SKF, PSO, and GA. Holm post hoc test reveals SAFIRO performed significantly better than SKF, ssSKF, PSO, and GA. Whereas, both MAFIRO and AFIRO performed significantly better than PSO and GA, but equivalent to SKF and ssSKF. SAFIRO, MAFIRO, and AFIRO provide on par performances. However, SAFIRO can be regarded as the best algorithm with the highest ranking of Friedman and the highest number of best performances in solving the CEC 2014 benchmark suite. Findings show that the concept of UFIR filter is a good inspiration for metaheuristic algorithm. These newly estimation-based metaheuristic algorithms can offer promising results for solving optimization problems.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

$\boldsymbol{Y}$	Measurement of solution
$\boldsymbol{X}$	Estimation of solution
X*_best_so_far*	The best-so-far solution
N	Horizon length
β	Coefficient
d	Dimension for agent/s
D	Maximum dimension
δ	Step size/radius for local neighbourhood
X_{min}	The lower limit of search space
X_{max}	The upper limit of search space
F_f	Friedman Statistic
χ^2	Chi-square
α	Significant level
p-value	Probability value
z	Static value of Holm

LIST OF ABBREVIATIONS

ABC	Artificial bee colony
AFIRO	Asynchronous finite impulse response optimizer
CEC	Congress on evolutionary computation
DTI	Discrete time-invariant
DOF	Degree of freedom
EAs	Evolutionary algorithms
FES	Function evaluation
FIR	Finite impulse response
FIROs	Finite impulse response optimizers
Fn	Function
GA	Genetic algorithm
GSA	Gravitational search algorithm
GWO	Grey wolf optimizer
HKA	Heuristic Kalman algorithm
KF	Kalman filter
MAFIRO	Multi-agent finite impulse response optimizer
maxFES	Maximum function evaluation
NIA	Nature-inspired algorithm
no.	Number
PSO	Particle swarm optimization
SAFIRO	Single-agent finite impulse response optimizer
SA	Simulated annealing
SI	Swarm-inspired
SKF	Simulated Kalman filter
TS	Tabu Search
UFIR	Ultimate iterative unbiased finite impulse response
VNS	Variable neighborhood search

CHAPTER 1

INTRODUCTION

1.1 Introduction

Chapter 1 provides an introduction to this research. It begins with an overview of optimization and metaheuristic algorithms. Then, the research motivation, problem statement, research questions, research aim and objectives, research scopes, and research design are presented. The overall organization of the thesis is also presented before the summary of chapter 1.

1.2 Overview of Optimization and Metaheuristic Algorithms for global optimization problems

One of the issues emphasized in areas such as industry, accounting, economics, and engineering is the optimization problem. In general, optimization refers to the process of finding the best either minimum or maximum solution. Optimization problems can be differentiated according to the following criteria:

i. the type of variables, either continuous or combinatorial (discrete) optimization problem. A continuous optimization problem has an infinite number of solution spaces. In contrast, a combinatorial optimization problem has a finite number of solution spaces.
ii. the number of the objective of the given optimization problem, either single-objective, bi-objectives, or multi-objective optimization problem. A single-objective optimization problem involves only one objective function and has only one optimal solution, whereas bi-objectives involves two objective functions. On the other hand, a multi-objective optimization problem involves more than one objective function and has more than one optimal solution.

iii. the constraints applied to variables either constrained or unconstrained optimization problem. A constraint optimization problem has some limitations that the solution must satisfy. As the name suggests, an unconstrained optimization problem refers to the problem without restriction.

iv. either the time-independent (static optimization problem) or time-dependent (dynamic optimization problem). In a static optimization problem, the objective function does not change over time. On the contrary, for a dynamic optimization problem, the objective function is deterministic at a given time and changes over time.

Figure 1.1 depicts a general optimization flow. Variables, constraints, and objective functions are elements that should be investigated in solving optimization problems. Variables are the input to the objective functions. Meanwhile, constraints are the limitation on values of variables. The objective functions (also known as fitness function) are the functions of the given optimization problem to be either minimized or maximized. The optimization problems can be solved efficiently (within a reasonable time with a global or also called an optimal solution) by applying any suitable optimization methods. Optimization methods can be defined as procedures or algorithms used to solve optimization problems. The aim of an optimization algorithm (also known as optimizer) is to find an optimal variable's value that can either minimize or maximize the objective function under the given constraint.

Typically, optimization methods can be categorized into two major categories: the exact methods and approximate methods (Talbi, 2009), as illustrated in Figure 1.2. Exact methods such as the Dynamic programming (Pombeiro, Machado, & Silva, 2017), the Branch-and-bound algorithm (Kadri, Kacem, & Labadi, 2016) and the Constraint programming (Carlsson, Johansson, & Larson, 2017) can be applied to solve optimization problems with a guaranteed optimal solution. However, the exact methods are not suitable to solve a complex optimization problem due to computational cost in terms of time and memory. Furthermore, exact methods normally developed as a problem-dependent algorithm. Thus, they are not flexible to handle various types of optimization problems (Dumitrescu & Stutzle, 2003).

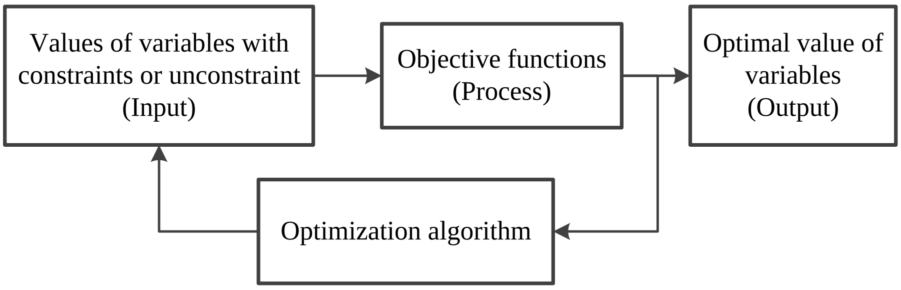

Figure 1.1 A general optimization flow

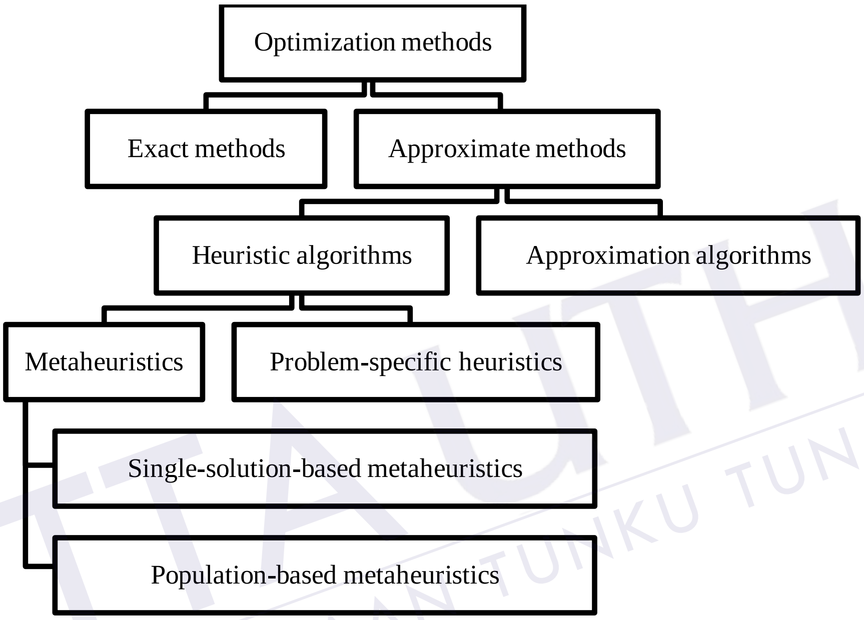

Figure 1.2 Classification of optimization methods
Source: Talbi (2009)

Therefore, approximate methods are the other option which can solve complex optimization problems with a near-optimal solution within a reasonable computational cost. Approximate methods can be further categorized into two categories: heuristic algorithms and approximation algorithms (Talbi, 2009). Approximation algorithms can offer the solution within the range that meet the minimum requirement as determined by the given problem. However, the solution is usually far from optimal (Baykasoğlu, Hamzadayi, & Akpinar, 2019). Heuristic algorithms have simple rules in finding a near-optimal solution which requires the problem domain knowledge as they are problem-dependent algorithms. Problem-specific heuristics and metaheuristics are other categories of heuristic algorithms. The former is implemented based on the problem's characteristics. The latter, on the other hand, is more general algorithms (problem-independent algorithms) that can be used for various types of optimization problems.

The terminology of metaheuristic was first used by Glover in (Glover, 1986). The words *meta* and *heuristic* originated from Greek words. The former means higher-level methodology, while the latter means the ways of finding new strategies or rules in problem-solving (Talbi, 2009). In other words, metaheuristic means higher-level strategies that provide a set of guidelines for finding an adequately good solution for optimization problems. Metaheuristic algorithms have gained huge popularity and attracted researchers' attention because of the flexibility and ability in solving a variety of optimization problems.

Over the past twenty years, various metaheuristic algorithms have been designed and improved to achieve an optimal solution in solving optimization problems. A wide range of applications such as in power system stabilizer (M. Singh, Patel, & Neema, 2019), medical dataset (Mahendru & Agarwal, 2019), Internet of Things (IoT) application (Ali, Ejaz, Lee, & Khater, 2019), business forecasting (Puchalsky, Ribeiro, da Veiga, Freire, & Santos Coelho, 2018), image processing (Anita Christaline, Ramesh, Gomathy, & Vaishali, 2018), teaching and learning process (De Souza et al., 2018), logistics and transportation management (Ting, Liao, Huang, & Liaw, 2017), and decision-making process (Amiri, Sardroud, & Soto, 2017) have been effectively handled using metaheuristic algorithms. The success of metaheuristic algorithms is mainly due to the ability to reach an optimal or near-optimal solution within a reasonable execution time, as well as simple and convenient to be applied for solving different types of optimization problems.

