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ATILIM UNIVERSITY 2019

RECIPROCAL ALTRUISM BASED PATH PLANNING USING PARTICLE SWARM OPTIMIZATION (PSO)

THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
ATILIM UNIVERSITY

ALI FADHIL ALI MAEEDI

A MASTER OF SCIENCE THESIS
IN
THE DEPARTMENT OF MECHATRONICS ENGINEERING

SEPTEMBER 2019

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A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
ATILIM UNIVERSITY

BY

ALI FADHIL ALI MAEEDI

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
THE DEPARTMENT OF MECHATRONICS ENGINEERING

SEPTEMBER 2019

Approval of the Graduate School of Natural and Applied Sciences, Atilim University.

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I certify that this thesis satisfies all the requirements as a thesis for the degree of **Master of Science Engineering in Mechatronics Atilim University**.

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This is to certify that we have read the thesis RECIPROCAL ALTRUISM BASED PATH PLANNING USING PARTICLE SWARM OPTIMIZATION (PSO) submitted by Ali Maeedi and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science-Architecture /Doctor of Philosophy.

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

RECIPROCAL ALTRUISM BASED PATH PLANNING USING PARTICLE SWARM OPTIMIZATION (PSO)

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September 2019 - 72 pages

Encountering the problems of nature that has always been a challenging task, what makes it more difficult is the change in operating conditions over time. Therefore, a robust algorithm is needed that is able to track the continuously changing optima over time. In this thesis, a novel particle swarm optimization based population kinship connectivity is proposed with the intent to improve the performance by introducing the sharing of particles information. The proposed algorithm, Reciprocal Altruism based Particle Swarm Optimization, utilizes the kinship relatedness between particles during the optimization process to reciprocate the significant data regarding the environment.

Reciprocal altruism theory is regularly conjured to clarify why irrelative particles helped as pairs in different types of intra-group cooperative conduct, e.g., egg exchanging among hermaphroditic fishes, blood spewing forth among vampire bats, assessment of predator among sticklebacks, allogrooming among vervet monkeys and impala, sustenance share among humans, brown capuchin monkeys, and basic chimpanzees.

Utilizing the concept of reciprocation, the RAPSO will ensure that all particles remain in close contact with each other through information exchange. Moreover, the amount of information that is exchanged between the particles is dependent upon their physical placement in the search space regions. Depending upon their region, they can be either classified as a donor or a recipient; furthermore, the amount of information exchanged between the particles is directly monitored through their associated health indicator.

The performance of the proposed approach shows that the reciprocal sharing has played its role effectively in order to control the movement of the swarm along the optimized path. The simulation results proved that RAPSO outperforms the conical PSO algorithm both in terms of error reduction and close connectivity.

Keywords: Path Planning, Reciprocal Altruism, Particle Swarm Optimization, PSO, RAPSO, Kinship.

ÖZ

PARÇA SWARM OPTİMİZASYONUNU (PSO) KULLANARAK RESİPROKAL ALTRUİZM TABANLI YOL PLANLAMASI

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Eylül 2019 - 72 sayfa

Doğanın sorunları ile başa çıkmak, her zaman zorlu bir görev olmuştur, bunu daha zorlaştıran şey ise zamanla çalışma koşullarındaki değişimdir. Bu nedenle, zaman içinde sürekli değişen optimayı takip edebilecek sağlam bir algoritmaya ihtiyaç vardır. Bu tezde, partikül bilgisinin paylaşılmasını sağlayarak performansın geliştirilmesi amacıyla bir parçacık sürüsü optimizasyonuna dayalı popülasyon akrabalık bağlantısının önerilmiştir. Karşılıklı Fedakarlığa Dayalı Parçacık Sürü Optimizasyonu (RAPSO) olarak tanımlanan algoritma, optimizasyon işlemi sırasında partiküller arasındaki benzerliği, peyzajla ilgili anlamlı verileri geri almak için kullanır.

Resiprokal altruizm (Karşılıklı Özgecilik) teorisi, örneğin farklı grup içi işbirlikçi davranış biçimlerinde neden olan ilgisiz parçacıkların çiftler olarak yardımcı olduğunu açıklığa kavuşturmak için düzenli olarak düzenlenmiştir; hermafroditik balıklar arasında yumurta alışverişi, vampir yarasalar arasında kan yayılması, geri tepmeler arasında yırtıcı hayvanların değerlendirilmesi, vervet maymunları ve impala arasında serbest bırakma, insanlar arasında yaşama payı, kahverengi capuchin maymunları ve temel şempanzeler.

Karşılıklı hareket kavramını kullanan RAPSO, bilgi alışverişi yoluyla tüm parçacıkların birbiriyle yakın temasta kalmasını sağlayacaktır. Ayrıca, parçacıklar arasında değiştirilen bilgi miktarı, arama alanı bölgelerine fiziksel olarak yerleştirilmelerine bağlıdır. Bölgelerine bağlı olarak, bağışçı veya alıcı olarak sınıflandırılabilirler; ayrıca, parçacıklar arasında değiştirilen bilgi miktarı doğrudan ilişkili sağlık göstergeleri ile izlenir.

Önerilen yaklaşımın performansı, karşılıklı paylaşımın, sürünün optimize edilmiş yol boyunca hareketini kontrol etmek için etkin bir rol oynadığını göstermektedir. Simülasyon sonuçları, RAPSO'nun konik PSO algoritmasını hem hata azaltma hem de yakın bağlantı açısından daha iyi performans gösterdiğini kanıtladı.

Anahtar Kelimeler: Yol Planlama, Resiprokal Altruizm (Karşılıklı Özgecilik), Parçacık Sürü Optimizasyonu, PSO, RAPSO, Akrabalık.

To my parents and wife…

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my mentor and supervisor Asst. Prof. Dr. Muhammad Umer KHAN for his friendly advice, constant support, endless patience and encouragement.

I shall also thank Mohammed Abdi, Mustafa Hasan, Faisal Khalid, Mohammed Shakir, Mohammed Falah, Humam Mahmood, Hayder Faaeq, Harith Mahdi, Asaad Alhilali, Wesam Ali and Ahmed Amer for their technical insight; and I owe thanks to my friends Amjed Alkateb, Mustafa Abd Al Settar, Adhab Azeez, Maher Hassini, Mustafa Alhasani and Qasim Nori for their helping efforts.

Furthermore, I thank the members of KARBALA SATELLITE CHANNELS GROUP especially the general manager Hayder Jalwkhan and the engineering manager Mustafa Mahdi for their support and motivational guidance.

The financial support of The Scientific and Technical Research Council of Turkey (TUBITAK) is also acknowledged.

Finally, I would like to thank all my true friends and family for not giving up on me, although I didn't always have enough time for them in the last two years. At the times I’ve lost my way through my life, they’ve been invaluable in showing me the light with their encouraging boundless love.

