NORMATIVE FISH SWARM ALGORITHM FOR GLOBAL OPTIMIZATION WITH APPLICATIONS

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by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

a	Diode ideality factor
$a_l^t/\ a_g^t$	Acceleration factor
D	Duty cycle
D_k	Stochastically selected dimension
d	Target point in terms of duty cycle D
df	Degree of freedom
d_{cg}^t	Selected guideline similar to $\boldsymbol{X}_{cg}^t$
d_{gbest}^t	Global best point of population at t^{th} iteration
$d_{i,cl}^t$	Selected guideline similar to $\boldsymbol{X}_{i,cl}^t$
$d_{i,lbest}^t$	Local best point of i^{th} candidate at t^{th} iteration
d_{ij}	Distance between j^{th} adjacent comrade and i^{th} candidate
d_i^t	Target point of i^{th} candidate at t^{th} iteration
d_i^{t-1}	Target point of i^{th} candidate at $(t$-1$)^{th}$ iteration
G	Irradiance level under
$G_{nominal}$	Nominal irradiance level, $1000Wm^{-2}$
I_d	Diode current
$\boldsymbol{I}_k$	Enclosed spacing for index k
I_o	Reverse bias saturation
$I_{o,nominal}$	Reverse bias saturation current under nominal condition
I_{ph}	Generated current from incident light
$I_{ph,nominal}$	Current produced from incident sunlight under nominal condition
I_{pv}	PV terminal current
I_R	Load current
I_{sc}	Short-circuit current

$I_{sc,nominal}$	Short-circuit current under nominal condition
K_I	Temperature coefficient of short-circuit current
k	Index of dimension
k_b	Boltzmann constant, $1.3806503 \times 10^{-23}\, JK^{-1}$
$\boldsymbol{L}_k^t$	$\boldsymbol{L}_k^t = f(\boldsymbol{l}_k^t)$, is the objective fitness of $\boldsymbol{l}_k^t$
$\boldsymbol{l}$	Lower bound of feasible space
$\boldsymbol{l}_k$	Lower bound of feasible space for k^{th} dimension
$\boldsymbol{l}_k^t$	Lower bound of feasible space for k^{th} dimension at t^{th} iteration
m	Objective number
N	Dimension
No_{try}	Number of tries
N_c	Cell number per module
N_m	Module number per string
N_p	String number
N_s	Cell number per string
n	Fish population
$nGrid$	Number of grids per dimension
$nRep$	Maximum allowable number of repository members or repository size
n_f	Entire range of adjacent comrades that satisfies the prerequisite of $d_{ij} < visual$
$\boldsymbol{PS}$	Pareto solution
$P_{crossover}$	Crossover probability
P_{delete}	Roulette probability
P_{max}	Maximum power
P_{mp}	Maximum power point
P_{pv}	PV terminal power

P_R	Load power
$\boldsymbol{Rep}$	Decision vector of a repository member
$\boldsymbol{R}_i$	Range of an available variation for i^{th} objective in adaptive grid mechanism
R_s	Series resistor
R_{sh}	Equivalent shunt resistor
$radius^t$	Reconnaissance radius at t^{th} iteration
step	Largest allowable step length of each candidate
$step_{min}$	Minimum allowable *step* size
$T_{nominal}$	Nominal operating temperature, $25℃$ or 298.15K
t	Index of iteration
t_{limit}	Limited number of iterations that allows the best fitness to remain unchanged without updating
t_{max}	Maximum number of iterations
$\boldsymbol{U}_k^t$	$\boldsymbol{U}_k^t = f(\boldsymbol{u}_k^t)$, is the objective fitness of $\boldsymbol{u}_k^t$
$\boldsymbol{u}$	Upper bound of feasible space
$\boldsymbol{u}_k$	Upper bound of feasible space for k^{th} dimension
$\boldsymbol{u}_k^t$	Upper bound of feasible space for k^{th} dimension at t^{th} iteration
V_{oc}	Open-circuit voltage
$V_{oc,nominal}$	Open-circuit voltage under nominal condition
V_{pv}	PV terminal voltage
V_R	Load voltage
V_t	Thermal voltage of PV cell
$V_{t,nominal}$	Thermal voltage of PV cell under nominal condition
visual	Perception range to assemble the surrounding information
$visual_{min}$	Minimum allowable *visual* size
$\boldsymbol{v}^t$	Velocity vector of candidate at t^{th} iteration
$\boldsymbol{X}$	Feasible solution or location vector of a candidate

$\boldsymbol{X}^{t}$	Feasible solution or location vector of candidate at t^{th} iteration
$\boldsymbol{X}^{t-1}$	Feasible solution or location vector of candidate at $(t\text{-}1)^{\text{th}}$ iteration
$\boldsymbol{X}\boldsymbol{1}_{i}^{t+1}$	Updated location vector of i^{th} candidate through the normative communication behavior
$\boldsymbol{X}\boldsymbol{2}_{i}^{t+1}$	Updated location vector of i^{th} candidate through the normative memory behavior
$\boldsymbol{X}\boldsymbol{3}_{i}^{t+1}$	Updated location vector of i^{th} candidate through the follow behavior
$\boldsymbol{X}\boldsymbol{4}_{i}^{t+1}$	Updated location vector of i^{th} candidate through the swarm behavior
$\boldsymbol{X}_{C}$	Central location vector of a group of candidates within *visual* perception
$\boldsymbol{X}_{cg}^{t}$	Supplementary guideline selected within the reconnaissance range which originates from $\boldsymbol{X}_{gbest}^{t}$
$\boldsymbol{X}_{cg}^{t-1}$	Supplementary guideline selected within the reconnaissance range which originates from $\boldsymbol{X}_{gbest}^{t-1}$
$\boldsymbol{X}_{cl}^{t}$	Supplementary guideline selected within the reconnaissance range which originates from $\boldsymbol{X}_{lbest}^{t}$
$\boldsymbol{X}_{cl}^{t-1}$	Supplementary guideline selected within the reconnaissance range which originates from $\boldsymbol{X}_{lbest}^{t-1}$
$\boldsymbol{X}_{gbest}$	Global best solution
$\boldsymbol{X}_{gbest}^{t}$	Global best location vector of population at t^{th} iteration
$\boldsymbol{X}_{gbest}^{t-1}$	Global best location vector of population at $(t\text{-}1)^{\text{th}}$ iteration
$\boldsymbol{X}_{i}$	Feasible solution or location vector of i^{th} candidate
$\boldsymbol{X}_{i}^{t}$	Feasible solution or location vector of i^{th} candidate at t^{th} iteration
$\boldsymbol{X}_{i}^{t-1}$	Feasible solution or location vector of i^{th} candidate at $(t\text{-}1)^{\text{th}}$ iteration
$\boldsymbol{X}_{i,cl}^{t}$	Selected guideline for i^{th} candidate which originates from $\boldsymbol{X}_{i,lbest}^{t}$
$\boldsymbol{X}_{i,cl}^{t-1}$	Selected guideline for i^{th} candidate which originates from $\boldsymbol{X}_{i,lbest}^{t-1}$
$\boldsymbol{X}_{i,k}$	Feasible solution or location vector of i^{th} candidate for k^{th} dimension