Besides metaheuristic, there is one more upper-level of heuristic, called hyperheuristic (Cowling, Kendall, & Soubeiga, 2001). Hyperheuristic algorithms are another option in searching a good enough solution for optimization problems which allowed metaheuristic algorithms to be selected adaptively or generated automatically during the search process (Zamli, Din, Kendall, & Ahmed, 2017). However, the approach of metaheuristic algorithms is still relevant due to some limitations in hyperheuristic algorithms. Metaheuristic algorithms attempt to solve an optimization problem directly. Unlike metaheuristic algorithms, hyperheuristic algorithms are seen more to find the right method or sequence of heuristic (Burke et al., 2013). Thus, the user needs to know several metaheuristic algorithms to apply the hyperheuristic algorithm to solve the problem.

Many new metaheuristic algorithms have been proposed which either based on nature or non-nature inspired. As can be extracted from the *No free lunch* (NFL) theorem (Wolpert & Macready, 1997), there is no single optimization algorithm able to solve all types of optimization problems. A certain metaheuristic algorithm may give good results for a set of optimization problems, while other metaheuristic algorithms may provide good results for another set of optimization problems. Since metaheuristic algorithms cannot promise an optimal solution for all types of problems, the development of new optimizer or modification of an existing algorithm is still an active research domain.

Nonetheless, a new or a modified algorithm should have improvement and promising direction of metaheuristic algorithm (Koohi, Abdul Hamid, Othman, & Ibragimov, 2019; Sörensen, 2013). An increasing number of metaheuristic algorithms also gives more choice to researchers in choosing a potential optimizer that can work well for their problem (Lones, 2019).

1.3 Research Motivation

An inspirational source is important to produce an efficient optimizer. An efficient search strategy by an optimizer contributes to the quality of the solution (X.-S. Yang, 2013). Nevertheless, the challenge is on how to get an inspirational source in developing a new algorithm or improving the existing algorithm. The trend is to use the inspiration by infusing biological behaviours or natural phenomena. A new inspiration other than this trend is not frequently observed, while there are still many inspirational sources that have not yet gain attention. Therefore, there is immense room for investigating more new inspirational sources other than biological behaviours or natural phenomena.

The inspirational source can also be taken from the work procedure of an estimator in a state-space model. A state-space model is a mathematical representation to describe the input, output, and variables of a system. It was introduced by mathematically-oriented engineers and applied mathematicians in the late 1950s. A state-space model is often used in solving various problems, including estimation problems in control engineering. The use of a state-space model for improving the control design process was investigated by Rudolf Emil Kalman and his team in the 1960s (Friedland, 2012). The Infinite impulse response (IIR) filter (including Kalman filter) and Finite impulse response (FIR) filter

(Kwon, Kim, & Han, 2002) are two types of estimators that are popular among engineers in solving state estimation problems (Shmaliy, Zhao, & Ahn, 2017).

Kalman filter (Kalman, 1960) able to provide an optimal solution for estimation problems. However, the outputs of Kalman filter (KF) are always corrupted with the noise and numerical data error (Ojstersek, Zhang, Palcic, & Buchmeister, 2017). KF needs correct values of the initial state, $\boldsymbol{X}(0)$, initial error covariance, $P(0)$, process noise, Q, and measurement noise, R. In real-world, it is difficult to determine the correct values of those parameters, especially under a poor operational condition (Shmaliy et al., 2017). Without correct values of those parameters, KF unable to produce a good performance and may affect the next estimation process due to its infinite impulse response structure.

Hence, an estimator with FIR structure (Jazwinski, 1968) has been introduced to overcome the limitation of KF. FIR filter is able to ignore the $\boldsymbol{X}(0)$, $P(0)$, Q, and R, thus has a strong practical feature (Zhao, Shmaliy, Ahn, & Liu, 2018). Instead of KF that needs four parameters to start the estimation process, FIR only needs one parameter. FIR filter increasingly being chosen compared to KF due to the robustness and stability in its finite structure (Ahn, Zhao, Shmaliy, & Sakthivel, 2018; Shmaliy & Simon, 2013). Subsequently, several FIR versions have been introduced. One of the versions is the ultimate iterative unbiased finite impulse response (UFIR) filter. UFIR filter offers a fast near-optimal estimation with a simple form of mathematical modeling (Shmaliy et al., 2017). With these promising features, the UFIR filter has been applied in many engineering applications.

In literature, there is a new class of metaheuristic algorithms named as the estimation-based metaheuristic algorithms (Ibrahim, Abdul Aziz, Ab. Aziz, Razali, & Mohamad, 2016). In this classification, the process of solving estimation problems in state-space modeling is transformed into the process of solving optimization problems. An optimal solution for optimization problems is estimated by using the framework of an estimator. The heuristic Kalman algorithm (HKA) (Toscano & Lynonnet, 2009) and Simulated Kalman filter (SKF) algorithm (Ibrahim et al., 2015) are among the earlier estimation-based metaheuristic algorithms. The HKA and SKF algorithm mimic the work procedure of KF.

The potential for any metaheuristic algorithm to solve other problems can sometimes be predicted from the pattern of performance of that algorithm in solving the previous problems (Lones, 2019). Since algorithms under the estimation-based have competitive performances as reported in (Abdul Aziz, Ibrahim, Razali, & Ab Aziz, 2016), it motivates this work to look into the potential of another estimator other than KF to be a source of inspiration for a new optimizer. As previously mentioned, the UFIR filter is one of the popular estimators besides KF. A good capability of UFIR filter drives this research to adopt the framework of this estimator into new metaheuristic optimizers.

1.4 Problem Statement

A multi-agent-based SKF algorithm (Ibrahim et al., 2015) has been inspired by two steps of KF's framework in estimating the state variables. The two steps are prediction and estimation. SKF generates its own measurement since it is an optimizer and no physical system exists to provide the measurement values. Thus, there are three main steps in SKF. The search strategy starts with the prediction of the position, followed by the measurement, and lastly, the estimation of an optimal solution.

Similar to its inspirational source, KF, SKF needs four parameters value: the initial state, $\boldsymbol{X}(0)$, the initial covariance, $P(0)$, the process noise, Q, and the measurement noise, R to start the optimization process. In KF, the setting value for all parameters is very important to estimate the state variable efficiently. Without correct values of these parameters, KF unable to provide good performance. In SKF, besides the number of agents, the parameters' values that need to be assigned in the algorithm are $P(0)$, Q, and R. The value of $\boldsymbol{X}(0)$ is generated randomly as an initial solution.

In the original SKF, the value of $P(0)$ is set as 1000. Meanwhile, both Q and R are set as 0.5. These values are given based on the nature of KF as an estimator. Until now, no study on experimental tuning being performed to determine the optimal value for all parameters used in SKF as an optimizer. All existing works either for improvement of SKF such as in (Ab.Aziz, Ibrahim, Abdul Aziz, & Ab. Rahman, 2018; Md Yusof et al., 2018; Mohd Azmi et al., 2019; Muhammad et al., 2016) or application of SKF for real engineering problems such as in (Abdul Aziz et al., 2016; Ahmad Zamri, Bhuvaneswari, Ab. Aziz, & Abdul Aziz, 2018; Muhammad et al., 2018) used the same value of $P(0)$, Q, and R, as in original SKF.

In 2016, a parameter-less SKF was proposed (Abdul Aziz, Ibrahim, Ab Aziz, & Razali, 2017) as another version of SKF. Instead of using constant values in original SKF, the value of $P(0)$, Q, and R are randomized in parameter-less SKF. However, no significant improvement is shown by parameter-less SKF as both versions demonstrated equivalent performances in solving the CEC 2014 benchmark test suite.

Setting optimal parameter values can optimize the performance of an algorithm (Ab.Aziz, Abdul Aziz, Zulkifli, Ibrahim, & Ab Rahman, 2018). If parameters $P(0)$, Q, R, and also the number of agents are set with the optimal value, it is possible that the SKF can provide better performance than the original SKF as well as the parameter-less SKF.

Algorithm employing more than two parameters need extra effort to be understood and more complex to be tuned compared to algorithms with lesser than two parameters. Hence, this study attempts to adopt a new source of inspiration from the framework of another estimator that require a lesser parameter to estimate the state. The inspirational source is from the work procedure of the FIR filter, specifically the UFIR filter (Shmaliy et al., 2017). UFIR filter works with only one parameter which is the horizon length, N. UFIR has shown higher robustness than the KF, subject to errors in the presence of temporary model uncertainties and the noise statistics (Zhao et al., 2018). Unlike KF that has two steps of procedures in estimating the state, UFIR filter only needs one step, which is the estimation step, without the prediction step. UFIR has a finite impulse structure where the estimation is performed based on the information of N recent measurements and does not require the information of $\boldsymbol{X}(0)$, $P(0)$, Q, and R. It is easier to determine an optimal value of N in UFIR filter compared to determine an optimal value of $\boldsymbol{X}(0)$, $P(0)$, Q, and R in KF (Shmaliy et al., 2017).

As aforementioned, this research looks into the potential of using the UFIR filter's framework in metaheuristic optimizers. The single-agent-based or multi-agent-based (either with synchronous update or asynchronous update) are categories of optimizers. Unlike the other algorithms such as Particle swarm optimization (PSO) (Eberhart & Kennedy, 1995), Grey wolf optimizer (GWO) (Mirjalili, Mirjalili, & Lewis, 2014), and Hill-climbing (HC) (Hinson & Staddon, 1983) where they are inspired by physical behaviour, single-agent-based or multi-agent-based is a clear decision for those algorithms. However, for FIR optimizer, since it is inspired by a mathematical representation in the state-space model, a single-agent-based or multi-agent-based (either with synchronous update or asynchronous update) are subjects of investigations in this study. The purpose of this investigation is to determine the best algorithm structure for FIR optimizer and subsequently can facilitate the problem statement.

Therefore, based on the advantages of the UFIR filter against Kalman filter, it is expected that a new search strategy from the framework of the UFIR filter can provide lesser parameter and better performances compared to the algorithms inspired by Kalman filter in solving optimization problems.

1.5 Research Questions

The research questions of this study are as follows:

RQ1. Is FIR filter able to be a good inspirational source for metaheuristic algorithms as KF?

RQ2. How to transform the FIR filter from an estimator into an optimizer framework?

RQ3. What is the best structure for this new FIR optimizer? Is it better as a single-agent-based algorithm or as a multi-agent-based algorithm? As a multi-agent-based algorithm, is it better with synchronous iteration strategy or asynchronous iteration strategy?

RQ4. Are these algorithms able to solve optimization problems? Do they show better results than the algorithm inspired by KF?