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LIST OF SYMBOLS/ABBREVIATIONS

RA	Reciprocal Altruism
PSO	Particle Swarm Optimization
RAPSO	Reciprocal Altruism based Particle Swarm Optimization
PAM	Proportional Altruism Model
GA	Genetic Algorithms
DR	Diminishing Returns
UN	Unimpeded Investment
ESS	Evolutionarily Stable Strategy

NOMENCLATURE

$\boldsymbol{C}$	: fitness cost of performing an altruistic act
$\boldsymbol{r}$	: coefficient of relationship
$\Delta\boldsymbol{I}$	: unit of investment’s size
$\boldsymbol{a}$	: change’s rate in fitness per unit investment
$\boldsymbol{cost_{alt}}$	: fitness cost altruism’s one act to altruist
$\boldsymbol{p}$	: current particle position
$\boldsymbol{v}$	: current particle velocity
$\boldsymbol{cost}$	: cost of the particle
$\boldsymbol{c^r}$	: center of PAM regions
$\boldsymbol{p^{best}}$	: best personal particle’s position
$\boldsymbol{p^{gbest}}$	: best global particle’s position
$\boldsymbol{u}$	: current fitness level
$\boldsymbol{d}$	: distances from particles to the region's center
$\boldsymbol{k}$	: kinship coefficient
$\boldsymbol{\Sigma I}$	: sum of the previous investments
$\Delta\boldsymbol{u}$	: change of fitness for every potentially recipient
$\Delta\boldsymbol{u_{inc}}$	: expected change of inclusive fitness for the altruist in every kin in investing
$\boldsymbol{N}$	: population of the swarm
$\boldsymbol{i_{max}}$	: maximum iteration
$\boldsymbol{b}$	: health indicator represent the controllability and connectivity
$\boldsymbol{w}$	: Inertia weight
$\boldsymbol{c}$	: parameter of constriction
$\boldsymbol{r^r}$	: space categorized in three regions two circles with deferent radiuses and the rest of the space
$\boldsymbol{I}$	: unit of investment
$\Delta\boldsymbol{I}$	: size of investment
$\boldsymbol{p_s}$	: starting point

$\boldsymbol{p_g}$	: ending or goal point
$\boldsymbol{\sigma}$	: value of (30) point related to health indicator
$\boldsymbol{\gamma}$	: maximum rate of health indicator
$\boldsymbol{\beta}$	: minimum rate of health indicator

CHAPTER 1

INTRODUCTION

1.1 Reciprocal Altruism (RA)

The topic of altruism has been of real significance in evolutionary psychology and sociobiology. The establisher of sociobiology, Edward O. Wilson, depicted the focal hypothetical issue of sociobiology: "How can altruism, which by definition reduces personal fitness, possibly evolve by natural selection" -Wilson [1]. The theory of kin selection has a partial answer to this inquiry -Hamilton [2], so that altruistic behavior's adaptiveness is introduced to the beneficiary as genetic relatedness's linear function. The term reciprocal altruism is presented by Trivers [3] to clarify the altruism between particles that are unrelated. Giving an advantage to a non-related particle is advantageous to the fitness of an actor if this action costs less than the advantages obtained in the long standing. The better off particles in the long standing expression which are eager to give advantages to non-related others than particles that receive rewards from altruistic others with no reciprocation trials, "provided that altruists respond to cheaters by curtailing all future possible altruistic gestures to such individuals" Trivers [3].

1.2 Particle Swarm Optimization (PSO)

Over the past decades, the theory that has been growing rapidly is the one that with regard of particle swarm optimization (PSO). People have utilized Particle Swarm Optimization (PSO) in order to solve problems from various fields. The behavior of animal societies that don't have any leader in their gathering or swarm imitates by the algorithm of PSO, like fish schooling and bird flocking. Ordinarily, it is discovering sustenance by arbitrary flock of animals that have no leaders, the potential solution is that the one animal or particle that has the nearest position to the food source of the group will be followed by the rest. With the help of communication among members, the flock accomplish their best condition at the same time. However, when the individual particle inform the flock about a better condition, all other particles will move simultaneously to that position. This process will repeat itself until all the particles find a sustenance source or the best conditions. The work of these animal's environment is accomplished by finding out optimal values defining the procedure of the PSO algorithm. A swarm of particles comprised from PSO, where a potential solution is represented by a particle.

1.3 Reciprocal Altruism Particle Swarm Optimization (RAPSO)

Recently, the modified version of PSO named as RAPSO utilizes the concept of kinship connectivity, which tried to improve the overall performance by increasing the sharing of particle's information. The proposed algorithm utilizes the kinship relatedness between particles during the optimization process to reciprocate the significant data associated to the environment. New benefits in addition to the variety of issues that are treated will be provided with this improvement.

Reciprocal altruism theory is regularly conjured to clarify why irrelative particles helped as pairs in different types of intra-group cooperative conduct, for example, egg exchanging among hermaphroditic fishes, blood spewing forth among vampire bats, assessment of predator among sticklebacks, allogrooming among vervet monkeys and impala, and sustenance share among humans, brown capuchin monkeys, and basic chimpanzees.

Utilizing this reciprocation, the PSO algorithm is improved to treat connection and control of all particles; however, it differs from region to region depending upon its displacement from the optimized particle. It means that whenever the distance increases, the controllability of the particles will be less so the reciprocation will increase to get it back to the safe zone of controlling and keep it near to the optimized path. Furthermore, some new mechanisms are introduced for the purpose of knowing the indicating factor related to controlling and what its loss is from one region to another and when it is at its highest level and the opposite. In addition to that, there is the exploration of the sharing information of the particles between regions and how it could happen and which region deserve the priority. Also, exploring the health status for three particles considered as samples and how the altruism will work with these particles in each iteration. Moreover, investigation has been made on the distribution of the particles in each iteration and how the algorithm will treat this issue and how it differs from the conical.

This thesis will describe the effect of modification on the proposed algorithm by the mentioned comparison, then make a conclusion from it. The starting will be with the literature survey, mathematical modeling, implementation details, results and discussion and the last chapter highlights conclusion and future work.

CHAPTER 2

LITERATURE SURVEY

2.1 Reciprocal Altruism (RA)

In this chapter, the hypothesis is formed first followed by discussing the existence of evolutionary psychology. The term ‘reciprocal altruism’ was first introduced by Trivers.

With the basis of reciprocity he also introduced a psychological system, and during the Pleistocene he also observed the development of reciprocal altruism from hominid species and how to deal with the prerequisites according to this development (like, living in small space with reciprocally supporting social-able gathering). In these circumstances, his concentration was on the reciprocal altruism’s potential costs in the first step and its advantages. Furthermore, with the use of game theoretical argument, the reciprocal altruism’s strategy or mechanism dedication was popular by last scholars, instead of the ancestral environment analyzations of a particular adaptive issues.

Furthermore, Trivers pointed out the Prisoner’s Dilemma’s with the analogy, which were defined through Rapoport and Chammah [5], and Luce and Raiffa [4]. With the iteration of Prisoner’s Dilemma, Trivers’ reciprocal altruism’s concept was similar as compared with the optimal strategy Trivers [3]. Once more, the strategy of a reciprocal altruism has confirmed its successes by the theorists of the evolutionary game. Different competition strategies were simulated by actors within the iteration of Prisoner's Dilemmas in a case study of Axelrod [6], a mechanism defined as “Tit-for-Tat” as the most successful then, which started the cooperation in the first step and then taking the imitation of the interactive partner. As a result, the punishment will be a defection for the defecting behavior and a cooperation reward for the cooperative behavior. The reciprocal altruism embodiment of Trivers is known and also came from this strategy.