$\boldsymbol{X}_{i,lbest}^{t}$	Local best location vector of i^{th} candidate at t^{th} iteration
$\boldsymbol{X}_{i,lbest}^{t-1}$	Local best location vector of i^{th} candidate at $(t\text{-}1)^{th}$ iteration
$\boldsymbol{X}_j$	Arbitrary location vector chosen within the allowable *visual* range
$\boldsymbol{X}_k^{t+1}$	Location vector of candidate for k^{th} dimension at $(t+1)^{th}$ iteration
$\boldsymbol{X}_{lbest}^{t}$	Local best location vector of candidate at t^{th} iteration
$\boldsymbol{X}_{lbest}^{t-1}$	Local best location vector of candidate at $(t\text{-}1)^{th}$ iteration
$\boldsymbol{X}_{min}$	Location vector of adjacent comrade who at present possesses the most advantageous objective fitness
$\boldsymbol{X}_{new,k}^{t+1}$	Location vector of a newly born offspring for k^{th} dimension at $(t+1)^{th}$ iteration
X[i]	$\boldsymbol{X}_i$
X(t-1)[i]	$\boldsymbol{X}_i^{t-1}$
XCGBEST[i]	$\boldsymbol{X}_{gbest}^{t}$
XCLBEST[i]	$\boldsymbol{X}_{i,lbest}^{t}$
XPGBEST[i]	$\boldsymbol{X}_{gbest}^{t-1}$
XPLBEST[i]	$\boldsymbol{X}_{i,lbest}^{t-1}$
x̃	Mean
$\boldsymbol{x}_{i,k}$	Candidate solution vector of i^{th} candidate for k^{th} dimension
$\boldsymbol{x}_{i,k}^{new}$	Homologous new mutated vector of i^{th} candidate for k^{th} dimension
$\boldsymbol{x}_{i,k}^{old}$	Former solution vector of i^{th} candidate for k^{th} dimension
$\boldsymbol{Y}$	$\boldsymbol{Y} = f(\boldsymbol{X})$, is the nourishment density or objective fitness of $\boldsymbol{X}$
$\boldsymbol{Y}^t$	Objective function of $\boldsymbol{X}^t$
$\boldsymbol{Y}_C$	Objective function of $\boldsymbol{X}_C$
$\boldsymbol{Y}_{gbest}$	Objective function of $\boldsymbol{X}_{gbest}$
$\boldsymbol{Y}_i$	$\boldsymbol{Y}_i = f(\boldsymbol{X}_i)$, is the objective fitness of $\boldsymbol{X}_i$
$\boldsymbol{Y}_i^t$	Objective function of $\boldsymbol{X}_i^t$
$\boldsymbol{Y}_j$	Objective function of $\boldsymbol{X}_j$

$\boldsymbol{Y}_{min}$	Objective function of $\boldsymbol{X}_{min}$
β_1	Speed factor in normative communication behavior
β_2	Speed factor in normative memory behavior
ξ_t	Current effective factors
ξ_{t-1}	Effective factor of extended memory
$\boldsymbol{\rho}_g^t$	Best-known location vector of the entire population at t^{th} iteration
$\boldsymbol{\rho}_l^t$	Best-known individual location vector at t^{th} iteration
γ	Deletion selection pressure
σ	Declining scale factor
ψ	Global best selection portion
α	Grid inflation rate
δ	Crowding factor
μ	Population mean
σ	Adaptive variable in determining the degree of variation in adaptive parameters
φ	Scaling factor of crossover probability in multi-objective optimization approach
ω	Inertia weight
ϑ	Rotation variable

LIST OF ABBREVIATIONS

AF	Artificial Fish
AFSA	Artificial Fish Swarm Algorithm
BIA	Bio-Inspired Algorithm
CAFSA	Cultural Artificial Fish Swarm Algorithm
CD	Crowding Distance
CI	Computational Intelligence
CIAFSA	Comprehensive Improved Artificial Fish Swarm Algorithm
CICMOPSO	Chaotic Multi-Objective Particle Swarm Optimization Approach Incorporating Clone Immunity
GAFSA	Global Artificial Fish Swarm Algorithm
GD	Generation Distance
GSOA	Global Search and Optimization Algorithm
MO-NFSA	Multi-Objective Optimization Approach Based on Normative Fish Swarm Algorithm
MOPSO	Multi-Objective Particle Swarm Optimization
MOPSO_MS	Multi-Swarm Multi-Objective Particle Swarm Optimization Based on Decomposition
MOPSO-CD	Multi-Objective Particle Swarm Optimization with Crowding Distance
MOSFET	Metal-Oxide-Semiconductor Field-Effect Transistor
MPP	Maximum Power Point
MPPT	Maximum Power Point Tracking
NFSA	Normative Fish Swarm Algorithm
NICPSO	Multi-Objective Particle Swarm Optimization with Non-Dominated Neighbor Immune Strategy
PSO	Particle Swarm Optimization

PSOEM	Particle Swarm Optimization with Extended Memory
PSOEM-FSA	Fish Swarm Algorithm Optimized by Particle Swarm Optimization with Extended Memory
PV	Photovoltaic
S	Spacing Index
SD	Standard Deviation

ALGORITMA GEROMBOLAN IKAN NORMATIF UNTUK PENGOPTIMUMAN GLOBAL DENGAN APLIKASI-APLIKASI

ABSTRAK

Algoritma-algoritma Gerombolan Ikan Buatan (AFSA) telah menjadi teknik pengoptimuman yang popular, digunakan untuk menyelesaikan pelbagai masalah. Namun, menurut kajian-kajian, algoritma gerombolan ikan yang sedia ada masih mempunyai kekurangan untuk mendapat optimum yang tepat dalam kadar penumpuan sewajarnya. Oleh itu, kerja ini mencadangkan strategi carian tempatan dan global yang berdaya maju untuk mencapai optimum global yang menarik pada kadar penumpuan yang terbaik. Dirujuk sebagai Algoritma Gerombolan Ikan Normatif (NFSA), Algoritma Gerombolan Ikan yang dicadangkan, dioptimumkan oleh Pengoptimuman Gerombolan Partikel dengan Memori Lanjutan (PSOEM-FSA) telah ditingkatkan dengan menggabungkan pengetahuan normatif untuk menyediakan garis panduan tambahan bagi pencapaian optimum global dan kadar penumpuan yang lebih dipercayai. NFSA menggabungkan pelarasan pembolehubah parameter *visual*, $visual_{min}$, *step* and $step_{min}$ untuk menyesuaikan ketidaksejajaran antara prospek dan eksploitasi. Di samping itu, teknik pelintas global yang diubahsuai diperbadankan untuk mengukuhkan perhubungan antara calon-calon penyelesaian. Prestasi NFSA telah diuji ke atas sepuluh fungsi penanda aras. Hasil yang diperoleh menunjukkan bahawa NFSA mencapai hasil utama daripada segi penyelesaian optimum dan kelajuan penumpuan. Selain itu, NFSA telah diaplikasi pada pengoptimuman pelbagai objektif dan masalah pengesanan titik kuasa maksimum (MPPT). Keputusan yang diperoleh daripada kedua-dua aplikasi telah membuktikan bahawa NFSA yang dicadangkan adalah lebih efektif dalam

pendekatan-pendekatan pengoptimuman pelbagai objektif dan MPPT berbanding beberapa algoritma evolusi perbandingan lain.

NORMATIVE FISH SWARM ALGORITHM FOR GLOBAL OPTIMIZATION WITH APPLICATIONS

ABSTRACT

Artificial Fish Swarm Algorithm (AFSA) have become popular optimization technique used to solve various problems, Nevertheless, according to surveys, the existing fish swarm algorithms still have some deficiencies to strike the exact optimum within appropriate convergence rate. Therefore, this work proposes a viable local and global seeking strategy to achieve compelling global optimum at predominant convergence rate. Referred to as Normative Fish Swarm Algorithm (NFSA), the proposed Fish Swarm Algorithm, Optimized by Particle Swarm Optimization with Extended Memory (PSOEM-FSA) is expanded by amalgamating the normative knowledge to provide supplementary guidelines for better global optimum achievement and convergence rate. NFSA incorporates adjustments of $visual$, $visual_{min}$, $step$ and $step_{min}$ parameters to adjust the inconsistency between the prospection and exploitation. In addition, the technique of modified global crossover is incorporated to strengthen the relationship between the candidate solutions. The performance of the NFSA has been tested on ten benchmark functions. The obtained results demonstrated that NFSA accomplished predominant outcomes in terms of optimized solution and convergence speed. Besides that, NFSA has been applied on multi-objective optimization and Maximum Power Point Tracking (MPPT) problems. The results obtained from both applications have proved that the proposed NFSA is more effective in multi-objective optimization and MPPT approaches in comparison to few compared evolutionary algorithms.