RQ5. What is the optimal value for the parameter/s used in the newly proposed algorithms?

1.6 Research Aim and Objectives

This research aims to investigate the potential of the FIR filter, specifically the UFIR filter as a new search strategy in metaheuristic algorithm which expected to provide lesser parameter and better performance than the algorithm inspired by the Kalman filter's framework in estimating an optimal or near-optimal solution for optimization problems. To achieve the aim, the objectives of this research are listed below:

i. to develop a single-agent-based metaheuristic algorithm named Single-agent finite impulse response optimizer (SAFIRO).
ii. to develop a multi-agent-based metaheuristic algorithm with synchronous update mechanism, named Multi-agent finite impulse response optimizer (MAFIRO) and a multi-agent-based metaheuristic algorithm with asynchronous update mechanism, named Asynchronous finite impulse response optimizer (AFIRO).
iii. to evaluate the performances of SAFIRO, MAFIRO, and AFIRO in solving a standard benchmark test suite and compare their performances against the other existing metaheuristic algorithms.

1.7 Research Scopes

The scopes of this research are as follows:

i. the proposed SAFIRO, MAFIRO and AFIRO are developed for continuous single-objective optimization problems with bounded constraint.
ii. the proposed algorithms are implemented and tested using MATLAB. The other algorithms involved in the benchmarking of this research are also implemented using MATLAB.
iii. the performances of the proposed algorithms are evaluated and compared with other metaheuristic algorithms based on the mean fitness value and statistical ranking that obtained in solving the IEEE Congress on evolutionary computation (CEC) 2014 benchmark suite (J. J. Liang, Qu, & Suganthan, 2013). Besides, the boxplots of the algorithms are produced to observe the stability of the results. The patterns of convergence curves are also generated to observe the ability of the algorithms in finding the solution.
iv. four algorithms are considered to compare the results of the proposed algorithms against other algorithms, which are the SKF algorithm (Abdul Aziz et al., 2017), single-solution SKF (ssSKF) algorithm (Abdul Aziz, Ibrahim, Ab Aziz, Mohamad, & Watada, 2018), Genetic algorithm (GA) (Holland, 1992), and PSO algorithm (Kennedy & Eberhart, 1995).
v. the Friedman test is applied in this research for statistical analysis as it is suitable for multi-comparison where performances of all tested algorithms are compared and ranked with each other. Besides Friedman test, the post hoc analysis using Holm's method is also applied to characterize the significant differences of

REFERENCES

Ab. Aziz, N. A. (2016). *An Adaptively Switching Iteration Strategy for Population Based Metaheuristics*. University of Malaya. https://doi.org/10.1016/j.lindif.2007.11.007

Ab. Aziz, N. A., Mubin, M., Ibrahim, Z., & Nawawi, S. W. (2015). Statistical Analysis for Swarm Intelligence - Simplified. *International Journal of Future Computer and Communication*, *4*(3), 193–197. https://doi.org/10.7763/IJFCC.2015.V4.383

Ab.Aziz, N. A., Abdul Aziz, N. H., Zulkifli, A., Ibrahim, Z., & Ab Rahman, T. (2018). Is Gravitational Search Algorithm' s Initial Gravitational Constant a Function Dependent Parameter? In *Proceedings of the 2018 International Conference on E-Business and Mobile Commerce - ICEMC* (pp. 60–66). Association for Computing Machinery. https://doi.org/10.1145/3230467.3230480

Ab.Aziz, N. A., Ibrahim, Z., Abdul Aziz, N. H., & Ab. Rahman, T. (2018). Asynchronous Simulated Kalman Filter Optimization Algorithm. *International Journal of Engineering and Technology*, *7*(4.27), 44–49. https://doi.org/10.14419/ijet.v7i4.27.22478

Ab Aziz, N. A., & Ibrahim, Z. (2012). Asynchronous Particle Swarm Optimization for Swarm Robotics. *Procedia Engineering*, *41*, 951–957. https://doi.org/10.1016/j.proeng.2012.07.268

Ab Aziz, N. A., Ibrahim, Z., Mubin, M., & Sudin, S. (2017). Adaptive Switching Gravitational Search Algorithm: An Attempt to Improve Diversity of Gravitational Search Algorithm Through Its Iteration Strategy. *Sadhana*, *42*(7), 1103–1121. https://doi.org/10.1007/s12046-017-0674-0

Ab Aziz, N. A., Ibrahim, Z., Nawawi, S. W., Sudin, S., Mubin, M., & Ab. Aziz, K. (2014). Synchronous Gravitational Search Algorithm vs Asynchronous Gravitational Search Algorithm: A Statistical Analysis. *New Trends in Software Methodologies, Tools and Techniques, 265*, 160–169. https://doi.org/10.3233/978-1-61499-434-3-160

Ab Aziz, N. A., Mubin, M., Mohamad, M. S., & Ab Aziz, K. (2014). A Synchronous-asynchronous Particle Swarm Optimisation Algorithm. *The Scientific World Journal*, *2014,* 17. https://doi.org/10.1155/2014/123019

Ab Aziz, N. A., Nawawi, S. W., Ibrahim, Z., Ibrahim, I., Mohd Zaidi, M. T., & Mubin, M. (2014). Synchronous vs Asynchronous Gravitational Search Algorithm. *Proceedings - 1st International Conference on Artificial Intelligence, Modelling* *and Simulation, AIMS 2013*, 37–42. https://doi.org/10.1109/AIMS.2013.14

Abdul Aziz, N. H., Ab Aziz, N. A., Ibrahim, Z., Adam, A., Mat Jusof, M. F., Razali, S., & Shapiai, M. I. (2018). An Analysis on the Number of Agents Towards the Performance of the Simulated Kalman Filter Optimizer. In *2018 8th International Conference on Intelligent Systems, Modelling and Simulation* (pp. 16–21). https://doi.org/10.1109/ISMS.2018.00013

Abdul Aziz, N. H., Ab Aziz, N. A., Ibrahim, Z., Razali, S., Abas, K. H., & Mohamad, M. S. (2016). A Kalman Filter Approach to PCB Drill Path Optimization Problem. In *IEEE Conference on Systems, Process and Control (ICSPC 2016)* (pp. 16–18). https://doi.org/10.1109/SPC.2016.7920699

Abdul Aziz, N. H., Ibrahim, Z., Ab Aziz, N. A., Mohamad, M. S., & Watada, J. (2018). Single-solution Simulated Kalman Filter Algorithm for Global Optimisation Problems. *Sadhana*, *123*(4), 2333–2335. https://doi.org/12.3456/s78910-011-012-3

Abdul Aziz, N. H., Ibrahim, Z., Ab Aziz, N. A., & Razali, S. (2017). Parameter-less Simulated Kalman Filter. *International Journal of Software Engineering and Computer Systems (IJSECS)*, *3*(February), 129–137. https://doi.org/http://dx.doi.org/10.15282/ijsecs.3.2017.9.0031

Abdul Aziz, N. H., Ibrahim, Z., Razali, S., & Ab Aziz, N. A. (2016). Estimation-based Metaheuristics : A New Branch of Computational Intelligence. In *The National Conference for Postgraduate Research 2016 (NCON-PGR)* (pp. 469–476). Retrieved from http://umpir.ump.edu.my/id/eprint/14583/1/P064 pg469-476.pdf

Abdullah, J. M., & Rashid, T. A. (2019). Fitness Dependent Optimizer: Inspired by the Bee Swarming Reproductive Process. *IEEE Access*, *7*, 43473–43486. https://doi.org/10.1109/ACCESS.2019.2907012

Abedinpourshotorban, H., Shamsuddin, S. M., Beheshti, Z., & Jawawi, D. N. A. (2016). Electromagnetic Field Optimization: A Physics-inspired Metaheuristic Optimization Algorithm. *Swarm and Evolutionary Computation*, *26*, 8–22. https://doi.org/10.1016/j.swevo.2015.07.002

Adam, A., Ibrahim, Z., Mokhtar, N., Shapiai, M. I., Mubin, M., & Saad, I. (2016). Feature Selection using Angle Modulated Simulated Kalman filter for Peak Classification of EEG Signals. *SpringerPlus*, *5*(1), 1580. https://doi.org/10.1186/s40064-016-3277-z

Ahmad Zamri, N., Bhuvaneswari, T., Ab. Aziz, N. A., & Abdul Aziz, N. H. (2018). Feature Selection using Simulated Kalman Filter (SKF) for Prediction of Body Fat Percentage. In *2018 7th International Conference on Software and Computing*

Technologies (ICSCT 2018). https://doi.org/10.1145/3274250.3274264

Ahn, C. K., Zhao, S., Shmaliy, Y. S., & Sakthivel, R. (2018). A Revisit to Strictly Passive FIR Filtering. *IEEE Transactions on Circuits and Systems II: Express Briefs*, *65*(4), 516–520. https://doi.org/10.1109/TCSII.2017.2742145

Akyol, S., & Alatas, B. (2016). Plant Intelligence Based Metaheuristic Optimization Algorithms. *Artificial Intelligence Review*. https://doi.org/10.1007/s10462-016-9486-6

Alatas, B. (2017). Sports Inspired Computational Intelligence Algorithms for Global Optimization. *Artificial Intelligence Review*, 1–49. https://doi.org/10.1007/s10462-017-9587-x

Alcalá-Fdez, J., Sánchez, L., García, S., del Jesus, M. J., Ventura, S., Garrell, J. M., … Herrera, F. (2009). KEEL: A Software Tool to Assess Evolutionary Algorithms for Data Mining Problems. *Soft Computing*, *13*(3), 307–318. https://doi.org/10.1007/s00500-008-0323-y

Ali, H. M., Ejaz, W., Lee, D. C., & Khater, I. M. (2019). Optimising the Power using Firework-based Evolutionary Algorithms for Emerging IoT Applications. *The Institution of Engineering and Technology (IET) Networks*, *8*(1), 15–31. https://doi.org/10.1049/iet-net.2018.5041

Amiri, R., Sardroud, J. M., & Soto, B. G. De. (2017). BIM-based Applications of Metaheuristic Algorithms to Support the Decision-making Process: Uses in the Planning of Construction Site Layout. *Procedia Engineering*, *196*(June), 558–564. https://doi.org/10.1016/j.proeng.2017.08.030