The altruistic behavior's evolution as stated in Hamilton's [2], attract the theorists to the significant relationship between social behavior and degrees of genetic relatedness for making investigations on a number of animals, as conducted by (Weigel [11]; Kaplan [10]; Massey [9]; Kurland [8];Trivers and Hare [7]). In all over kin types (benefit to the recipient/ cost to altruist) a constant ratio given, from Hamilton's equation: k > l/r, predicted that the probability of a given altruistic act occurring will be greater as the coefficient of relationship between the altruist and his beneficiary increases. Eusocial insects' (Trivers and Hare [7]) colony mates supplying like this clearly altruistic behavior's performance, and a closer kinship affinity has clearly witnessed growth in macaques with the agonistic aiding (Kaplan [10]; Massey [9]; Kurland [8]) and grooming (Kurland [8]). The inclusive fitness hypothesis of Hamilton's [2] supports (Kurland [8] and Massey's [9]) data as their consideration.

With regards of the performance of a given altruistic act from Hamilton's forecast observed one logical derivation concerns altruistic acts of an individual's distribution among his kin. (The distribution of altruism by Hamilton [2] doesn't have obvious forecasts, but may be close to kin's preference conclusion from the declaration "If [a particle] could learn to recognize those of its neighbors which were really close relatives and devote its beneficial actions to them alone an advantage to inclusive fitness would at once appear".) Furthermore, Kurland's [8] theory states "altruistic acts increase and selfish acts decrease as the degree of relatedness between individuals' increases." Kurland's use of Pearson correlation coefficients in reporting data implies the acceptance of a linear model, but without specification of the predicted slope of the regression line, the expectation of the altruism distribution among kin is not exactly cleared. A direct proportion to the coefficient of relationship will occur when it predicts an individual's approach to other group members that model formulated explicitly by Weigel [11], though the making of altruism with a priori association is missed. A prediction with confirmed data of Trivers and Hare [7] that directs proportion to relatedness will occur with the altruistic investment, however the logical cause of that belongs to their assumption of sisters investing with the female workers is three times (r-3/4) if compared to brothers (r-1/4) a sex ratio 3:1 ought to produce and with regard of the siblings of a worker, the combined reproductive success will be maximized; i.e., it is recipient’s sex consideration, that it came as a replacement of genetic relatedness alone, which the prediction is introduced by. Trivers and Hare’s [7] work was pointed by Barash [12] by confirming “... important support has been provided for Hamilton’s theory by the demonstration that workers provide about three times the food for their sisters (other workers) as they do for their brothers (the drones), consistent with the three-fourths versus one-fourth genetic relationship”. The next state of Barash [12] declared “Kinship theory implies that the interest of one animal in the well-being of another should vary directly with the proportion of genes shared by virtue of common descent”; but it doesn’t mean that “altruistic behavior” referred by “interest.” Dawkin’s [13] perhaps provides the clearest explanation statements of the relationship between altruistic investment’s distribution and kinship: “If B is really my baby brother, then I should care for him up to half as much as I care for myself, and fully as much as I care for my own child.... If C is my identical twin, then I should care for him twice as much as I care for any of my children. ” (However, in contrast, see Dawkins [14]). The distribution of altruistic behavior among an individual’s kin will be in proportion to relationship’s coefficient, and that may be the explicit forecast of defining the “Proportional Altruism Model” (PAM). A “gambler’s fallacy” or investment strategy is the direct translation of the PAM that Altmann [15] has argued this in one of his latest papers. It states, maintenance that was accomplished by making all of the things alike, with the agreement of the constant benefit accruement of per unit’s investment assumption, when an individual’s altruistic behavior is investing entirely on another’s, the most close kin then would have the maximum inclusive fitness, and the greatest values will then be increasing to inclusive fitness.

By introducing the concept ESS which is an evolutionarily stable strategy. A 'strategy' is a behavioral phenotype, which means that it is a specifying the behavior of an individual in any circumstances where it would finds itself. An ESS is a strategy adopted by all the members of a population, where no another similar strategy could invade the populace under the influencing of the natural selection. Because of the concept arose in the context of animal behavior therefore, it is couched in terms of a 'strategy'. Like any kind of phenotypic variation can applied this idea equally well, and the word phenotype will be the replacement of the word strategy; e.g., a strategy could be the relative numbers of sons and daughters produced by a parent, or the age at first reproduction, or the growth form of a plant. The definition of an ESS can be made more precise in particular cases under the term of an uninvadable strategy; which is, if the evolving population made by precise assumptions about the nature.

Individual recognition in higher organisms can depend on cooperation. Packer's [27] demonstrated the reciprocal altruism between pairs of male olive baboons which is possibly the clearest example, when any genetic relationship are missed in any two interactants. With TIT FOR TAT as the ESS, Reciprocal altruism is a type of easily be modelled as a game. Questions about the nature of the 'hereditary' mechanism-genetic or cultural-underlying the evolutionary process raised when these ideas applied baboons, and a *fortiori* to men. Therefore, with the assumption that individuals who are in some sense successfully pass their characteristics on to more 'descendants' than those who are not, concluded a stable outcome of that cooperative behavior.

2.2 Particle Swarm Optimization (PSO)

Kennedy and Eberhart [16] proposed a stochastic populace with the basis of an optimization method defined as Particle swarm optimization (PSO). Poli [18]; Engelbrecht [17] proved that PSO has successful trials with multiple issues like pattern classification, fuzzy control, function optimization, and artificial neural network training, by mentioning a few. Because it converged very fast and implemented in an easy way to achieve acceptable results, PSO has received broad attention in recent years Poli [18]. PSO is modified in many different aspects and multiple deviations suggested from the original form since 1995.

A lot of evolutionary computation processes like Genetic Algorithms (GA) have similarities with the PSO. With the update of generations a populace of arbitrary activities and search for optima will initialize the system. However, there is no mutation and crossover found in PSO and GA because it doesn't have evolution operators. Potential solutions defined as particles in PSO are the present optimum particles followed by the other particles flying in the concern space.

Eberhart, Kennedy [19]; Eberhart and Kennedy [16] originally introduced and designed the Particle swarm optimization (PSO). It is a populace with the basis of scan algorithm with the basis of a school of fishes, honey bees and the social conduct of birds. The unpredictable and graceful choreography of a bird folk is originally the plan of this algorithm to graphically simulate it. In multidimensional pursuit space, each individual of the swarm is represented by a vector. The decision of the next movement of the particle occurs by an allocated vector in each one, defined as the velocity vector. Likewise is the decision of updating the particle's velocity of the PSO algorithm. Each particle updates its velocity based on current velocity and the best position it has investigated so far. Furthermore, Engelbrecht [21]; Sadri, Ching [20]; Engelbrecht [17] argued that it should be influenced bythe global best position of swarm.

At that point, the procedure of the PSO should start iterations with a specific number of times or until achieving the minimum errors with the basis of the required accomplishment. PSO algorithm was demonstrated to deal with the difficult optimization issues as a straightforward model efficiently. The real valued spaces is the original reason behind the PSO development however many issues are known where the variables' domain is finite for discrete valued spaces. Engelbrecht [17] gave routing, scheduling and programming as standard examples for such issues.