CHAPTER 1

INTRODUCTION

1.1 Background

Optimization problem is defined as an issue to search the most effective resolution among feasible solutions. Global optimization is one of the solutions, specifically looking for global minima or maxima in a given optimization problem. Typically, optimization problem can be a single-objective or multi-objective optimization type. Single-objective optimization is considerably simple and straightforward because it only contains a distinctive global optimum, regardless of whether the output is the largest or the smallest, or more directly because performance evaluation can be performed by inspecting relative objective values or fitness. Multi-objective or multi-criteria optimization on the other hand is a multi-criteria choice making with respect to an optimization issue including at least two objective functions to be optimized at the same time. As an example, in economic, multi-objective optimization is utilized to maximize the profits and customers' demands, and conversely minimize the business risks whenever the business problems involve the subsequent aspects: customers' demands, risks and profits. Multi-objective optimization deals with a group of Pareto optimal solutions, rather than a single optimality in single-objective optimization, aimed at achieving the Pareto solutions with superior convergence, spread and distribution.

Complex optimization problems that cannot be solved using step-by-step programming based on statistical or conventional methods require intelligent approaches. Computational Intelligence (CI) is one of them, and one of its sub-branches is swarm intelligence. The Global Search and Optimization Algorithm (GSOA) is the latest category introduced in CI. GSOA typically resolves the specified optimization problem by finding the appropriate global best solution, which has the advantage of providing metrics to indicate how good or bad the selection is. Meanwhile, the Bio-Inspired Algorithm (BIA) is categorized as part of the GSOA and is technically known as a swarm-based intelligent algorithm. In general, BIA is created by impersonating the behavioral patterns of designated creature in the real world. They have received extensive attention in several application areas, such as document clustering analysis [1–3] and Maximum Power Point Tracking (MPPT) [4].

Other relatively popular swarm-based algorithms are Ant Colony Optimization (ACO) [5, 6], Particle Swarm Optimization (PSO) [7, 8], Artificial Bee Colony (ABC) [9–11] and Artificial Fish Swarm Algorithm (AFSA). Among these, AFSA has been taken into account as one of the most interesting swarm intelligence algorithms, projected by Li, Shao and Qian in 2002 [12]. AFSA is favored due to its beneficial merits over other evolutionary algorithms: simplification, fast convergence, enhanced global search, parallelism and low sensitivity to the necessities of the target functions [13].

Generally, fish swarm resides in associate surroundings with glorious nourishment density. AFSA impersonates the fish swarm's behaviors living in the real-life circumstance. Every Artificial Fish (AF) is tutored to act consistently with the real-time scenario. Every AF is taught to execute four basic activities: swarm behavior, prey behavior, follow behavior and random behavior. Swarm behavior upgrades the steadiness and algorithm's global merging. Prey behavior establishes the convergence of algorithm. Follow behavior speeds up the convergence of algorithm. Finally, random behavior equalizes the inconsistency of the other behaviors. The *visual* and *step* are assigned to every AF, where *visual* represents the perception and *step* denotes the movable step length. Naturally, AFs employ *visual* to accumulate the information and utilize *step* to carry on a move. Each AF performs any from those behaviors in regard to current situation and condition.

It can be seen from the history of AFSA that the development and improvement of AFSA is mainly divided into two aspects: the modification of the existing AFSA and the hybridization of AFSA with other meta-heuristic methods. Among the most effective AFSA, Improved Artificial Fish-Swarm Optimization (IAFSO2) [14] which was proposed in 2005, enhances the stability of the algorithm and the ability of global search, while introducing the leaping behavior of the random candidate to explicitly change its parameters in the definable region. Cultural Artificial Fish Swarm Algorithm (CAFSA) was proposed in 2011 to involve the implementation of normative knowledge, where normative knowledge can be a set of reliable variations that provide individually adjustable standards for individual behavior and guidance. The latest valid AFSA can be Fish Swarm Algorithm Optimized by Particle Swarm Optimization with Extended Memory (PSOEM-FSA) [15] and the Comprehensive Improved Artificial Fish Swarm Algorithm (CIAFSA) [4], which were formally presented in 2016 and 2017 respectively. They boldly integrated the guidance strategy of Particle Swarm Optimization with Extended Memory (PSOEM) [16] into the standard AFSA to generate communication behavior and memory behavior guided by global and local indicators, respectively. This idea has the advantage of avoiding any contradictory search because the theoretical global search and local search were operated separately.

AFSA variants have been effectively utilized in a wide extend of optimization issues. The most typical optimization problems that have been addressed include document clustering and data mining. In 2014, Modified Artificial Fish Swarm Algorithm (MAFSA) accomplished the optimization of association rule mining [17]. In 2015, the Novel Artificial Fish Swarm Algorithm (NAFSA) was effectively applied to the recalibration of fiber optic gyroscope error parameters [18]. In the following year, in 2016, the Improved Artificial Fish Swarm Algorithm (IAFSA) was successfully applied to robot path planning [19]. Subsequently, in 2017, CIAFSA achieved a satisfactory solution in the global MPPT for Photovoltaic (PV) application system [4]. It has to be noted that the application of AFSA variants has recently become a hot topic for researchers in swarm intelligence area.

1.2 Problem Statements

Thus far, AFSA has been designed to resolve optimization issues, mainly single-objective optimization problems. Each optimization issue encompasses a unique solution (i.e. global optimal solution), where the outcome is optimized (i.e. global optimum). Each optimization algorithm gives the result of the global best value by finding the global best solution. The closer the global best value results are to the global optimum, the better the global optimum achievements, and so the better the performance of the algorithm. If the global best value is found to be equal to the global optimum, then the global optimum achievement is the best. The convergence rate is concerned to determine the relative speed where the optimum is approached. The higher the convergence rate, the shorter the time required for the algorithm to approach the global optimum, so the better the performance. However, there is no correlation between global optimum achievement and convergence rate. In other words, AFSA has been designed to achieve effective global best solution at superior convergence rates.

In spite of the fact that numerous advancements and modifications have been recently introduced on AFSA, they generally centered on adjusting the conflict between prospection and exploitation, but have not specify exhaustive route for precise and accurate heading. For example, the Artificial Fish Swarm Optimization Algorithm Aided by Ocean Current Power (AFSAOCP) [13] proposed in 2017, has presented a new search strategy that persuade the AF candidates to swim while relying on ocean flow. The velocity of ocean current affects the motion of each group of AF, whether it is to increase the speed of movement or hinder the ability to move forward. This strategy only suggests an enhanced method of controlling the motion step size, and despite the greedy selection method, the target direction is still randomly determined. This might be beneficial to enhance the ability to exploit and explore, but it is definitely not a favorable way to lead the AF group to an accurate pathway. As can be seen from the results of AFSAOCP, in general that the global best results have indeed improved, but obviously still far from the exact optimum, where the exact optimum is simply referred to as the global optimum. The overall convergence rate did not seem to have any significant improvement. Meanwhile, PSOEM-FSA [15] and CIAFSA [4] have recognized the importance of accurate guidelines and attempted to propose new behavioral patterns in their algorithms, suggesting that candidates follow global best and local best in different manners. As can be seen from the results that it is not completely ideal, although they have certainly achieved significant improvements in the global best solutions. In addition, the convergence rate was not satisfactory. The reality is that they have come to neither the genuine ideal solution nor an amazingly great convergence speed. It reserves a colossal potential for the advancement of AFSA.