Anita Christaline, J., Ramesh, R., Gomathy, C., & Vaishali, D. (2018). Nature Inspired Metaheuristics for Improved JPEG Steganalysis. *Multimedia Tools and Applications*, *77*(11), 13701–13720. https://doi.org/10.1007/s11042-017-4983-4

Arasaratnam, I., Haykin, S., & R. Hurd, T. (2010). Cubature Kalman Filtering for Continuous-Discrete Systems: Theory and Simulations. *IEEE Transacrions on Signal Processing*, *58*(10), 4977–4993. https://doi.org/10.1109/TSP.2010.2056923

Askarzadeh, A. (2014). Bird Mating Optimizer: An Optimization Algorithm Inspired by Bird Mating Strategies. *Communications in Nonlinear Science and Numerical Simulation*, *19*(4), 1213–1228. https://doi.org/10.1016/j.cnsns.2013.08.027

Aziz, N. A. A., Sudin, S., Mubin, M., Nawawi, S. W., & Ibrahim, Z. (2015). A Random Synchronous- Asynchronous Particle Swarm Optimization Algorithm with a New

Iteration Strategy. *ARPN Journal of Engineering and Applied Sciences*, *10*(21), 9937–9942. Retrieved from https://umexpert.um.edu.my/file/publication/00005798_131223.pdf

Back, T., Hammel, U., & Schwefel, H.-P. (1997). Evolutionary Computation : Comments on the History and Current State. *IEEE Transactions on Evolutionary Computation*, *1*(1), 3–17. https://doi.org/10.1109/4235.585888

Back, T., & Schwefel, H.-P. (1993). An Overview of Evolutionary Algorithms for Parameter Optimization. *Evolutionary Computation*, *1*(1), 1–23. https://doi.org/10.1162/evco.1993.1.1.1

Bakhshipour, M., Ghadi, M. J., & Namdari, F. (2017). Swarm Robotics Search & Rescue: A Novel Artificial Intelligence-Inspired Optimization Approach. *Applied Soft Computing Journal*, *57*, 708–726. https://doi.org/10.1016/j.asoc.2017.02.028

Baykasoğlu, A., Hamzadayi, A., & Akpinar, S. (2019). Single Seekers Society (SSS): Bringing Together Heuristic Optimization Algorithms for Solving Complex Problems. *Knowledge-Based Systems*, *165*, 53–76. https://doi.org/10.1016/j.knosys.2018.11.016

Beheshti, Z., & Shamsuddin, S. M. (2013). A Review of Population-based Meta-Heuristic Algorithms. *International Journal Advance Soft Computing Application*, *5*(1), 1–35. Retrieved from https://www.academia.edu/3589014

Birattari, M., Paquete, L., Stutzle, T., & Varrentrapp, K. (2001). *Classification of Metaheuristics and Design of Experiments for the Analysis of Components*. Darmstadt, Germany. Retrieved from https://eden.dei.uc.pt/~paquete/papers/AIDA-01-05.pdf

Blum, C., & Roli, A. (2003). Metaheuristics in Combinatorial Optimization: Overview and Conceptual Comparison. *ACM Computing Surveys*, *35*(3), 268–308. https://doi.org/10.1145/937503.937505

Bonnabel, S., Martin, P., & Salaun, E. (2009). Invariant Extended Kalman Filter: Theory and Application to a Velocity-aided Attitude Estimation Problem. In *48h IEEE Conference on Decision and Control (CDC) held jointly with 2009 28th Chinese Control Conference* (pp. 1297–1304). https://doi.org/10.1109/CDC.2009.5400372

Boussaid, I., Lepagnot, J., & Siarry, P. (2013). A Survey on Optimization Metaheuristics. *Information Sciences*, *237*, 82–117. https://doi.org/10.1016/j.ins.2013.02.041

Burke, E. K., Gendreau, M., Hyde, M., Kendall, G., Ochoa, G., Ozcan, E., & Rong, Q. (2013). Hyper-heuristics : A Survey of The State of The Art. *Journal of the Operational Research Society*, *64*, 1695–1724. https://doi.org/10.1057/jors.2013.71

Burke, E. K., Hyde, M., Kendall, G., Ochoa, G., Ozcan, E., & Qu, R. (2009). *A Survey of Hyper-heuristics*. *Computer Science Technical Report*. Retrieved from http://www.cs.nott.ac.uk/~gxo/papers/hhsurvey.pdf

Carlisle, A., & Dozier, G. (2001). An Off-The-Shelf PSO. *Population English Edition*, *1*, 1–6. Retrieved from http://antho.huntingdon.edu/publications/Off-The-Shelf_PSO.pdf

Carlsson, M., Johansson, M., & Larson, J. (2017). Scheduling Double Round-robin Tournaments with Divisional Play using Constraint Programming. *European Journal of Operational Research*, *259*(3), 1180–1190. https://doi.org/10.1016/j.ejor.2016.11.033

Chen, C. C., Tsai, Y. C., Liu, I. I., Lai, C. C., Yeh, Y. T., Kuo, S. Y., & Chou, Y. H. (2016). A Novel Metaheuristic: Jaguar Algorithm with Learning Behavior. *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015*, 1595–1600. https://doi.org/10.1109/SMC.2015.282

Chen, C., & Chen, C. (2018). Application of Artificial Bee Colony Algorithm in Vehicle Routing Problem With Time Windows. In *International Conference on Information Resources Management (CONF-IRM)* (pp. 1–8). Association for Information Systems AIS Electronic Library (AISeL). Retrieved from http://aisel.aisnet.org/confirm2018/14

Chen, X., Gu, Q., Qi, J., & Chen, D. (2010). Applying Particle Swarm Optimization to Pairwise Testing. In *2010 34th Annual IEEE Computer Software and Applications Conference* (pp. 107–116). IEEE. https://doi.org/10.1109/COMPSAC.2010.17

Cheng, M. Y., & Prayogo, D. (2014). Symbiotic Organisms Search: A New Metaheuristic Optimization Algorithm. *Computers and Structures*, *139*, 98–112. https://doi.org/10.1016/j.compstruc.2014.03.007

Cheraghalipour, A., Hajiaghaei-Keshteli, M., & Paydar, M. M. (2018). Tree Growth Algorithm (TGA): A Novel Approach for Solving Optimization Problems. *Engineering Applications of Artificial Intelligence*, *72*(April), 393–414. https://doi.org/10.1016/j.engappai.2018.04.021

Civicioglu, P. (2013). Backtracking Search Optimization Algorithm for Numerical Optimization Problems. *Applied Mathematics and Computation*, *219*(15), 8121–8144. https://doi.org/10.1016/j.amc.2013.02.017

Coleman, V. (1989). *The DEME Model: An Asyncronous Genetic Algorithm.* Retrieved from https://web.cs.umass.edu/publication/docs/1989/UM-CS-1989-035.pdf

Cowling, P., Kendall, G., & Soubeiga, E. (2001). A Hyperheuristic Approach to Scheduling a Sales Summit. In *The Third International Conference on Practice and Theory of Automated Timetabling III* (pp. 176–190). Springer-Verlag Berlin, Heidelberg. Retrieved from https://dl.acm.org/citation.cfm?id=692903#citedby

Cox, H. (1964). On the Estimation of State Variables and Parameters for Noisy Dynamic Systems. *IEEE Transactions on Automatic Control*, 5–12. https://doi.org/10.1109/9780470544198.ch33

Cuevas, E., Cienfuegos, M., Zaldivar, D., & Perez-Cisneros, M. (2014). A Swarm Optimization Algorithm Inspired in the Behavior of the Social-spider. *Expert Systems with Applications*, *41*(2), 412–425. https://doi.org/10.1016/j.eswa.2013.07.067

Das, C. K., Bass, O., Kothapalli, G., Mahmoud, T. S., & Habibi, D. (2018). Optimal Placement of Distributed Energy Storage Systems in Distribution Networks using Artificial Bee Colony Algorithm. *Applied Energy*, *232*, 212–228. https://doi.org/10.1016/j.apenergy.2018.07.100

De Souza, G. N., De Deus, D. F., Tadaiesky, V., De Araújo, I. M., Monteiro, D. C., & De Santana, Á. L. (2018). Optimizing Tasks Generation for Children in the Early Stages of Literacy Teaching: A Study using Bio-inspired Metaheuristics. *Soft Computing*, *22*(20), 6811–6824. https://doi.org/10.1007/s00500-018-3409-1

Del Ser, J., Osaba, E., Yang, X.-S., & Salcedo-Sanz, S. (2019). Bio-inspired Computation: Where We Stand and What's Next. *Swarm and Evolutionary Computation*, *48*(April), 220–250. https://doi.org/10.1016/j.swevo.2019.04.008

Derrac, J., García, S., Molina, D., & Herrera, F. (2011). A Practical Tutorial on the use of Nonparametric Statistical Tests as A Methodology for Comparing Evolutionary and Swarm Intelligence Algorithms. *Swarm and Evolutionary Computation*, *1*(1), 3–18. https://doi.org/10.1016/j.swevo.2011.02.002

Dhiman, G., & Kumar, V. (2017). Spotted Hyena Optimizer: A Novel Bio-inspired Based Metaheuristic Technique for Engineering Applications. *Advances in Engineering Software*, *114*, 48–70. https://doi.org/10.1016/j.advengsoft.2017.05.014

Dhiman, G., & Kumar, V. (2018). Emperor Penguin Optimizer: A Bio-inspired Algorithm for Engineering Problems. *Knowledge-Based Systems*, *159*(October 2017), 20–50. https://doi.org/10.1016/j.knosys.2018.06.001

Dogan, B., & Olmez, T. (2015). A New Metaheuristic for Numerical Function Optimization: Vortex Search Algorithm. *Information Sciences*, *293*, 125–145. https://doi.org/10.1016/j.ins.2014.08.053

Dorigo, M., & Blum, C. (2005). Ant Colony Optimization Theory: A Survey. *Theoretical Computer Science*, *344*(2–3), 243–278. https://doi.org/10.1016/j.tcs.2005.05.020

Dumitrescu, I., & Stutzle, T. (2003). Combinations of Local Search and Exact Algorithms. *Applications of Evolutionary Computing. EvoWorkshops 2003. Lecture Notes in Computer Science*, *2611*, 211–223. https://doi.org/10.1007/3-540-36605-9_20