2.2.1 Distance between Particles Relationship

Particle swarm optimization (PSO), the analytical vision of the behavior of birds gathering food is the origination of PSO, where American scholars introduced it in the early 1990s. During the analysis of the American scholars Kennedy and Eberhart [16] found that the flying birds often changed, concentrated, or scattered directions in an instant, adjusting their flight – fact, regularly in unexpected moment. When rules has been summarized, they discovered that the flying pace of the flock generally keep consistent, and a proper distance was maintained between all its members. Furthermore, with the continuous analyze of the other social animals behavior, like ants, fishes, birds, etc…, a conclusion was raised, there must be a hidden platform of information sharing for those apparently unstructured and dispersed biological groups.

In addition to, the simulation of the constant behavior of birds, scholars Inspired and proposed the concept of particle swarm optimization.

In recent years, Particle swarm optimization has become a better-developed optimization algorithm. Furthermore, through the continuing iterations it will search for the optimal solution, then it employs the size of the objective function's value, in order to evaluate the quality of the solution.

In consideration of convenient study, particles of life without volume and mass are the consideration of birds in the algorithm. The initialization of each particle's position into the solution to be optimized is defining the proposed algorithm. In the particle swarm movement process, the information that shared between particles will influence the others, and the speed and direction with regard of the moving status of each particle will be influenced by the particles colleagues, in addition to that the whole particle swarm, so according to the historical optimal positions of each particle and its colleagues it will adjusts its own speed and direction, with keep of fly and search for the optimal solution. In the process of flying, according to particles external information, they will update their position and direction; this is the proof of particle's memory functionality, and particles that have the tendency to approach the optimal solution those with good positions and directions. Along with the proposed algorithm, through competition and cooperation between particles, the optimization will be performed effectively.

2.2.2 Conical Procedure

As mentioned earlier, the bird flock's behavior using PSO is demonstrated through simulation where arbitrary searching is done by a group of birds Furthermore, with the investigation of the area, the result is that there is a single piece of nourishment. The position of the nourishment is not known for all the birds. However, throughout each iteration process, the birds' inter-communications teach them what the distance to the nourishment is. Therefore, following the closest bird to the nourishment's position to find it, is the best plan. That bird flocking scenario is the source of PSO learning, and optimization issues are solved by using it. In the pursuit space of PSO a "bird" represent each single result. "Particle" was its definition. We must have a fitness function for evaluating the fitness values for all of the particles where this function means the optimization of the cost function, and all of the particles have velocities to direct its flying. In the problem space, the present optimum particles are what the other particles follows. In the first step the PSO initialization will be with a random gathering particles solution then by updating the generations to search for optima. Each particle isto update its position and health status while taking into consideration two best values throughout every iteration. The best solution of the position vector or fitness accomplished so far by this particle is the first one. Additionally putting away the fitness value. This position defined as ***pbest***. The other best position is that followed by the particle gathering optimizer best position, so far attained, from any of the individuals in the swarm. The current global best defined as ***gbest*** is the best position. The velocity and position of each particle will be updated with regard to eqs. (2.1) and (2.2), respectively.

$$v_{k+1}^{i} = wv_{k}^{i} + c_1 r_1 \left(pbest^{i} - x_{k}^{i}\right) + c_2 r_2 \left(gbest_{k} - x_{k}^{i}\right) \tag{2.1}$$

$$x_{k+1}^{i} = x_{k}^{i} + v_{k+1}^{i} \tag{2.2}$$

Where, at the $\boldsymbol{k^{th}}$ iteration, the velocity of $\boldsymbol{i^{th}}$ particle is $\boldsymbol{v_k^i}$, the present position or solution of the $\boldsymbol{i^{th}}$ particle is $\boldsymbol{x_k^i}$. Generating numbers between **0** and **1** uniformly as $\boldsymbol{r_1}$ and $\boldsymbol{r_2}$. The cognitive or self-confidence factor is $\boldsymbol{c_1}$ and the swarm social or confidence factor is $\boldsymbol{c_2}$. The range of $\boldsymbol{c_1}$ and $\boldsymbol{c_2}$ usually is 1.5 - 2.5. At last, Haupt and Haupt [22] recommended that according to a specified number of iterations, the factor of inertia w should be directed in decrement values from **1** to **0**. The inertia's effect of the particle represented by the first term of eq. (2.1), the memory influence of the particle represented by the second term, and the society or swarm influence represented by the third term. The PSO processes are shown as a flow chart in fig. (2.1). The velocities of the particles on each dimension may be clamped to a maximum velocity $\boldsymbol{V_{max}}$, where the user is specifying that parameter. Any velocity greater than the maximum value will be limited according to Haupt and Haupt [22]. The second variable that clamped is the current solution's position in a certain range meaning that the valid value limits the solution, otherwise the solution is meaningless Haupt and Haupt [22].