Modifications and improvements based on existing AFSA are quite a challenging topic. Different optimization problems require different solutions in the algorithm. In order to unravel numerous optimization issues, the progressed algorithm must be designed in terms of high compatibility (ability to implement into different optimization functions and applications), robustness (ability to withstand or overcome adverse conditions or rigorous testing) and exactness (ability to get accurate and precise results). Besides that, it has to be noted that some real-world problems are multi-objective. The primary difference between multi-objective optimization and single-objective optimization is that multi-objective optimization does not apply greedy selection, mainly because there are multiple optima in a given multi-objective optimization problem. Hence, an appropriate and more suitable solution has been recognized, such as the concept of Pareto dominance. Although it has been introduced, it has neither provided a clear positioning nor the quality of each Pareto solution. Therefore, it makes it difficult to determine the ascendancy of a solution over another.

1.3 Objectives

To overcome the problems discussed in Section 1.2, this work proposes an improved AFSA algorithm. Among the research objectives set forth to achieve this aim are:

i. To develop a variant of AFSA with improved convergence rate and global best solution.

ii. To assess the performance of the modified AFSA on various benchmark functions through comparison with existing AFSA variants.

iii. To validate the capability of the modified fish swarm algorithm at solving real-world optimization application and multi-objective optimization problem.

1.4 Scope of Research

The scope of research is restricted to the architectures of soft-computing, in regard to modification of AFSA. The proposed modified AFSA variant is simulated in Matlab R2016a.

During the simulation process, the maximum iterative number t_{max} is united to 1000 for ease of comparison with related algorithms, as the related articles set the number of iterations to 1000 as well. Generally, 1000 is a satisfactory iterative number, since it is not way too long, but has sufficient cycles to perform the search behaviors at the best situation.

The proposed AFSA is also introduced to operate ten times autonomously on each of the benchmark functions used to gather the means and Standard Deviations (SDs) of the global best fitness. Ten benchmark functions are used for the purpose of evaluating the proposed AFSA algorithm. This number is sufficient for performance assessment. In order to make a reasonable comparison with the different comparative algorithms revealed in the work of [4], the adopted parameters are exactly taken from the work of [4]. The dimensions, N=10 and N=30 are assigned to each benchmark function.

In terms of multi-objective optimization approach, most parameters remain the same as single-objective optimization, but additional parameters are adopted due to the introduction of additional features in the quest of solving the multi-objective problems. The maximum iterative number t_{max} is kept at 1000.

The proposed multi-objective AFSA is suggested to execute ten times autonomously on each test function. Four test functions are taken from *ZDT* test function set to validate the proposed algorithm's capability. The dimension, N=10 is assigned to *ZDT 1*, *ZDT 2* and *ZDT* 3, whilst dimension, N=30 is assigned to *ZDT 6*, as given and adopted in the works of [20, 21] for proper comparison with related algorithms.

1.5 Thesis Outline

This thesis is divided into six chapters. This chapter briefly introduces the types of optimization problems, the classification of CI, the swarm intelligence algorithms that were rarely popular in the past, and the development of AFSA. It mainly highlights the advantages of optimization algorithms, AFSA, normative knowledge, communication and memory behaviors. It then explains the problems of the existing AFSA in general. After that, it gets into the research objectives and research scope.

In Chapter 2, the organization of an AFSA is illustrated. It elaborates the development and evolution of AFSA as a part of the bio-inspired algorithms under the category of CI. It then reviews the relevant knowledge, evolutionary algorithms and benchmark functions that are applicable to the implementation. Multi-objective optimization and PV system are studied in Chapter 2 as a part of reviews to highlight the problems of respective applications.

After reviewing the related works in Chapter 2, Chapter 3 indices the layout of the modified AFSA to be proposed. Previous methods and process flow are explained in detailed expressions and steps, supported by the formulas and flow chart respectively. It explains the methods that are integrated into the existing AFSA in the process of improving the algorithm.

Chapter 4 describes the application of the modified AFSA in multi-objective optimization and MPPT. Each application will detail the proposed method according to the modified AFSA discussed in Chapter 3. It explains every minor modification and transformation in the application and the concepts used in that application. It also demonstrates the experimental setup for both applications.

Chapter 5 collects and analyzes the numerical outcomes. The performance of the proposed algorithm on each benchmark function is evaluated by inspecting the respective convergence rate, global best solution and precision of the relative outcomes, thereby validating and comparing them with some comparative algorithms to show the ascendancies of the newly suggested algorithm. The performance evaluation of the multi-objective optimization approach is executed by examining the obtained Generation Distance (GD) and Spacing Index (S), and then comparing them with the comparative algorithms to show the contributions made in Chapter 4. The MPPT evaluation is performed under appropriate conditions, modeling and parameter settings, as described in Chapter 4, to inspect the maximum extracted output power from the terminals of PV panel.

Chapter 6 concludes the research work by summarizing the achieved research objectives. Future work is suggested as well to contribute to further evolution in the region of CI.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

In this chapter, Section 2.2 described the background of AFSA and covered some of the evolutionary history from CI to AFSA. Section 2.3 depicted the structural concept of the standard AFSA, supported by subsections that described the details of each behavioral pattern and problems regarding the standard AFSA. Section 2.4 explained the concept of normative knowledge and further analyzed its advantages in CAFSA. Section 2.5 described the structural concept of PSOEM-FSA. The following subsections discussed the predecessors of PSOEM-FSA, such as PSO in Section 2.5.1 and PSOEM in Section 2.5.2. Section 2.6 explained the global crossover strategy and mentioned the reasons why it must be applied to AFSA. Section 2.7 studied the relevant knowledge of multi-objective optimization and highlighted its problems, while Section 2.8 reviewed the PV application system and highlighted its problems. The chapter summary was depicted in Section 2.9 before the end of this chapter.

2.2 Background of AFSA

As mentioned in Chapter 1, swarm intelligence is a sub-branch of CI, and AFSA is a kind of swarm intelligence algorithms. With reference to Figure 2.1, AFSA categorized as a portion of BIA has been classified beneath the category of GSOA. GSOA plays a role to seek out the global best solution for a designated optimization issue. The major concern for the advancement of GSOA is to obtain superior global best solution with quicker convergence rate and greater precision. The AFSA, which has been categorized under the group of BIA is a nature-inspired heuristic algorithm [22] that depends on the field of mathematics, biology and computer science [23]. AFSA has been studied in this work due to its five beneficial characteristics [13]:

i. Parallelism
ii. Simplification
iii. Global search capability (ability to achieve excellent global best results)
iv. Fast convergence
v. Low sensitivity to the necessities of the target functions

AFSA is related to the swarm evolutionary algorithm, propelled by the collective behavior of fish [24]. This nature-inspired behavior is explained in the following section.

2.3 Standard AFSA

A great deal of research work has been done on the subject of AFSA with different adjustments and various applications. The works of [25–27] are cited to demonstrate that AFSA has preserved its prestige in 2019.

AFSA is enlightened by the behavioral characteristics of fish population when looking for the most extreme nourishment density. The habitat where AF resides is a feasible space with the boundaries given by *[**l**, **u**]* [28], where ***l*** is defined as the lower bound of feasible space and ***u*** is defined as the upper bound of feasible space. Presuming that a state vector $\boldsymbol{X} \in \{\boldsymbol{X}_1, \boldsymbol{X}_2 \ldots \boldsymbol{X}_n\}$ is assigned to each AF group, where n denotes the population number of concerned AFs, whilst $\boldsymbol{X}_{i\in\{1,2\ldots n\}}$ denotes the location vector of i^{th} individual [29], the nourishment density can be computed from the objective function $\boldsymbol{Y}_i = f(\boldsymbol{X}_i)$, where $\boldsymbol{Y}_i$ denotes the objective fitness of $\boldsymbol{X}_i$.