Duong, P. L. T., & Raghavan, N. (2018). Heuristic Kalman Optimized Particle Filter for Remaining Useful Life Prediction of Lithium-Ion Battery. *Microelectronics Reliability*, *81*(2018), 232–243. https://doi.org/10.1016/j.microrel.2017.12.028

Eberhart, R., & Kennedy, J. (1995). A New Optimizer Using Particle Swarm Theory. In *Sixth International Symposium on Micro Machine and Human Science* (pp. 39–43). https://doi.org/10.1109/MHS.1995.494215

Fathollahi-Fard, A. M., Hajiaghaei-Keshteli, M., & Tavakkoli-Moghaddam, R. (2018). The Social Engineering Optimizer (SEO). *Engineering Applications of Artificial Intelligence*, *72*(January), 267–293. https://doi.org/10.1016/j.engappai.2018.04.009

Fausto, F., Cuevas, E., Valdivia, A., & González, A. (2017). A Global Optimization Algorithm Inspired in the Behavior of Selfish Herds. *BioSystems*, *160*, 39–55. https://doi.org/10.1016/j.biosystems.2017.07.010

Fister Jr., I., Yang, X.-S., Fister, I., Brest, J., & Fister, D. (2013). A Brief Review of Nature-Inspired Algorithms for Optimization. *Electrotechnical Review*, *80*(3), 1–7. Retrieved from http://arxiv.org/abs/1307.4186

Friedland, B. (2012). *Control System Design: An Introduction to State-Space Methods*. Dover Publications Incorporated. Retrieved from http://books.google.com/books?hl=en&lr=&id=9WRKZlaCnF8C&pgis=1

Gandomi, A. H., Yang, X. S., & Alavi, A. H. (2013). Cuckoo Search Algorithm: A Metaheuristic Approach to Solve Structural Optimization Problems. *Engineering with Computers*, *29*(1), 17–35. https://doi.org/10.1007/s00366-011-0241-y

Glover, F. (1986). Future Paths for Integer Programming and Links to Artificial Intelligence. *Computers and Operations Research*, *13*(5), 533–549.

https://doi.org/http://dx.doi.org/10.1016/0305-0548(86)90048-1

Glover, F., & Laguna, M. (1993). *Tabu Search Modern Heuristic Techniques for Combinatorial Optimization*. (C. R. Reeves, Ed.). Blackwell Scientific Publications, Oxford. Retrieved from https://dl.acm.org/citation.cfm?id=166655

Hansen, N., Auger, A., Finck, S., & Ros, R. (2010). *Real-Parameter Black-Box Optimization Benchmarking 2010: Experimental Setup*. Retrieved from https://hal.inria.fr/inria-00462481/document

Hansen, N., Auger, A., Mersmann, O., Tusar, T., & Brockhoff, D. (2016). *COCO: A Platform for Comparing Continuous Optimizers in a Black-Box Setting*. Retrieved from http://arxiv.org/abs/1603.08785

Harifi, S., Khalilian, M., Mohammadzadeh, J., & Ebrahimnejad, S. (2019). Emperor Penguins Colony: A New Metaheuristic Algorithm for Optimization. *Evolutionary Intelligence*. https://doi.org/10.1007/s12065-019-00212-x

Haupt, R. L., & Haupt, S. E. (2014). *Practical Genetic Algorithms (Second Edition)*. John Wiley & Sons, Inc., Hoboken, New Jersey. Retrieved from https://onlinelibrary.wiley.com/doi/book/10.1002/0471671746

Heidari, A. A., Mirjalili, S., Faris, H., Aljarah, I., Mafarja, M., & Chen, H. (2019). Harris Hawks Optimization: Algorithm and Applications. *Future Generation Computer Systems*. https://doi.org/10.1016/j.future.2019.02.028

Hinson, M. H., & Staddon, J. E. R. (1983). Hill-climbing by Pigeons. *Journal of the Experimental Analysis of Behavior*, *39*(1), 25–47. Retrieved from https://onlinelibrary.wiley.com/doi/pdf/10.1901/jeab.1983.39-25

Holladay, K., Pickens, K., & Miller, G. (2017). The Effect of Evaluation Time Variance on Asynchronous Particle Swarm Optimization. In *2017 IEEE Congress on Evolutionary Computation (CEC)* (pp. 161–168). IEEE. https://doi.org/10.1109/CEC.2017.7969309

Holland, J. H. (1992). Genetic Algorithms. *Scientific American*, *267*(1), 66–72. https://doi.org/10.1038/scientificamerican0792-66

Hultmann Ayala, H. V., dos Santos Coelho, L., & Reynoso-Meza, G. (2017). Heuristic Kalman Algorithm for Multiobjective Optimization. In *International Federation of Automatic Control (IFAC)* (Vol. 50, pp. 4460–4465). Elsevier B.V. https://doi.org/10.1016/j.ifacol.2017.08.374

Husseinzadeh Kashan, A. (2014). A New Metaheuristic for Optimization: Optics Inspired Optimization (OIO). *Computers and Operations Research*, *55*, 99–125. https://doi.org/10.1016/j.cor.2014.10.011

Ibarra-Manzano, O. G. (2011). Filtering of Discrete-Time State-Space Models with the p -Shift Kalman-like Unbiased FIR Algorithm. *Recent Researches in Telecommunications, Informatics, Electronics and Signal Processing*, 71–76. Retrieved from https://www.semanticscholar.org/paper/Filtering-of-discrete-time-state-space-models-with-Ibarra-Manzano/f9a150251ac4ab683d513d6f345da7b327054355

Ibrahim, A., Rahnamayan, S., & Martin, M. V. (2014). Simulated Raindrop Algorithm for Global Optimization. In *Canadian Conference on Electrical and Computer Engineering* (pp. 1–8). https://doi.org/10.1109/CCECE.2014.6901103

Ibrahim, Z., Abdul Aziz, N. H., Ab. Aziz, N. A., Razali, S., & Mohamad, M. S. (2016). Simulated Kalman Filter : A Novel Estimation-based Metaheuristic Optimization Algorithm. *Advanced Science Letters*, *22*(10), 2941–2946. https://doi.org/10.1166/asl.2016.7083

Ibrahim, Z., Abdul Aziz, N. H., Ab. Aziz, N. A., Razali, S., Shapiai, M. I., Nawawi, S. W., & Mohamad, M. S. (2015). A Kalman Filter Approach for Solving Unimodal Optimization Problems. *ICIC Express Letters, 9*(12), 3415–3422.

Immonen, E., & Putkonen, A. (2017). An Heuristic Genetic Algorithm for Strategic University Tuition Planning and Workload Balancing. *International Journal of Management Science and Engineering Management*, *9653*(October), 1–11. https://doi.org/10.1080/17509653.2017.1316219

Jaddi, N. S., Alvankarian, J., & Abdullah, S. (2017). Kidney-inspired algorithm for optimization problems. *Communications in Nonlinear Science and Numerical Simulation*, *42*, 358–369. https://doi.org/10.1016/j.cnsns.2016.06.006

Jain, M., Singh, V., & Rani, A. (2019). A Novel Nature-inspired Algorithm for Optimization : Squirrel Search Algorithm. *Swarm and Evolutionary Computation*, *44*(June 2017), 148–175. https://doi.org/10.1016/j.swevo.2018.02.013

Javidy, B., Hatamlou, A., & Mirjalili, S. (2015). Ions Motion Algorithm for Solving Optimization Problems. *Applied Soft Computing*, *32*, 72–79. https://doi.org/10.1016/j.asoc.2015.03.035

Jazwinski, A. H. (1968). Limited Memory Optimal Filtering. *IEEE Transactions on Automatic Control*, *13*(5), 558–563. https://doi.org/10.1109/TAC.1968.1098981

Jin, F. U., Jingping, S. U. N., Fei, G., & Songtao, L. U. (2014). Maneuvering Target Tracking with Improved Unbiased FIR Filter. In *IEEE 2014 International Radar Conference* (pp. 1–5). https://doi.org/10.1109/RADAR.2014.7060289

Jr. Fister, I., Mlakar, U., Brest, J., & Fister, I. (2016). A New Population-based Nature-Inspired Algorithm Every Month: Is the Current Era Coming to the End? In *3rd Student Computer Science Research Conference* (pp. 33–37). https://doi.org/10.1016/j.ins.2017.10.039

Julier, S. J., & Uhlmann, J. K. (1997). A New Extension of the Kalman Filter to Nonlinear Systems. In *Proceedings of SPIE - The International Society for Optical Engineering* (pp. 182–193). https://doi.org/10.1117/12.280797

K. De, J. (1999). Evolutionary Computation: Recent Developments and Open Issues. In K. Miettinen, P. Neittaanmaki, M. . Makela, & J. Periaux (Eds.), *Evolutionary Algorithms in Engineering and Computer Science* (pp. 43–51). John Wiley & Sons, Ltd. Retrieved from https://dl.acm.org/citation.cfm?id=554112

Kadri, A. A., Kacem, I., & Labadi, K. (2016). A Branch-and-bound Algorithm for Solving the Static Rebalancing Problem in Bicycle-Sharing Systems. *Computers and Industrial Engineering*, *95*, 41–52. https://doi.org/10.1016/j.cie.2016.02.002

Kallioras, N. A., Lagaros, N. D., & Avtzis, D. N. (2018). Pity Beetle Algorithm – A New Metaheuristic Inspired by the Behavior of Bark Beetles. *Advances in Engineering Software*, *121*(April), 147–166. https://doi.org/10.1016/j.advengsoft.2018.04.007

Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems. *Transaction of the ASME-Journal of Basic Engineering*, *82*, 35–45. https://doi.org/10.1115/1.3662552

Karaboga, D., & Basturk, B. (2007). Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems. In *Foundations of Fuzzy Logic and Soft Computing* (pp. 789–798). https://doi.org/10.1007/978-3-540-72950-1_77

Kaveh, A., & Dadras, A. (2017). A Novel Meta-heuristic Optimization Algorithm: Thermal Exchange Optimization. *Advances in Engineering Software*, *110*, 69–84. https://doi.org/10.1016/j.advengsoft.2017.03.014