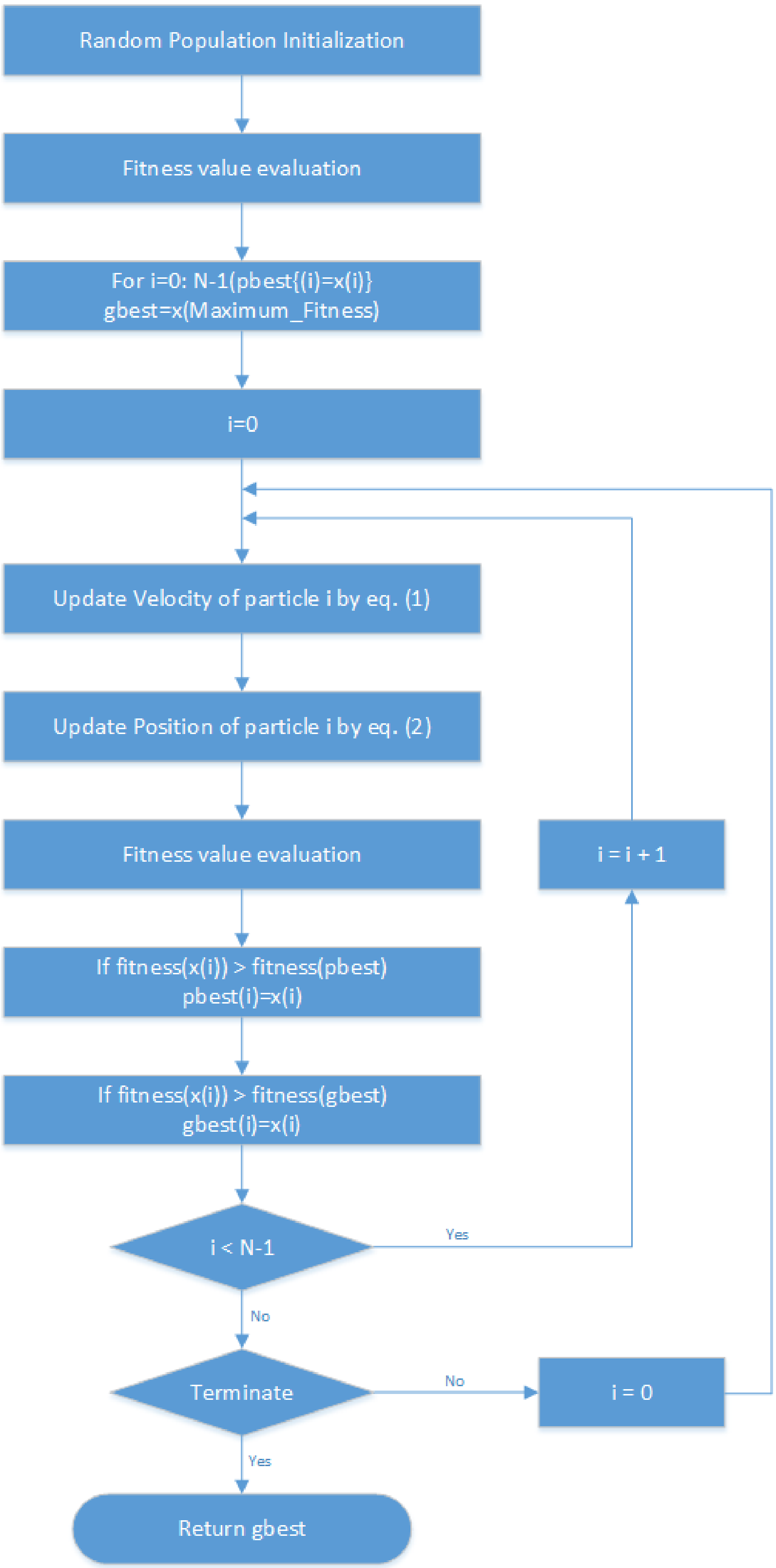

Figure 2.1 PSO Flow chart

2.3 Kin Selection

The sharing of some genes between related individuals considered as a vital behavior to the theorists. Moreover, some examples taken to clarify that as the following explanation; Hamilton [2] explained that the spreading individual's genes will be more successful by acting the relative's interest than done by acting in his own self-interest. Many tests occurred according to some studies that individuals provide less food to unrelated as compared to related individuals, without an explicit result shown. A significant bias in food transferring to related individuals of kin was found by Gurven [24]; Kaplan and Hill [23]. The empirical observation that related individuals share more than non-related individuals does not favor one of either mechanism, since both allow for different behavior towards kin. However, by the use of the model of reciprocal altruism in combination with the model of kin selection, one would expect those nonrelated individuals are more preoccupied with maintaining a balance of benefits given to another individual and benefits received from this individual, however the more tolerant of imbalances are the related particles.

CHAPTER 3

MATHEMATICAL MODELING

3.1 Reciprocal Altruism (RA)

Altruistic behavior's adaptiveness was introduced to the beneficiary as a linear function of the relatedness of the genetic. It is argued below:

3.1.1 The Proportional Altruism Model (PAM)

In the previous chapter, the term PAM was argued as an investment strategy, now its mathematical model will be explained as; if the coefficient of relationship and the altruistic investment are both in direct proportion, the investment's proportion is expected in every kin and achieved by the solution of the constant $\boldsymbol{c}$ in the equation: $\sum_{i=1}^{n} \boldsymbol{r_i c} = \mathbf{1}$ ($\boldsymbol{n}$ = kin's number; $\boldsymbol{r_i}$ = relationship's coefficient for kin $\boldsymbol{i}$), then $\boldsymbol{p_i} = \boldsymbol{r_i c}$ must be calculated in every kin ($\boldsymbol{p_i}$ = the expectancy of the investment's in every kin). For instance, if 1/2, 1/4, 1/8, and 1/16 are four kin values of $\boldsymbol{r}$ belong to an altruist, the description of the PAM will be by the function of regression: $\boldsymbol{p_i} = \mathbf{1.067}\boldsymbol{r_i}$, with decreasing $\boldsymbol{r}$ and values .533, .267, .133, and .067 of the predicted proportional investments.

3.1.2 The Diminishing Returns Investment Model

First the PAM is formed explicitly. After that, and according to Altmann's [15] a model of an alternative Diminishing Return will be referred by (DR), with DR developing and exploring its implications for social behavior.

3.1.2.1 Graphical Representation

With the consideration of a certain amount of fitness that belongs to a potential altruist (for example, energy) ready for an investment concerning the survival and the reproductive success of itself and another kin. If there is a consideration of a constant of the amount of increasing fitness per unit of energy investment, a type of linear relationship characterized in fig. (3.1) by the Unimpeded (UN) investment function that explained this procedure. In this instance, invest in oneself or all direct altruistic investment concerning the nearest kin is the best adaptiveness strategy. Altmann [15] clarifies that the most favorable expected outcome is the gene replication as a definition. However, with the benefits defined as constant in every new investment is meaningless. In the example of grooming with the best altruist acting, Altmann [15] makes clear that it is a good reason with an assumption of reaching altruistic investment to the point of diminishing returns, in other words, with the increasing of altruistic investment, the reduced rate of fitness increases. In fig. (3.1) the function of investment-benefit shown as the DR investment is labeled by the graphical curve