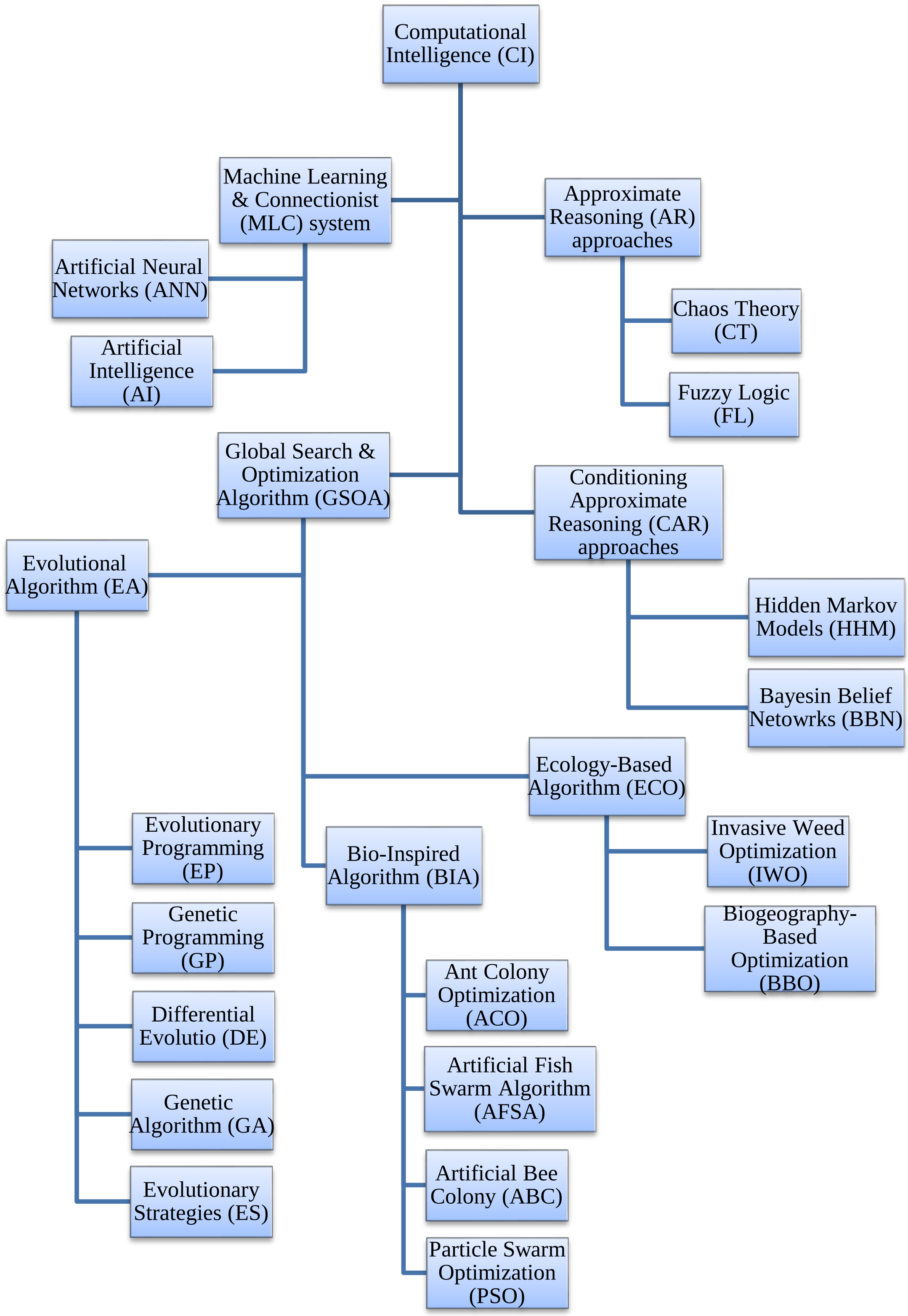

Figure 2.1 CI paradigms [22]

Figure 2.2 illustrates the visual concept assigned to each AF. Discernment is assigned to every AF in terms of *visual* to assemble the surrounding information for the purpose of hunting for a more robust solution and judging the current condition of comrades. Given that *step* represents the largest allowable step length of each AF [29] in approaching a target location. $\boldsymbol{X}_i^t$ denotes the feasible solution or location vector of i^{th} candidate at t^{th} iteration and $\boldsymbol{X}_i^{t+1}$ denotes the feasible solution or location vector of i^{th} candidate at $(t+1)^{th}$ iteration, where t is denoted as the index of iteration. In other words, $\boldsymbol{X}_i^{t+1}$ is represented as the updated location vector of $\boldsymbol{X}_i^t$. Other essential parameters embody the crowding factor δ, total number of tries, No_{try} and the maximum number of iterations, t_{max}.

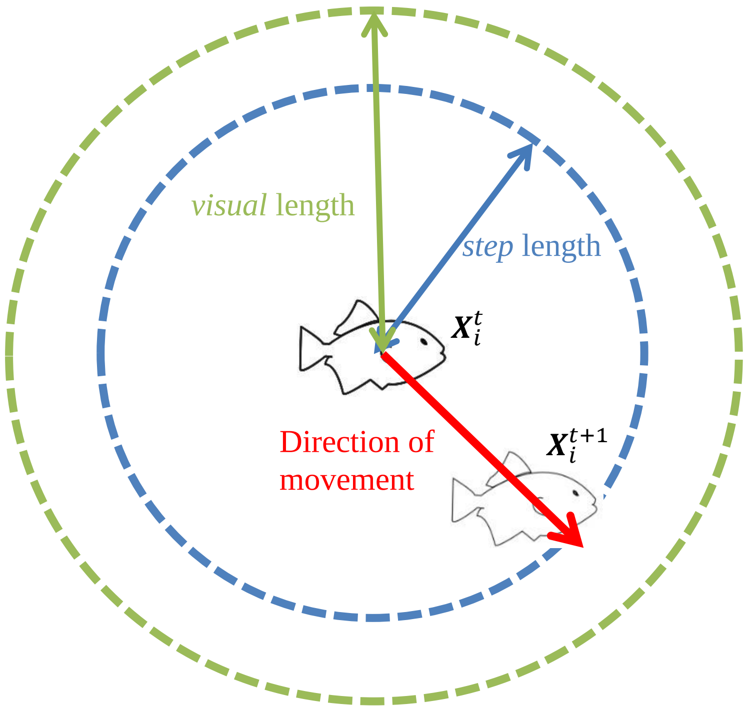

Figure 2.2 Concept of vision for each AF

Each AF is coached to execute an independent behavior (i.e. swarm, prey, follow or random behavior) corresponding to the current scenario. The pseudo code can be written as follows [22]:

Pseudo code of standard AFSA

```
Randomly initialize fish population
Initialize parameters
Initialize iteration, t
WHILE (t <= t_max)
        FOR i = 1 TO n
                Evaluate current AF
                Execute follow behavior
                IF (follow behavior fail) THEN
                        Execute swarm behavior
                        IF (swarm behavior fail) THEN
                                Execute prey behavior
                                IF (prey behavior fail) THEN
                                        Execute random behavior
                                END
                        END
                END
                i = i + 1
        END FOR
END WHILE
Output global best solution
```

Figure 2.3 displays the flow chart of a conventional AFSA. The complete behavioral design specified for each AF is delineated by an explanation of the sufficient preconditions. The architecture of the standard AFSA's behavioral patterns will be described in the following subsections. Subsection 2.3.1 explains the follow behavior, Subsection 2.3.2 explains the swarm behavior, Subsection 2.3.3 explains the prey behavior and Subsection 2.3.4 explains the random behavior. In addition, problems related to the standard AFSA will be highlighted in Subsection 2.3.5.