Kaveh, A., & Zolghadr, A. (2017). A Novel Meta-heuristic Algorithm: Tug of War. *International Journal of Optimization in Civil Engineering*, *6*(4), 469–492. Retrieved from http://ijoce.iust.ac.ir/browse.php?a_id=265&sid=1&slc_lang=en

Kennedy, J., & Eberhart, R. (1995). Particle Swarm Optimization. *IEEE International Conference on Neural Network*, *4*, 1942–1948 vol.4. https://doi.org/10.1109/ICNN.1995.488968

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by Simulated Annealing. *Science*, *220*(4598), 671–680. Retrieved from http://links.jstor.org/sici?sici=0036-8075%2819830513%293%3A220%3A4598%3C671%3AOBSA%3E2.0.CO%3B2-8

Knuth, D. E. (1976). Big Omicron and Big Omega and Big Theta. *SIGACT News*, *8*(Apr-June), 18–24. Retrieved from http://www.phil.uu.nl/datastructuren/10-11/knuth_big_omicron.pdf

Koohi, S. Z., Abdul Hamid, N. A., Othman, M., & Ibragimov, G. (2019). Raccoon Optimization Algorithm. *IEEE Access*, *7*, 5383–5399. https://doi.org/10.1109/ACCESS.2018.2882568

Koza, J. R. (1994). Genetic Programming as a Means for Programming Computers by Natural Selection. *Statistics and Computing*, *4*, 87–112. https://doi.org/Genetic programming as a means for programming computers by natural selection JOHN

Kwon, W. H., Kim, P. S., & Han, S. H. (2002). A Receding Horizon Unbiased FIR Filter for Discrete-time State Space Models. *Automatica*, *38*(3), 545–551. https://doi.org/10.1016/S0005-1098(01)00242-4

Labbi, Y., Attous, D. Ben, Gabbar, H. A., Mahdad, B., & Zidan, A. (2016). A New Rooted Tree Optimization Algorithm for Economic Dispatch with Valve-point Effect. *International Journal of Electrical Power and Energy Systems*, *79*, 298–311. https://doi.org/10.1016/j.ijepes.2016.01.028

Liang, J. J., Qu, B. Y., & Suganthan, P. N. (2013). *Problem Definitions and Evaluation Criteria for the CEC 2014 Special Session and Competition on Single Objective Real-Parameter Numerical Optimization*. *Technical Report 201311*. Retrieved from http://web.mysites.ntu.edu.sg/epnsugan/PublicSite/Shared Documents/Forms/AllItems.aspx?RootFolder=%2Fepnsugan%2FPublicSite%2FShared Documents%2FCEC-2014&FolderCTID=&View=%7BDAF31868-97D8-4779-AE49-9CEC4DC3F310%7D

Liang, Y., & Cuevas Juarez, J. R. (2015). A Novel Metaheuristic for Continuous Optimization Problems : Virus Optimization Algorithm. *Engineering Optimization*, (January 2015), 37–41. https://doi.org/10.1080/0305215X.2014.994868

Liu, L. L., Hu, R. S., Hu, X. P., Zhao, G. P., & Wang, S. (2015). A Hybrid PSO-GA

Algorithm for Job Shop Scheduling in Machine Tool Production. *International Journal of Production Research*, *53*(19), 5755–5781. https://doi.org/10.1080/00207543.2014.994714

Lones, M. A. (2019). *Mitigating Metaphors: A Comprehensible Guide to Recent Nature-Inspired Algorithms*. *Neural and Evolutionary Computing* (Vol. arXiv:1902). Edinburgh, United Kingdom. Retrieved from http://arxiv.org/abs/1902.08001

Mahendru, S., & Agarwal, S. (2019). Feature Selection Using Metaheuristic Algorithms on Medical Datasets. In N. Yadav, A. Yadav, J. Bansal, K. Deep, & J. Kim (Eds.), *Harmony Search and Nature Inspired Optimization Algorithms, Advances in Intelligent Systems and Computing* (Vol. 741, pp. 923–937). Springer, Singapore. https://doi.org/10.1007/978-981-13-0761-4

Mandal, S. (2018). Elephant Swarm Water Search Algorithm for Global Optimization. *Sadhana*, *43*(1), 1–21. https://doi.org/10.1007/s12046-017-0780-z

Mcnabb, A., & Seppi, K. (2014). Serial PSO Results Are Irrelevant in a Multi-core Parallel World. In *2014 IEEE Congress on Evolutionary Computation (CEC)* (pp. 3143–3150). IEEE. https://doi.org/10.1109/CEC.2014.6900226

Md Yusof, Z., Ibrahim, Z., Adam, A., Mohd Azmi, K. Z., Ab Rahman, T., Muhammad, B., … Muhammad, M. S. (2018). Distance Evaluated Simulated Kalman Filter with State Encoding for Combinatorial Optimization Problems Zulkifli. *International Journal of Engineering & Technology*, *7*(4.27), 22–29. https://doi.org/10.14419/ijet.v7i4.27.22431

Md Yusof, Z., Ibrahim, Z., Ibrahim, I., Mohd Azmi, K. Z., Ab Aziz, N. A., Abd Aziz, N. H., & Mohamad, M. S. (2016a). Angle Modulated Simulated Kalman Filter Algorithm for Combinatorial Optimization Problems. *ARPN Journal of Engineering and Applied Sciences*, *11*(7), 4854–4859. Retrieved from http://www.arpnjournals.org/jeas/research_papers/rp_2016/jeas_0416_4036.pdf

Md Yusof, Z., Ibrahim, Z., Ibrahim, I., Mohd Azmi, K. Z., Ab Aziz, N. A., Abd Aziz, N. H., & Mohamad, M. S. (2016b). Distance Evaluated Simulated Kalman Filter Algorithm for Combinatorial Optimization Problems. *ARPN Journal of Engineering and Applied Sciences*, *11*(7), 4911–4916. Retrieved from http://www.arpnjournals.org/jeas/research_papers/rp_2016/jeas_0416_4045.pdf

Md Yusof, Z., Satiman, S. N., Mohd Azmi, K. Z., Muhammad, B., Razali, S., Ibrahim, Z., … Ismail, S. (2015). Solving Airport Gate Allocation Problem using Simulated Kalman Filter. *International Conference on Knowledge Transfer*, 875–885. Retrieved from http://umpir.ump.edu.my/id/eprint/15722

Merrikh-Bayat, F. (2015). The Runner-root Algorithm: A Metaheuristic for Solving Unimodal and Multimodal Optimization Problems Inspired by Runners and Roots of Plants in Nature. *Applied Soft Computing*, *33*, 292–303. https://doi.org/10.1016/j.asoc.2015.04.048

Meshkat, M., & Parhizgar, M. (2018). Sine Optimization Algorithm (SOA): A Novel Optimization Algorithm by Change Update Position Strategy of Search Agent in Sine Cosine Algorithm. *Proceedings - 3rd Iranian Conference on Signal Processing and Intelligent Systems, ICSPIS 2017*, *2017–Decem*, 11–16. https://doi.org/10.1109/ICSPIS.2017.8311581

Mirjalili, S. (2015a). Moth-flame Optimization Algorithm: A Novel Nature-inspired Heuristic Paradigm. *Knowledge-Based Systems*, *89*, 228–249. https://doi.org/10.1016/j.knosys.2015.07.006

Mirjalili, S. (2015b). The Ant Lion Optimizer. *Advances in Engineering Software*, *83*, 80–98. https://doi.org/10.1016/j.advengsoft.2015.01.010

Mirjalili, S. (2016a). Dragonfly Algorithm: A New Meta-heuristic Optimization Technique for Solving Single-objective, Discrete, and Multi-objective Problems. *Neural Computing and Applications*, *27*(4), 1053–1073. https://doi.org/10.1007/s00521-015-1920-1

Mirjalili, S. (2016b). SCA: A Sine Cosine Algorithm for Solving Optimization Problems. *Knowledge-Based Systems*, *96*, 120–133. https://doi.org/10.1016/j.knosys.2015.12.022

Mirjalili, S., Gandomi, A. H., Mirjalili, S. Z., Saremi, S., Faris, H., & Mirjalili, S. M. (2017). Salp Swarm Algorithm: A Bio-inspired Optimizer for Engineering Design Problems. *Advances in Engineering Software*, 1–29. https://doi.org/10.1016/j.advengsoft.2017.07.002

Mirjalili, S., & Lewis, A. (2016). The Whale Optimization Algorithm. *Advances in Engineering Software*, *95*, 51–67. https://doi.org/10.1016/j.advengsoft.2016.01.008

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey Wolf Optimizer. *Advances in Engineering Software*, *69*, 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007

Moghdani, R., & Salimifard, K. (2018). Volleyball Premier League Algorithm. *Applied Soft Computing Journal*, *64*, 161–185. https://doi.org/10.1016/j.asoc.2017.11.043

Mohd Azmi, K. Z., Ibrahim, Z., Pebrianti, D., Mat Jusof, M. F., Abdul Aziz, N. H., & Ab.Aziz, N. A. (2019). Enhancing Simulated Kalman Filter Algorithm using

Current Optimum Opposition-based Learning. *Journal of Intelligent Manufacturing & Mechatronics*, *01*(01), 1–13. https://doi.org/10.15282/mekatronika.v1i1.157

Mohd Azmi, K. Z., Md Yusof, Z., Satiman, S. N., Muhammad, B., Razali, S., Ibrahim, Z., … Abd Aziz, N. H. (2016). Solving Airport Gate Allocation Problem using Angle Modulated Simulated Kalman Filter. In *The National Conference for Postgraduate Research 2016 (ncon-pgr)* (pp. 875–885). Retrieved from http://umpir.ump.edu.my/id/eprint/15722/

Mohd Sabri, N., Puteh, M., & Mahmood, M. R. (2013). A Review of Gravitational Search Algorithm. *International Journal Advance Soft Computing and Applications*, *5*(3), 1–39. Retrieved from http://home.ijasca.com/data/documents/ijasc08_published.pdf

Mousavirad, S. J., & Ebrahimpour-Komleh, H. (2017). Human Mental Search: A New Population-based Metaheuristic Optimization Algorithm. *Applied Intelligence*, *47*(3), 850–887. https://doi.org/10.1007/s10489-017-0903-6