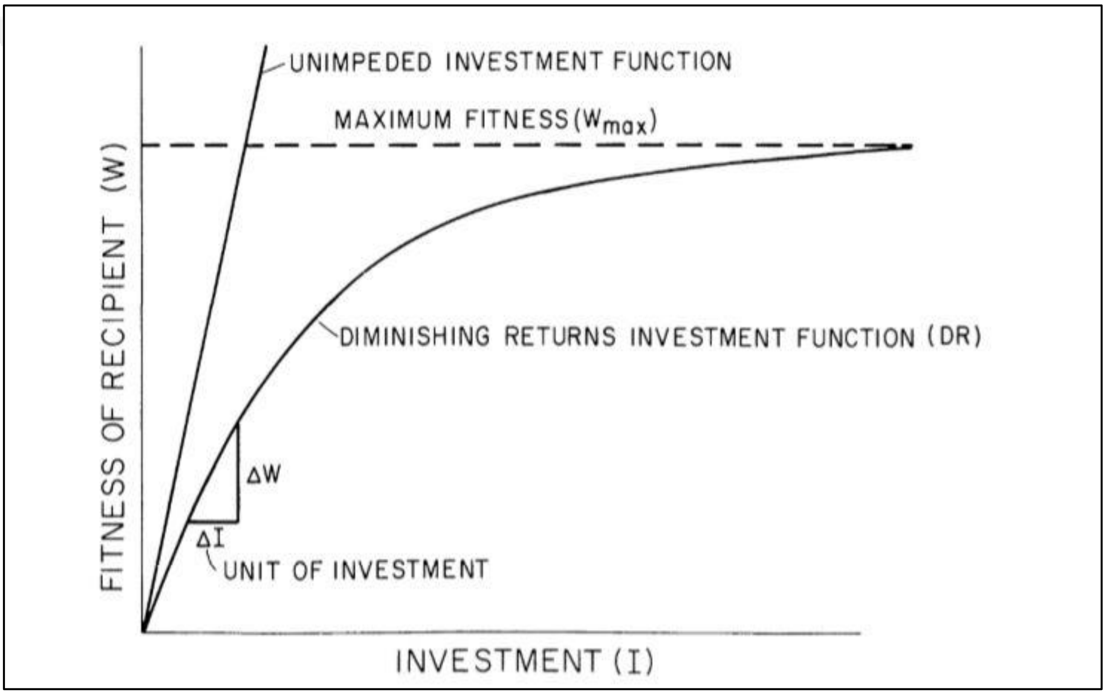

Figure 3.1 Comparison of Unimpeded and Diminishing Returns investment functions

representation. The altruism's fitness of any recipient is limited, it is determined with the help of recipient genotype's potential. The slope shows positive regular decrement with approaching $\boldsymbol{W_{max}}$ the maximized fitness by the DR function. Therefore, regarding the altruist of potential, in a specific point and time, where estimating every potential kin of a recipient that is located in his investment fitness curve would be the best adaptiveness strategy, when having $\boldsymbol{\Delta I}$ value given with the performance of an altruistic act and judging the expected fitness gain $\boldsymbol{\Delta W}$. Then in comparing among all kin (and possibly oneself), as Altmann [15] explained that, the decision will be based on the greatest product of $\Delta \boldsymbol{Wr}$ with an investment in that kin. With this plan, the investor's inclusive fitness would be maximized.

3.1.2.2 Mathematical Representation of Diminishing Returns Function

A consideration of the mathematical formation with a reasonable investment function of a diminishing returns is clarified with the following; the unimpeded function of investment can be described as $\boldsymbol{W = aI}$ also shown in fig. (3.1), where

$\boldsymbol{I}$ = invested amount of energy.
$\boldsymbol{a}$ = the increase of unimpeded rate per unit of investment.
$\boldsymbol{W}$ = recipient's individual fitness of altruism.

as long as a reduced rate of return on investment of the DR investment curve shown as the recipient's fitness, reached the achievable maximized fitness for the recipient's genotype $\boldsymbol{W_{max}}$, this curve will be at a lower fitness value than the UN curve for all $\boldsymbol{I > 0}$. The DR curve also described by another additional mathematical properties like:

(1) The DR curve's slope always positive $\boldsymbol{dW/dI > 0}$.
(2) $\boldsymbol{W = 0}$ when $\boldsymbol{I = 0}$.
(3) Always decreasing $\boldsymbol{d^2W/dI^2 < 0}$.
(4) The DR curve approaches $\boldsymbol{W_{max}}$ with the high investment values, as a horizontal asymptote as $\boldsymbol{W \to W_{max}, I \to \infty, dW/dI \to 0}$. At low investment values, the DR curve resembles the UN function as $\boldsymbol{dW/dI \to a, I \to 0}$.
(5) The DR curve resembles the UN function with the low investment values, as
$\boldsymbol{dW/dI \to a, I \to 0}$.
The following form of functions has been satisfied by all the conditions except (5):
$\boldsymbol{W = W_{max}(1 - k^{-aI})}$, where $\boldsymbol{k}$is a constant.

Also, eq. (3.1) has been satisfied by all these conditions including (5):

$$\boldsymbol{W = 1 - e^{-aI}} \tag{3.1}$$

Where $\boldsymbol{e}$ is the natural logarithmic rule. An interpretation required of the $\boldsymbol{W}$ axis in eq. (3.1) will be explained as follows. The maximum value of $\boldsymbol{W}$ is equal to one, and described as $\boldsymbol{W_{max} = 1}$, and the interpretation of $\boldsymbol{W}$ values as what has been realized from a proportion of the potential's total fitness of an individual. The following relationship between fitness and investment is specified by the use of the natural logarithmic rule $\boldsymbol{e}$ as a parameter in the DR model. The constant unit of investment given is $\Delta\boldsymbol{I}$, the beneficiary's fitness increased by the unused potential's constant fraction, for example, if the proportion of fitness potential realized is increased by one altruistic act with the range of $\boldsymbol{0}$ - $\boldsymbol{0.5}$ in other words increasing the unused potential by one-half, next the similar result to one-half of the not used potential is the next act of the same $\Delta\boldsymbol{I}$ in another words if $\Delta\boldsymbol{W} = [(\boldsymbol{0.5})(\boldsymbol{1 - 0.5}) = \boldsymbol{0.25}]$), then $\boldsymbol{W} = \boldsymbol{0.75}$ after two acts of altruism etc. Mathematically, when $\boldsymbol{W_i}$ = the value of $\boldsymbol{W}$ for the recipient before occurring the investment then it means that the fraction $(\Delta\boldsymbol{W})/(\boldsymbol{1 - W_i})$ will be constant. A reasonable assumption which appeared to be, the choice of $\boldsymbol{e}$ as the base for the exponential function appears to be a reasonable assumption.

3.1.2.3 Decision Process in Altruistic Investment

There is an expected influence on the decisions involved in the altruistic behavior's performance as shown below:

(1) The fitness cost $\boldsymbol{C}$ of performing an altruistic act is expected to affect altruistic decisions. In addition, the coefficient of relationship $\boldsymbol{r}$.
(2) The investment's total amount available.
(3) The unit of investment's size $\Delta\boldsymbol{I}$, in other words energy invested in the recipient.
(4) The rate of change in fitness per unit investment (related to the parameter $\boldsymbol{a}$).

In each value, parameters of the model are systematically varied as $\boldsymbol{a = 1, 0.1}$; ($\Delta\boldsymbol{I} = \boldsymbol{1, 0.1}$; $\boldsymbol{C}$=**0.01, 0.001**. This is related to the eight parameter values' combinations investigated. These parameter values were chosen to provide contrast (therefore tenfold changes in parameter values), subject to the conditions that altruistic behavior be expected to occur in most cases, for example, the little or no investment will be with the production of $\mathbf{0.1}$ by $\boldsymbol{C}$ values. The altruistic actual acts values are not the base of these values, but in different simulations relative values of parameters intend to provide comparisons of insight among altruistic acts that have naturally occurred. In the altruistic behavior distribution, in order of maximizing the fitness of the altruist inclusive then it is necessary to make decisions. Before the commences of an altruism simulation, a potential kin of every recipient should be under assumption of $\boldsymbol{I} = \mathbf{0}$, $\boldsymbol{W} = \mathbf{0}$ point on the curve of DR. For gaining the highest benefits of inclusive fitness from the behavior of altruism the altruist should be under assumption of having sufficient energy of investment available. The potential of every recipient has to be assumed of having an identical curve of DR. Furthermore, it has been assumed that the altruistic fitness cost acts would be equal in any specific simulation for all recipients. Fitness calculations would be made by the use of the values of the preselected parameter. The logical sequencing of calculations in the beginning and each following round of altruism will be as follows:

(1) Calculating the change of the expected fitness for every recipient's potential:

$$\Delta \boldsymbol{W} = \mathbf{1} - \boldsymbol{exp}^{(-\boldsymbol{a}(\boldsymbol{I_i}+\Delta \boldsymbol{I}))} - \boldsymbol{W_i} \tag{3.2}$$

(Where $\boldsymbol{W_i}$ = level of present fitness; $\boldsymbol{I_i}$ = sum of the last investment).