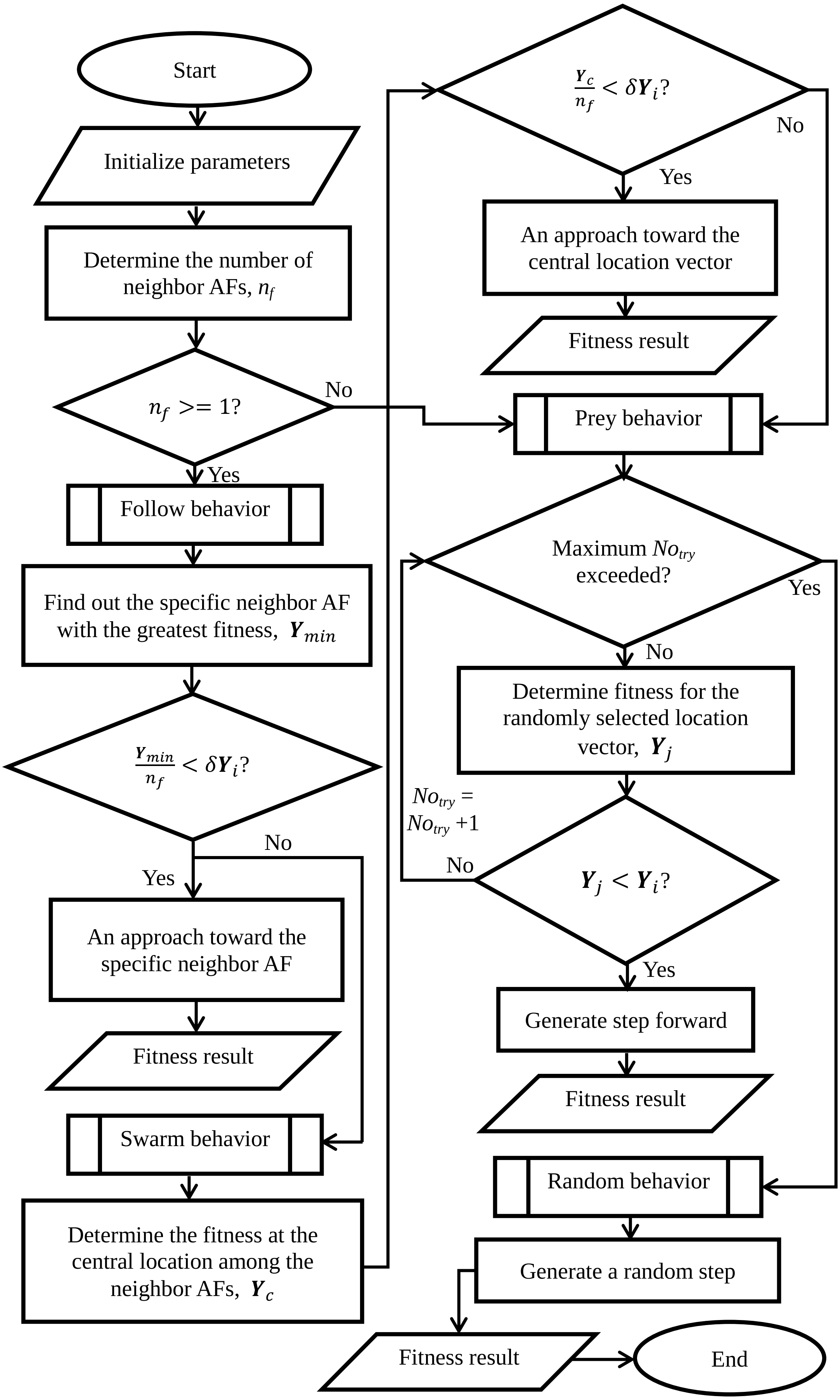

Figure 2.3 Flow chart of conventional AFSA

2.3.1 Follow Behavior

Follow behavior is analogous to the chasing behavior of fish in nature. Given that $i \in \{1, 2 \ldots n\}$ denotes the index of AF, the present location vector of i^{th} AF is denoted as $\boldsymbol{X}_i$, and the nourishment density at $\boldsymbol{X}_i$ is represented as $\boldsymbol{Y}_i$ [30]. The entire range of adjacent comrades that satisfies the prerequisite of $d_{ij} < visual$ is indicated as n_f, in which d_{ij} denotes the distance between j^{th} adjacent comrade and i^{th} AF. In the case of $n_f > 0$, a minimum of one adjacent comrade is identified from the *visual* perception, revealing that it is well-prepared to execute the follow behavior. Among the entire identified adjacent comrades, the AF candidate which at present possesses the most advantageous objective fitness $\boldsymbol{Y}_{min}$ is consulted as $\boldsymbol{X}_{min}$. As long as $\boldsymbol{Y}_{min}/n_f < \delta \boldsymbol{Y}_i$, it can be inferred that the nourishment concentration at $\boldsymbol{X}_{min}$ is definitely more prominent than $\boldsymbol{X}_i$. By the way, the i^{th} AF pursues the trustworthy comrade by utilizing the formulated equation as given [12]:

$$\boldsymbol{X}_i^{t+1} = \boldsymbol{X}_i^t + \frac{\boldsymbol{X}_{min} - \boldsymbol{X}_i^t}{|\boldsymbol{X}_{min} - \boldsymbol{X}_i^t|} rand \times step \tag{2.1}$$

where $\boldsymbol{X}_i^t$ is represented as the location vector of i^{th} candidate at t^{th} iteration, $\boldsymbol{X}_i^{t+1}$ is defined as the updated location vector of $\boldsymbol{X}_i^t$ and $rand$ is denoted as a random number between 0 and 1.

2.3.2 Swarm Behavior

Swarm behavior is analogous to the clustering behavior of fish swarm in nature. The entire range of adjacent comrades that satisfies the prerequisite of $d_{ij} < visual$ is indicated as n_f. As long as $n_f > 0$, a minimum of one adjacent comrade is identified from the *visual* perception, revealing that it is well-prepared to execute the swarm behavior. The entire identified adjacent comrades are composed and denoted as a swarm group. The central location vector of the group is computed and hence represented as $\boldsymbol{X}_C$ that outputs the central objective fitness $\boldsymbol{Y}_C$. As long as $\boldsymbol{Y}_C/n_f < \delta\boldsymbol{Y}_i$, it can be inferred that the nourishment concentration at $\boldsymbol{X}_C$ is definitely more prominent than $\boldsymbol{X}_i$. The i^{th} AF execute the swarm behavior by utilizing the following expression [12]:

$$\boldsymbol{X}_i^{t+1} = \boldsymbol{X}_i^t + \frac{\boldsymbol{X}_C - \boldsymbol{X}_i^t}{|\boldsymbol{X}_C - \boldsymbol{X}_i^t|} rand \times step \tag{2.2}$$

2.3.3 Prey Behavior

Prey behavior is analogous to the foraging behavior of fish in nature. AF executes an arbitrary prey behavior without referring to any information from any comrade. Arbitrary location vector $\boldsymbol{X}_j$ is chosen within the allowable *visual* range designated by [31]:

$$\boldsymbol{X}_j = \boldsymbol{X}_i^t + rand \times visual \tag{2.3}$$

In the case of $\boldsymbol{Y}_j < \boldsymbol{Y}_i$, it can be deduced that there exists a more prominent nourishment concentration at $\boldsymbol{X}_j$. The movement direction of each AF is decided by the selected $\boldsymbol{X}_j$. The prey behavior is formulated as follows [12]:

$$\boldsymbol{X}_i^{t+1} = \boldsymbol{X}_i^t + \frac{\boldsymbol{X}_j - \boldsymbol{X}_i^t}{|\boldsymbol{X}_j - \boldsymbol{X}_i^t|} rand \times step \tag{2.4}$$

Once $\boldsymbol{X}_j$ is unable to produce a more robust nutrient solution, another round of prey behavior is executed until it exceeds the limit of No_{try}.