Muhammad, B., Ibrahim, Z., Ghazali, K. H., Mohd Azmi, K. Z., Ab Aziz, N. A., Abd Aziz, N. H., & Mohamad, M. S. (2015). A New Hybrid Simulated Kalman Filter and Particle Swarm Optimization for Continuous Numerical Optimization Problems. *ARPN Journal of Engineering and Applied Sciences*, *10*(22), 17171–17176. Retrieved from https://pdfs.semanticscholar.org/3abc/bcf2d447af7832e7be6ffa8ad7a8a69da0d3.pdf

Muhammad, B., Ibrahim, Z., Mohd Azmi, K. Z., Abas, K. H., Ab Aziz, N. A., Abd Aziz, N. H., & Mohamad, M. S. (2016). Performance Evaluation of Hybrid SKF Algorithms : Hybrid SKF-PSO and Hybrid SKF-GSA. In *The National Conference for Postgraduate Research 2016 (NCON-PGR)* (pp. 865–874). Retrieved from http://umpir.ump.edu.my/id/eprint/15724/

Muhammad, B., Mat Jusof, M. F., Shapiai, M. I., Adam, A., Md Yusof, Z., Mohd Azmi, K. Z., … Mokhtar, N. (2018). Feature Selection using Angle Modulated Simulated Kalman Filter for Peak Classification of EEG Signals. In *2018 8th International Conference on Intelligent Systems, Modelling and Simulation Feature*. https://doi.org/10.1109/ISMS.2018.00010

Mussi, L., Cagnoni, S., & Daolio, F. (2009). Empirical Assessment of the Effects of Update Synchronization in Particle Swarm Optimization. *Proceeding of the AIIA Workshop on Complexity, Evolution and Emergent Intelligence*, (1), 1–10. Retrieved from https://mailserver.di.unipi.it/ricerca/proceedings/AIIA09workshops/CEEI/Mussi_al.pdf

Ojstersek, R., Hankun, Z., Shifeng, L., & Buchmeister, B. (2018). Improved Heuristic Kalman Algorithm for Solving Multi-Objective Flexible Job Shop Scheduling Problem. In *Procedia Manufacturing* (Vol. 17, pp. 895–902). https://doi.org/10.1016/j.promfg.2018.10.142

Ojstersek, R., Zhang, H., Palcic, I., & Buchmeister, B. (2017). Use of Heuristic Kalman Algorithm for JSSP. In *XVII International Scientific Conference on Industrial Systems* (pp. 72–77). Retrieved from https://www.iim.ftn.uns.ac.rs/is17/papers/13.pdf

Pakrashi, A., & Chaudhuri, B. B. (2016). A Kalman Filtering Induced Heuristic Optimization Based Partitional Data Clustering. *Information Sciences*, *369*, 704–717. https://doi.org/10.1016/j.ins.2016.07.057

Pijarski, P., & Kacejko, P. (2019). A New Metaheuristic Optimization Method: the Algorithm of the Innovative Gunner (AIG). *Engineering Optimization*, *0273*. https://doi.org/10.1080/0305215X.2019.1565282

Pombeiro, H., Machado, M. J., & Silva, C. (2017). Dynamic Programming and Genetic Algorithms to Control an HVAC System: Maximizing Thermal Comfort and Minimizing Cost with PV Production and Storage. *Sustainable Cities and Society Journal*, *34*(May), 228–238. https://doi.org/10.1016/j.scs.2017.05.021

Pramada, S. K., Mohan, S., & Sreejith, P. K. (2017). Application of Genetic Algorithm for the Groundwater Management of a Coastal Aquifer. *ISH Journal of Hydraulic Engineering*, *5010*(October), 1–7. https://doi.org/10.1080/09715010.2017.1378597

Puchalsky, W., Ribeiro, G. T., da Veiga, C. P., Freire, R. Z., & Santos Coelho, L. dos. (2018). Agribusiness Time Series Forecasting using Wavelet Neural Networks and Metaheuristic Optimization: An Analysis of the Soybean Sack Price and Perishable Products Demand. *International Journal of Production Economics*, *203*(July 2017), 174–189. https://doi.org/10.1016/j.ijpe.2018.06.010

Qi, X., Zhu, Y., & Zhang, H. (2017). A New Meta-heuristic Butterfly-Inspired Algorithm. *Journal of Computational Science*, *23*, 226–239. https://doi.org/10.1016/j.jocs.2017.06.003

Rada-Vilela, J., Zhang, M., & Seah, W. (2011a). A Performance Study on Synchronous and Asynchronous Updates in Particle Swarm Optimization. *The 13th Annual Conference on Genetic and Evolutionary Computation*, 21. https://doi.org/10.1145/2001576.2001581

Rada-Vilela, J., Zhang, M., & Seah, W. (2011b). Random Asynchronous PSO. In *The 5th International Conference on Automation, Robotics and Applications* (pp. 220–

225). https://doi.org/10.1109/ICARA.2011.6144885

Rada-Vilela, J., Zhang, M., & Seah, W. (2013). A Performance Study on Synchronicity and Neighborhood Size in Particle Swarm Optimization. *Soft Computing*, *17*(6), 1019–1030. https://doi.org/10.1007/s00500-013-1015-9

Rajeswari, K., & Neduncheliyan, S. (2017). Genetic Algorithm Based Fault Tolerant Clustering in Wireless Sensor Network. *The Institution of Engineering and Technology*, *11*(12), 1927–1932. https://doi.org/10.1049/iet-com.2016.1074

Ram Jethmalani, C. H., Simon, S. P., Sundareswaran, K., Srinivasa Rao Nayak, P., & Padhy, N. P. (2016). Auxiliary Hybrid PSO-BPNN-Based Transmission System Loss Estimation in Generation Scheduling. *IEEE Transactions on Industrial Informatics*, *13*(4), 1–1. https://doi.org/10.1109/TII.2016.2614659

Rashedi, E., Nezamabadi-pour, H., & Saryazdi, S. (2009). GSA: A Gravitational Search Algorithm. *Information Sciences*, *179*(13), 2232–2248. https://doi.org/10.1016/j.ins.2009.03.004

Rueda, J. L., & Erlich, I. (2015). MVMO for Bound Constrained Single-objective Computationally Expensive Numerical Optimization. In *2015 IEEE Congress on Evolutionary Computation* (pp. 1011–1017). https://doi.org/10.1109/CEC.2015.7257000

Salmani, M. H., & Eshghi, K. (2017). A Metaheuristic Algorithm Based on Chemotherapy Science : CSA. *Journal of Optimization*, *2017*. https://doi.org/https://doi.org/10.1155/2017/3082024

Samsuddin, S., Othman, M. S., & Yusuf, L. M. (2018). A Review of Single and Population-based Metaheuristic Algorithms Solving Multi Depot Vehicle Routing Problem. *International Journal of Software Engineering and Computer Systems (IJSECS)*, *4*(2), 80–93. https://doi.org/10.15282/ijsecs.4.2.2018.6.0050

Saremi, S., Mirjalili, S., & Lewis, A. (2017). Grasshopper Optimisation Algorithm: Theory and Application. *Advances in Engineering Software*, *105*, 30–47. https://doi.org/10.1016/j.advengsoft.2017.01.004

Shadravan, S., Naji, H. R., & Bardsiri, V. K. (2019). The Sailfish Optimizer: A Novel Nature-inspired Metaheuristic Algorithm for Solving Constrained Engineering Optimization Problems. *Engineering Applications of Artificial Intelligence*, *80*(January), 20–34. https://doi.org/10.1016/j.engappai.2019.01.001

Sharafi, Y., Khanesar, M. A., & Teshnehlab, M. (2016). COOA: Competitive

Optimization Algorithm. *Swarm and Evolutionary Computation*, *30*, 39–63. https://doi.org/10.1016/j.swevo.2016.04.002

Shayanfar, H., & Gharehchopogh, F. S. (2018). Farmland Fertility: A New Metaheuristic Algorithm for Solving Continuous Optimization Problems. *Applied Soft Computing*, *71*, 728–746. https://doi.org/10.1016/j.asoc.2018.07.033

Shmaliy, Y. S., Khan, S., & Zhao, S. (2016). Ultimate Iterative UFIR Filtering Algorithm. *Measurement*, *92*, 236–242. https://doi.org/https://doi.org/10.1016/j.measurement.2016.06.029

Shmaliy, Y. S., Neuvo, Y., & Khan, S. (2018). Review of Unbiased FIR Filters , Smoothers , and Predictors for Polynomial Signals. *Frontier in Signal Processing*, *2*(1), 1–29. https://doi.org/10.22606/fsp.2018.21001

Shmaliy, Y. S., & Simon, D. (2013). Iterative Unbiased FIR State Estimation: A Review of Algorithms. *EURASIP Journal on Advances in Signal Processing*, *2013*(1), 113. https://doi.org/10.1186/1687-6180-2013-113

Shmaliy, Y. S., Zhao, S., & Ahn, C. K. I. (2017). Unbiased Finite Impulse Response Filtering. *IEEE Control Systems Magazine*, (October). https://doi.org/10.1109/MCS.2017.2718830

Singh, M., Patel, R. N., & Neema, D. D. (2019). Robust Tuning of Excitation Controller for Stability Enhancement using Multi-objective Metaheuristic Firefly Algorithm. *Swarm and Evolutionary Computation*, *44*(February 2018), 136–147. https://doi.org/10.1016/j.swevo.2018.01.010

Singh, S. P., & Kesavan Nair, N. (2017). Artificial Bee Colony Algorithm for Inverter Complex Wave Reduction Under Line-load Variations. *Transactions of the Institute of Measurement and Control*, 1–15. https://doi.org/10.1177/0142331216687019

Sörensen, K. (2013). Metaheuristics — The Metaphor Exposed. *International Transactions in Operational Research*, *00*, 1–16. https://doi.org/10.1111/itor.12001

Spears, W. M., Jong, K. A. De, Back, T., Fogel, D. B., & Garis, H. De. (1993). An Overview of Evolutionary Computation. In P. B. Brazdil (Ed.), *Machine Learning: Lecture Notes in Computer Science (Lecture Notes in Artificial Intelligence)*. Springer, Berlin, Heidelberg. https://doi.org/10.1007/3-540-56602-3_163

Srivatsan, R. A., & Choset, H. (2016). Multiple Start Branch and Prune Filtering Algorithm for Nonconvex Optimization. In *The 12th International Workshop on*

The Algorithmic Foundations of Robotics. Retrieved from https://www.ri.cmu.edu/publications/multiple-start-branch-and-prune-filtering-algorithm-for-nonconvex-optimization/

Storn, R., & Price, K. (1997). Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces. *Journal of Global Optimization*, *11*, 341–359.