(2) Calculating the change of the expected inclusive fitness in the altruist investing of each kin:

$$\Delta \boldsymbol{W_{inc}} = (\Delta \boldsymbol{W} * \boldsymbol{r}) - \boldsymbol{C} \tag{3.3}$$

(Where $\boldsymbol{C}$ = cost of fitness to altruist in one action of altruistic behavior).

(3) The altruist will perform its acting whenever $\Delta \boldsymbol{W_{inc}}$ provided more than $\mathbf{0}$ by $\mathbf{1}$ at the minimum, the invest in the kin mentioned would be for the greatest $\Delta \boldsymbol{W_{inc}}$. Then updating the recipient's fitness level by $\Delta \boldsymbol{W}$.

The constitution of one round of the altruistic behavior would be by the steps from (1) to (3). Then the altruist will decide whether to perform another altruistic act based on the adjusted $\boldsymbol{W}$ values, in another words, the distribution of altruism will continue as long as $\Delta\boldsymbol{W}_{inc}$ is more than $\mathbf{0}$ at the minimum by **1**. When all of kin $\boldsymbol{C} > \Delta\boldsymbol{Wr}$**,** at that moment termination of altruism is executed.

The recipient of altruism having a fitness gains obtained should be under assumption of being permanent. The assumption of imagining this procedure happening sufficiently short during a time period that is reasonable. (e.g., animals waking every day with the need of grooming or nourishment, altruistic investment should satisfy these needs during the daytime). Otherwise, with making a steady improvement concerning increased fitness relatively by animals, for example, animal's behavior to be developed, the reproductive success in the future will increase until adulthood as expected, may be a consideration execute as the entire pre-reproductive period will be the same as the time period for altruistic investment.

3.2 Particle Swarm Optimization (PSO)

The term Particle Swarm Optimization explained by Kennedy & Eberhart [16] based on the gathering conduct by an adaptation of individuals population to its circumstances, Kennedy & Spears [25] clarifies that with the return to the regions' promised that were discovered before. The procedure with the adjustment of individuals to their circumstances, is defined as a stochastic one that relies upon two facts, which are the memory of every single point, called particle, and the population's gained knowledge that is defined as swarm. In this simple social model, every particle takes four features in the numeric implement as follows: particle position, particle velocity, particle track best position and swarm's best position. The procedure outlined as below:

1st Step: creating $\boldsymbol{N}$ particles as a swarm randomly.

2nd Step: calculating each particle's velocity with the base of its features.

3rd Step: the two new values of the velocity and position should be calculated from the present position.

4^{th} Step: stop with satisfaction of termination condition. Else, return to the 2^{nd} Step.

With the change of symbols according to the proposed algorithm for avoiding any redundancy of eq. (2.1) and to be more specific, Shi & Eberhart [26] introduced a scheme with the $\boldsymbol{i^{th}}$particle at time $\boldsymbol{t}$, the calculation of the new velocity vector $\boldsymbol{v_i^{t+1}}$ as below:

$$\boldsymbol{v_i^{t+1} = w^t v_i^t + c_1 R_1^t (p_i^t - x_i^t) + c_2 R_2^t (p_g^t - x_i^t)} \qquad (3.4)$$

With the explaining of eq. (3.4), there are three dependent factors as $\boldsymbol{w^t}$ the particles inertia, $\boldsymbol{c_1}$, $\boldsymbol{c_2}$ two trust parameters, random numbers from $\boldsymbol{0}$ to $\boldsymbol{1}$ as $\boldsymbol{R_1^t}$ and $\boldsymbol{R_2^t}$, the best $\boldsymbol{i^{th}}$ particle's position in its track is $\boldsymbol{p_i^t}$, the swarm's best position $\boldsymbol{p_g^t}$, the current $\boldsymbol{i^{th}}$ particle's position at time $\boldsymbol{t}$ is $\boldsymbol{x_i^t}$, the search direction's current vector $\boldsymbol{v_i^t}$, the $\boldsymbol{i^{th}}$ particle will calculate the search direction's next vector $\boldsymbol{v_i^{t+1}}$ with the consideration of $\boldsymbol{v_i^t}$, two directions considered with regard of $\boldsymbol{x_i^t}$ the present search position, both of these directions are started from $\boldsymbol{x_i^t}$ then one goes to $\boldsymbol{p_i^t}$ and the second goes to $\boldsymbol{p_g^t}$. Then, with the updated variables of eq. (2.2), this chapter outlined it as (3.5) that can be calculated as the new $\boldsymbol{i^{th}}$ particle's position $\boldsymbol{x_i^{t+1}}$ at time $\boldsymbol{t}$, also moves from $\boldsymbol{x_i^t}$ to $\boldsymbol{x_i^{t+1}}$ can be evaluated as below:

$$\boldsymbol{x_i^{t+1} = x_i^t + v_i^{t+1}} \qquad (3.5)$$

After the moving of a particle, a comparison is then required between the particle's cost $\boldsymbol{f}(\boldsymbol{x}_i^{t+1})$, with best track's position $\boldsymbol{f}(\boldsymbol{p}_i^t)$, then updates should start as if $\boldsymbol{f}(\boldsymbol{x}_i^{t+1})$ is best as compared to $\boldsymbol{f}(\boldsymbol{p}_i^t)$, then the best track's position will be updated as $\boldsymbol{p}_i^t = \boldsymbol{x}_i^{t+1}$. Moreover, if $\boldsymbol{f}(\boldsymbol{p}_i^{t+1})$ is best as compared to $\boldsymbol{f}(\boldsymbol{p}_g^t)$, then the best track's

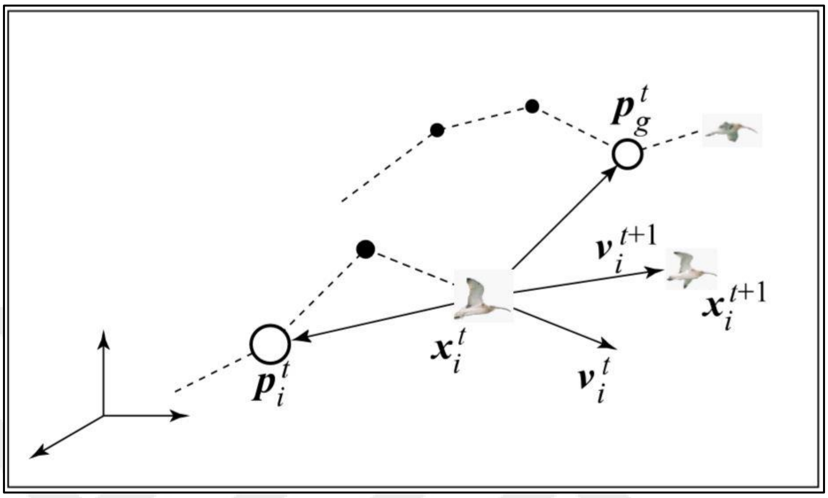

Figure 3.2 Movement of a particle in PSO [28]

position will be updated as $\boldsymbol{p}_g^{t+1} = \boldsymbol{p}_i^{t+1}$. The PSO ***gbest*** or global best is what the resulted algorithm refers to. Fig. (3.3) shows a general PSO pseudo code.