2.3.4 Random Behavior

For the most part, the execution of random behavior will only be concerned after the disappointment in follow, swarm and prey behaviors. In such case, AF tolerates to move a completely arbitrary step given by [12]:

$$\boldsymbol{X}_i^{t+1} = \boldsymbol{X}_i^t + rand \times step \tag{2.5}$$

2.3.5 Problems of Standard AFSA

It has been proven by several research works that the standard AFSA has a severe trouble in dealing with the contradiction between exploration (i.e. local search) and exploitation (i.e. local search) [28, 32]. Undoubtedly, the main reason is the invariant parameters in terms of *visual* and *step*. As inspected from Section 2.3.1 to Section 2.3.4, it is noticeable that all behaviors are highly dependent on the *step* as a movable distance and the *visual* as a detectable distance. The invariant parameter in terms of *visual* has caused every AF to lose the ability to search within a desirable distance, while the invariant parameter in terms of *step* has led to the inflexibility in determining a desirable length of movement.

The exploration and exploitation can be regarded as global search and local search, respectively. Both of these are important in an optimization algorithm. In AFSA, exploration and exploitation are indirectly determined by the *visual* and *step* parameters. In general, if *visual* and *step* are not controlled in an algorithm, they will stay as constants, i.e. unaltered throughout the iterations. Presuming that *visual* and *step* are given a colossal value, the AF group approaches quicker to the global optimum, since a larger *visual* seeks a wider environmental space, while migrating with a greater scale of *step* [28]. AF is much more competent to get rid of local pitfalls [28], but somehow it diminishes the precision of local exploitation because huge *step* and *visual* are greatly capable to draw closer to the global optimal locale but have to sacrifice the accuracy of local exploitation. On the contrary, if small values are assigned to *step* and *visual*, AF group becomes more competent to perform an advance local investigation but the convergence rate to achieve the global optimum must be sacrificed.

This dilemma has been resolved using the adaptive method as utilized in the work of [31]. This approach has been able to adjust the inconsistency between exploitation and exploration in AFSA. Considerably huge *step* and *visual* are appointed to each AF at the early iterative stage to improve the global exploration capacity to speed up the convergence rate [30]. During the iterations, these parameters are gradually declined to progressively enhance the local exploitation ability. In theory, global search is primarily executed at an early stage, and local search is mainly concentrated at the later stage. However, it has not achieved the effective results due to the incompatibility of its adaptive parameters with its search strategy. The *visual* and *step* parameters descend at an unexpectedly fast pace before the global search is completed. The local search begins before it is ready. This situation messes up the original intention of adaptive parameters. Hence, a number of AFSA variants have been proposed to overcome the problems faced by the standard AFSA. They are discussed in the following sections.

2.4 CAFSA with Normative Knowledge

CAFSA [33] is a modified AFSA variant, which deals with the implementation of normative knowledge. Normative knowledge is a group of reliable range of variation that offer a criteria for personal behavior and guidance that is individually adjustable [34]. For instance, it can be a collection of knowledge for every variable that depicts an attainable solution space for an optimization issue.

In CAFSA, normative knowledge is primarily utilized to alter the *step* size and *visual* range to offer an appropriate perception at each cycle. It guides every AF to "hop" into the palatable range [34]. The parameters that accept the function selection are utilized to compile the present worthy interval in the confidence space. It is designed to ensure that candidates remain conservative while minifying the spacing, while ensuring that candidates stay progressive as they expand the interval [35]. It acts as a variable parameter controller in CAFSA to determine the expansion and contraction of *visual* and *step* size. This implementation is one of the contradictory solutions in the AFSA for better convergence speed, and it sometimes greatly improves the global best achievement if a group of candidates can cluster properly without any dropout.

Normative knowledge works as follows. Let *N*-dimensional vector $\boldsymbol{I}_k$ to indicate an enclosed spacing for index $k \in (1, 2 \ldots N)$, where *k* denotes the index of dimension. $\boldsymbol{I}_k$ can be expressed as follows [34]:

$$\boldsymbol{I}_k = [\boldsymbol{l}_k, \boldsymbol{u}_k] = \{\boldsymbol{X}, \text{where } \boldsymbol{l}_k \leq \boldsymbol{X} \leq \boldsymbol{u}_k\} \tag{2.6}$$

where $\boldsymbol{l}_k$ and $\boldsymbol{u}_k$ are the lower and upper bounds of feasible space respectively for k^{th} variable. $\boldsymbol{l}_k$ and $\boldsymbol{u}_k$ are initialized with lower and upper bounds of the population [33] and are updated based on the following expressions [33]:

$$\boldsymbol{l}_k^{t+1} = \begin{cases} \boldsymbol{X}_{i,k} & \text{, if } \boldsymbol{X}_{i,k} < \boldsymbol{l}_k^t \ or \ f(\boldsymbol{X}_i^t) < \boldsymbol{L}_k^t \\ \boldsymbol{l}_k^t & \text{, otherwise} \end{cases}$$

$$\boldsymbol{u}_k^{t+1} = \begin{cases} \boldsymbol{X}_{j,k} & \text{, if } \boldsymbol{X}_{j,k} \geq \boldsymbol{u}_k^t \ or \ f\left(\boldsymbol{X}_j^t\right) < \boldsymbol{U}_k^t \\ \boldsymbol{u}_k^t & \text{, otherwise} \end{cases} \tag{2.7}$$

where $\boldsymbol{X}$ is represented as the state (location) vector of the candidate. The i^{th} individual influences the lower bound for variable k, whilst j^{th} individual influences the upper bound for variable k. $\boldsymbol{L}_k^t$ and $\boldsymbol{U}_k^t$ are denoted as the fitness function values associated with the lower bound $\boldsymbol{l}_k^t$ and upper bound $\boldsymbol{u}_k^t$ at t^{th} iteration [33]. The fitness functions $\boldsymbol{L}_k^t$ and $\boldsymbol{U}_k^t$ are updated as follows [33]:

$$\boldsymbol{L}_k^{t+1} = \begin{cases} f(\boldsymbol{X}_i^t) & \text{, if } \boldsymbol{X}_{i,k} < \boldsymbol{l}_k^t \text{ } or \text{ } f(\boldsymbol{X}_i^t) < \boldsymbol{L}_k^t \\ \boldsymbol{L}_k^t & \text{, otherwise} \end{cases}$$

$$\boldsymbol{U}_k^{t+1} = \begin{cases} f\left(\boldsymbol{X}_j^t\right) & \text{, if } \boldsymbol{X}_{j,k} \geq \boldsymbol{u}_k^t \text{ } or \text{ } f\left(\boldsymbol{X}_j^t\right) < \boldsymbol{U}_k^t \\ \boldsymbol{U}_k^t & \text{, otherwise} \end{cases} \tag{2.8}$$

where $\boldsymbol{L}_k^t$ and $\boldsymbol{U}_k^t$ are the conditional materials in equation (2.7). As long as the current fitness $f(\boldsymbol{X}_i^t)$ or $f\left(\boldsymbol{X}_j^t\right)$ is better than the stored $\boldsymbol{L}_k^t$ or $\boldsymbol{U}_k^t$, the lower bound $\boldsymbol{l}_k$ or upper bound $\boldsymbol{u}_k$ is replaced.