Suganthan, P. N. (2014). Particle Swarm Optimization Algorithm MATLAB code. Retrieved from http://www.ntu.edu.sg/home/epnsugan/

Tabari, A., & Ahmad, A. (2017). A New Optimization Method: Electro-Search Algorithm. *Computers and Chemical Engineering*, *103*, 1–11. https://doi.org/10.1016/j.compchemeng.2017.01.046

Talbi, E. G. (2009). *Metaheuristics from Design to Implementation*. Hoboken, New Jersey: John Wiley & Sons, Incorporated,Publication. Retrieved from https://www.wiley.com/en-us/Metaheuristics%3A+From+Design+to+Implementation+-p-9780470278581

Tanabe, R., & Fukunaga, A. S. (2014). Improving the Search Performance of SHADE Using Linear Population Size Reduction. *2014 IEEE Congress on Evolutionary Computation*. https://doi.org/10.1109/CEC.2014.6900380

Thoiba Meetei, K. (2014). A Survey : Swarm Intelligence vs. Genetic Algorithm. *International Journal of Science and Research*, *3*(5), 231–235. Retrieved from https://pdfs.semanticscholar.org/ee7f/4a1bb8525944951527645b0a62b929313404.pdf

Ting, C. K., Liao, X. L., Huang, Y. H., & Liaw, R. T. (2017). Multi-vehicle Selective Pickup and Delivery using Metaheuristic Algorithms. *Information Sciences*, *406–407*, 146–169. https://doi.org/10.1016/j.ins.2017.04.001

Topal, A. O. (2017). *A Novel Metaheuristic Algorithm: Dynamic Virtual Bats Algorithm for Global Optimization*. Epoka University. Retrieved from http://dspace.epoka.edu.al/handle/1/1812

Topal, A. O., & Altun, O. (2016). A Novel Meta-heuristic Algorithm: Dynamic Virtual Bats Algorithm. *Information Sciences*, *354*, 222–235. https://doi.org/10.1016/j.ins.2016.03.025

Toscano, R., & Ivan, I. A. (2014). Robust Structured Controllers for Piezoelectric Microactuators. *ISA Transactions*, *53*(6), 1857–1864.

https://doi.org/10.1016/j.isatra.2014.08.009

Toscano, R., & Lynonnet, P. (2009). Heuristic Kalman Algorithm for Solving Optimization Problems. *IEEE Transaction on Systems, Man and Cybernatics.*, *39*(5), 1231–44. https://doi.org/10.1109/TSMCB.2009.2014777

Toscano, R., & Lyonnet, P. (2009a). Mixed H2/H∞ Residual Generator Design via Heuristic Kalman Algorithm. In *7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes*. Retrieved from http://rosario.toscano.free.fr/HKAfdi.pdf

Toscano, R., & Lyonnet, P. (2009b). Robust PID Controller Tuning Based on the Heuristic Kalman Algorithm. *Automatica*, *45*(9), 2099–2106. https://doi.org/10.1016/j.automatica.2009.05.007

Toscano, R., & Lyonnet, P. (2012). A Kalman Optimization Approach for Solving Some Industrial Electronics Problems. *IEEE Transactions on Industrial Electronics*, *59*(11), 4456–4464. https://doi.org/10.1109/TIE.2011.2169637

Uymaz, S. A., Tezel, G., & Yel, E. (2015). Artificial Algae Algorithm (AAA) for Nonlinear Global Optimization. *Applied Soft Computing*, *31*, 153–171. https://doi.org/10.1016/j.asoc.2015.03.003

Van Den Bergh, F., & Engelbrecht, A. P. (2006). A Study of Particle Swarm Optimization Particle Trajectories. *Information Sciences*, *176*(8), 937–971. https://doi.org/10.1016/j.ins.2005.02.003

Varaee, H., & Ghasemi, M. R. (2016). Engineering Optimization Based on Ideal Gas Molecular Movement Algorithm. *Engineering with Computers*. https://doi.org/10.1007/s00366-016-0457-y

Vazquez-Olguin, M., Shmaliy, Y. S., & Ibarra-Manzano, O. G. (2017). Distributed Unbiased FIR FilteringWith Average Consensus on Measurements for WSNs. *IEEE Transactions on Industrial Informatics*, *13*(3), 1440–1447. https://doi.org/10.1109/TII.2017.2653814

Wolpert, D. H., & Macready, W. G. (1997). No Free Lunch Theorems for Optimization. *IEEE Transactions on Evolutionary Computation*, *1*(1), 67–82. https://doi.org/10.1109/4235.585893

Wu, D., & Gao, H. (2015). Study on Asynchronous Update Mechanism in Particle Swarm Optimization. *14th International Symposium on Communications and Information Technologies, ISCIT 2014*, 90–93.

https://doi.org/10.1109/ISCIT.2014.7011876

Xue, S., Zhang, J., & Zeng, J. (2009). Parallel Asynchronous Control Strategy for Target Search with Swarm Robots. *International Journal of Bio-Inspired Computation*, *1*(3), 151–163. https://doi.org/10.1504/IJBIC.2009.023811

Yang, J., Peng, Z., Pei, Z., Guan, Y., Yuan, H., & Wu, L. (2018). Remaining Useful Life Assessment of Lithium-ion Battery based on HKA-ELM Algorithm. *International Journal of Electrochemical Science*, *13*(2018), 9257–9272. https://doi.org/10.20964/2018.10.51 Interna

Yang, X.-S. (2012). Flower Pollination Algorithm for Global Optimization. In J. Durand-Lose & N. Jonoska (Eds.), *Unconventional Computation and Natural Computation. UCNC 2012. Lecture Notes in Computer Science* (Vol. 7445, pp. 240–249). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-32894-7_27

Yang, X.-S. (2013). Optimization and Metaheuristic Algorithms in Engineering. In X.-S. Yang, A. H. Gandomi, S. Talatahari, & A. . Alavi (Eds.), *Metaheuristics in Water, Geotechnical and Transport Engineering* (Vol. 356, pp. 1–23). Elsevier. https://doi.org/10.1007/978-3-642-20859-1

Yapici, H., & Cetinkaya, N. (2019). A New Meta-heuristic Optimizer: Pathfinder Algorithm. *Applied Soft Computing*. https://doi.org/10.1016/J.ASOC.2019.03.012

Zamli, K. Z., Din, F., Kendall, G., & Ahmed, B. S. (2017). An Experimental Study of Hyper-heuristic Selection and Acceptance Mechanism for Combinatorial T-way Test Suite Generation. *Information Sciences*, *399*, 121–153. https://doi.org/10.1016/j.ins.2017.03.007

Zhang, J., Xiao, M., Gao, L., & Pan, Q. (2018). Queuing Search Algorithm: A Novel Metaheuristic Algorithm for Solving Engineering Optimization Problems. *Applied Mathematical Modelling*, *63*, 464–490. https://doi.org/10.1016/j.apm.2018.06.036

Zhang, Q., Wang, R., Yang, J., Lewis, A., Chiclana, F., & Yang, S. (2018). Biology Migration Algorithm: A New Nature-inspired Heuristic Methodology for Global Optimization. *Soft Computing*, 1–26. https://doi.org/10.1007/s00500-018-3381-9

Zhao, S., Shmaliy, Y. S., Ahn, C. K., & Liu, F. (2018). Adaptive-Horizon Iterative UFIR Filtering Algorithm with Applications. *IEEE Transactions on Industrial Electronics*, *65*(8), 6393–6402. https://doi.org/10.1109/TIE.2017.2784405

Zhou, Y., Wang, Y., Chen, X., Zhang, L., & Wu, K. (2017). A Novel Path Planning

Algorithm Based on Plant Growth Mechanism. *Soft Computing*, *21*(2), 435–445. https://doi.org/10.1007/s00500-016-2045-x

Zoghby, N. El, Loscri, V., Natalizio, E., & Cherfaoui, V. (2014). Robot Cooperation and Swarm Intelligence. In *Wireless Sensor and Robot Networks: From Topology Control to Communication Aspects* (pp. 168–201). World Scientific Publishing Company. Retrieved from https://hal.archives-ouvertes.fr/hal-00917542/document

APPENDIX A
LIST OF PUBLICATIONS

1. Ab Rahman, T., Ibrahim, Z., Ab Aziz, N.A, Zhao, S., Abdul Aziz, N.H. (2018). Single-agent Finite Impulse Response Optimizer for Numerical Optimization Problems. *IEEE Access*, 6 (2018), 9358-9374. https://doi.10.1109/ACCESS.2017.2777894.

2. Ab Rahman, T., Ibrahim, Z., Ab Aziz, N.A, Zha, S., Abdul Aziz, N.H., Mohammed, S.K., Mohamad, B., Md Yusof, Z. (2018). A Study on the Effect of Local Neighbourhood Parameter towards the Performance of SAFIRO. *International Journal of Engineering and Technology*, 7 (4.27) (2018) 30-37. https://doi.10.14419/ijet.v7i427.22476.

3. Ab Rahman, T., Ibrahim, Z., Ab Aziz, N.A, Zha, S., Abdul Aziz, N.H., Shapiai, M.I.& Mohamed, M.S. (2019). Evaluation of Different Horizon Lengths in Single-agent Finite Impulse Response Optimizer. ICCIS 2019: *International Conference on Computer and Information Sciences*. https://doi.10.1109/ICCISci.2019.8716455.

4. Ab Rahman, T., Ab Aziz, N.A, Abdul Aziz, N.H., Mohamad, B., Ibrahim, Z., Mohamed, M.S. (2019). Single-agent Finite Impulse Response Optimizer versus Simulated Kalman Filter Optimizer. *Journal of Mechatronics and Intelligent Manufacturing* (accepted).

5. Ab Rahman, T., Ibrahim, Z., Ab Aziz, N.A, Zhao, S., Abdul Aziz, N.H., Shapiai, M.I. Multi-agent Finite Impulse Response Optimizer for Numerical Optimization Problems. *Sadhana* (under review).