2.5 PSOEM-FSA

In 1995, PSO was first presented in the work of [7]. In 2011, the work of [16] upgraded PSO with the extension of memory to become PSOEM. Then, in 2016, the work of [15] had merged AFSA with PSOEM, generating PSOEM-FSA. Hence, PSOEM-FSA is another AFSA variant.

This algorithm utilizes communication and memory behaviors. In communication behavior, AFs are tutored to swim while consulting the present and former global extreme location vectors of the society, $\boldsymbol{X}_{gbest}^t$ and $\boldsymbol{X}_{gbest}^{t-1}$. This behavior promotes to enhance the endowment to share and trade the information between candidates during the search procedure and reduces the perception disorder [15]. The vector is updated as follows [15]:

$$\boldsymbol{v}^{t+1} = \omega\boldsymbol{v}^t + rand[0,1] \times step\left[\left(\frac{\xi_t\left(\boldsymbol{X}^t_{gbest}-\boldsymbol{X}^t\right)+\xi_{t-1}\left(\boldsymbol{X}^{t-1}_{gbest}-\boldsymbol{X}^{t-1}\right)}{\left|\xi_t\left(\boldsymbol{X}^t_{gbest}-\boldsymbol{X}^t\right)+\xi_{t-1}\left(\boldsymbol{X}^{t-1}_{gbest}-\boldsymbol{X}^{t-1}\right)\right|}\right)\right] \quad (2.9)$$

where $\boldsymbol{v}_t$ represents the velocity vector of the candidate at t^{th} iteration, hence $\boldsymbol{v}_{t+1}$ represents the updated velocity vector, $\boldsymbol{X}^t_{gbest}$ represents the current global best location vector of the population at t^{th} iteration, $\boldsymbol{X}^{t-1}_{gbest}$ represents the global best location vector of the population at $(t\text{-}1)^{\text{th}}$ iteration, $\boldsymbol{X}^t$ is represented as the current location vector of the candidate at t^{th} iteration, $\boldsymbol{X}^{t-1}$ is represented as the location vector of the candidate at $(t\text{-}1)^{\text{th}}$ iteration, ξ_t represents the present effective element and ξ_{t-1} represents the efficiency element of expanded memory.

In memory behavior, AFs are taught to swim while consulting to the present and former local extreme location vectors, $\boldsymbol{X}^t_{lbest}$ and $\boldsymbol{X}^{t-1}_{lbest}$. This scheme definitely promotes to diminish the perception disorder of candidate during the local search procedure [15]. The vector is updated as follows [15]:

$$\boldsymbol{v}^{t+1} = \omega\boldsymbol{v}^t + rand[0,1] \times step\left[\left(\frac{\xi_t(\boldsymbol{X}^t_{lbest}-\boldsymbol{X}^t)+\xi_{t-1}(\boldsymbol{X}^{t-1}_{lbest}-\boldsymbol{X}^{t-1})}{\left|\xi_t(\boldsymbol{X}^t_{lbest}-\boldsymbol{X}^t)+\xi_{t-1}(\boldsymbol{X}^{t-1}_{lbest}-\boldsymbol{X}^{t-1})\right|}\right)\right] \quad (2.10)$$

where $\boldsymbol{X}^t_{lbest}$ denotes the current local best location vector of the candidate at t^{th} iteration and $\boldsymbol{X}^{t-1}_{lbest}$ denotes the local best location vector of the candidate at $(t\text{-}1)^{\text{th}}$ iteration.

PSOEM-FSA has solved the inaccurate search problem in PSOEM by separating global search and local search into different behaviors. In brief, communication behavioral style (equation (2.9)) primarily reinforces the global exploration, whereas memory behavioral style (equation (2.10)) basically fortifies the local exploitation capability. The utilization of $(t\text{-}1)^{\text{th}}$ iterative information demonstrates the adoption of expanded memory. The acceleration factors of a^l_t and

a_t^g in PSOEM has been replaced by *step* parameter, which means that the mobile features are more biased towards the characteristics of AFSA. By proposing self-adaptive parameters in terms of *visual* and *step* in this algorithm, the contradiction between exploration and exploitation in AFSA has been solved, and the convergence speed has been improved as well.

PSOEM-FSA is, without exaggeration, an extremely efficient optimization algorithm. However, communication behavior is entirely dependent on the global best guides, while memory behavior is entirely dependent on local best guides, so they have become less flexible in deciding the search direction. Therefore, there is still great potential for further improvement. The following subsections describe the predecessors of PSOEM-FSA, such as the standard PSO in Subsection 2.5.1 and the PSOEM in Subsection 2.5.2.

2.5.1 Standard PSO

PSO is another series of swarm-based optimization algorithms in addition to AFSA. PSO was first presented by Kennedy and Eberhart in 1995 [7]. PSO mimics the social collective behavior of organisms and imitates the nature of social behavior by distributing a swarm of agents, named as particles. The social achievement of a candidate is influenced by the personal diligence and the shared information in the community [36]. The particle swarm transits a multidimensional feasible space to look for the optima along the generations [37]. The motions of particles are led by the claimed best-known individual location vector ($\boldsymbol{\rho}_l$) and the best-known location vector of the entire population ($\boldsymbol{\rho}_g$) [38] given by [39].

$$\boldsymbol{\rho}_{i,l}^t = argmin[f(\boldsymbol{X}_i^t)] \tag{2.11}$$

$$\boldsymbol{\rho}_g^t = argmin[f(\boldsymbol{X}^t)] \tag{2.12}$$

where $i \in \{1, 2 \dots n\}$ denotes the index of particle and n indicates the population number of concerned particles. The index $t \in \{1, 2 \dots t_{max}\}$ represents the iteration, in which t_{max} denotes the maximum iterative number. $\boldsymbol{X}$ indicates the state vector of particle and f is represented as the objective function. $\boldsymbol{\rho}_{i,l}^t$ is denoted as the local extreme location vector of i^{th} particle at t^{th} iteration, whilst $\boldsymbol{\rho}_g^t$ is denoted as the global extreme location vector of the entire population at t^{th} iteration.

The standard PSO can be expressed as follows [15]:

$$\boldsymbol{v}^{t+1} = \omega \boldsymbol{v}^t + a_l^t(\boldsymbol{\rho}_l^t - \boldsymbol{X}^t) + a_g^t\left(\boldsymbol{\rho}_g^t - \boldsymbol{X}^t\right) \tag{2.13}$$

$$\boldsymbol{X}^{t+1} = \boldsymbol{X}^t + \boldsymbol{v}^{t+1} \tag{2.14}$$

where $\boldsymbol{v}^t$ signifies the velocity vector of particle at t^{th} iteration and hence it can be deduced that $\boldsymbol{v}^{t+1}$ signifies the updated velocity vector, while ω is denoted as inertia weight [15]. Both a_l^t and a_g^t represents the acceleration factors. $\boldsymbol{X}^t$ is represented as the location vector of designated particle at t^{th} iteration, whilst $\boldsymbol{X}^{t+1}$ is represented as the location vector of the given particle to be updated at t^{th} iteration. In theory, ω was suggested in equation (2.13) to supply essential momentum for the candidates to wander around the feasible space [39]. PSO has been extensively studied that numerous PSO-based works have been conducted since 1995. For instance, Singh surveyed the evolution of PSO from 1995 to 2014 [40].

2.5.2 PSOEM

From a psychological viewpoint, extended memory enhances the convergence rate by accumulating the search experiences of particular individual [15]. PSOEM is