In the conical PSO technique will face some problems, but it is not an obstacle to go on with the Reciprocal Altruism method like; local optimal stopping that problem is not a big deal. To manage with these downsides of the first PSO technique, incorporation of the bisection method and a homomorphous mapping executed to carry out the search considering constraints. Furthermore, a proposition of the Reciprocal

Altruism based Particles Swarm Optimization (RAPSO) method suggested to discuss and compare the results with the conical PSO in the next chapters.

```
for each particle i ∈ 1,...,s do
  Randomly initialize x_i
  Set v_i to zero
  Set y_i = x_i
endfor
Repeat
  for each particle i ∈ 1,...,s do
    Evaluate the fitness of particle i, f(x_i)
    Update y_i
    Update ŷ using equation (3)
    for each dimension j ∈ 1,...,N_d do
      Apply velocity update using equation (2)
    endloop
    Apply position update using equation (1)
  endloop
Until some convergence criteria is satisfied
```

Figure 3.3 General pseudo-code of PSO

CHAPTER 4

PROPOSED METHOD

Path planning process from one point to another must be implemented with this technique by keeping all particles closer to the optimized particle to obtain better information sharing between them. MATLAB has been used as a simulation tool in order to test the proposed algorithm and its effectiveness.

4.1 Starting Up

First, 64 particles are initialized in a random manner near to the starting point (0, 0) to take the trajectory from that point to the goal point (40, 40) with total iterations of 23 needed for this process. Inertia factor 0.7 is used with correction factor 2.0 for the next optimized point in the space in each iteration.

4.2 Proportional Altruism Model (PAM)

Two circles proposed which have the same center, but different radiuses. The small and big circles mentioned as the first and second regions respectively and the rest of the space as the third region. The radiuses of the first and second regions are 15 and 22.

The performance of the expected influence on the decisions involved in the altruistic behavior are:

(1) The fitness cost $\boldsymbol{C}$ of performing an altruistic act is expected to affect altruistic decisions. In addition, the coefficient of relationship $\boldsymbol{r}$.
(2) The investment's total available amount.
(3) The unit of investment's size $\Delta\boldsymbol{I}$, in other words the invested energy in the recipient.
(4) In relation to $\boldsymbol{a}$ parameter, the change's rate in fitness of per unit invested.

In each value, parameters of the model parameters are systematically varied $\boldsymbol{a}$ **= 1, 0.1**; $\Delta\boldsymbol{I}$ **= 1, 0.1**; $\boldsymbol{cost_{alt}}$ **= 0.01, 0.001**.

So, the unit of investment considered $\boldsymbol{I}$ is $\mathbf{0.01}$ and the fitness cost of altruism's one act to altruist $\boldsymbol{cost_{alt}}$ is $\mathbf{0.1}$. Furthermore, the change in fitness rate per unit invested $\boldsymbol{a}$ set as **1**, and the unit investment's magnitude $\Delta\boldsymbol{I}$ is **1**.

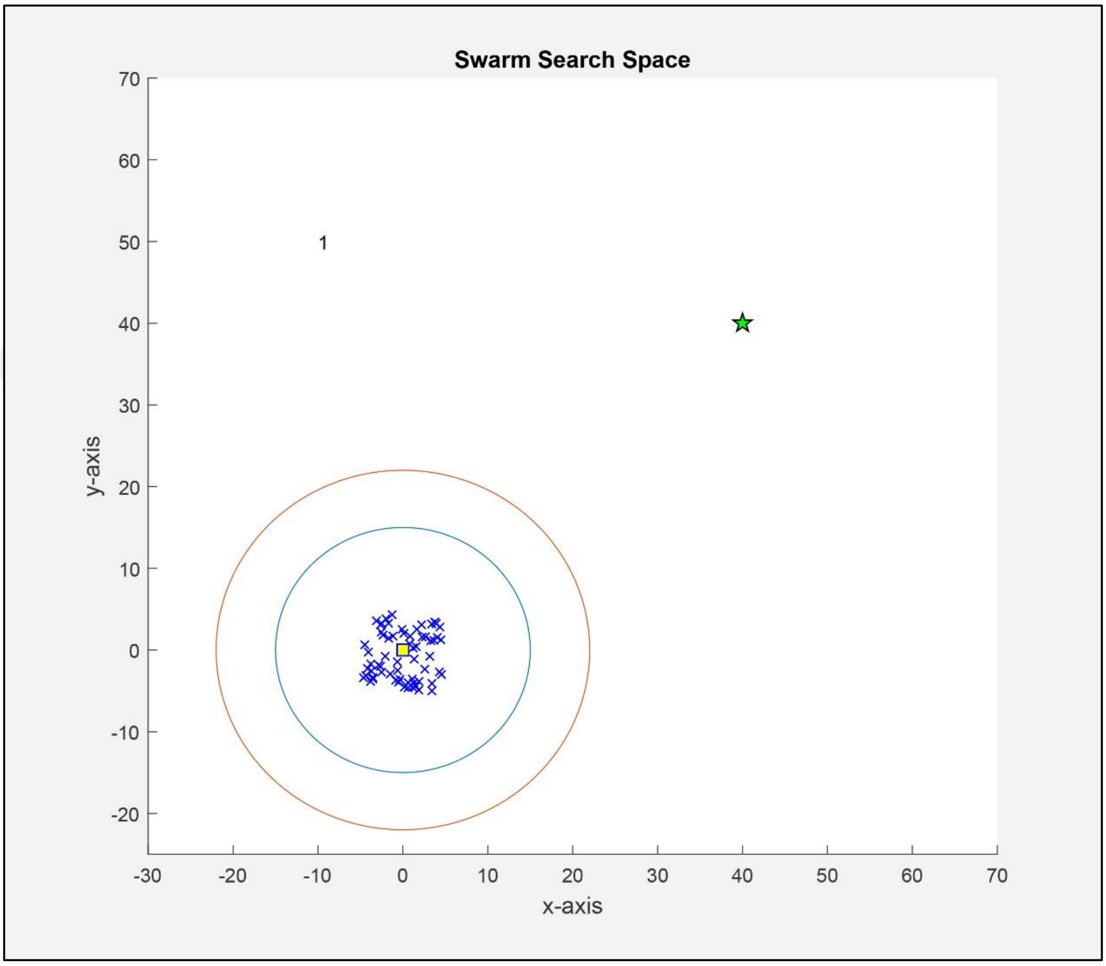

Figure 4.1 Swarm Search Space in Iteration 1

4.3 Generate Particles Template

First, with the generation of the 64 particle's positions that was mentioned before randomly around the starting point by using Matlab as shown in fig (4.1), with zero velocities. The best value up to now or best particle cost in high value, for example infinity or 1000 because a comparison should start with the minimum optimized particle's cost. The variable indicator of health status started with 100% or full energy, because all the particles started in the first region near to the optimized particle with a maximum health status.

4.4 Reciprocal Altruism Particle Swarm Optimization (RAPSO)

As this method is an iterative one, so next is about discussing the procedure in one iteration to get results for each individual iteration and compare it with a previous one to have the final best results accordingly.

4.4.1 Calculate the Positions and Costs of the Particles

Starting with the update of the particle's positions $\boldsymbol{p}$ by using eq. (4.1) as it is the update of eq. (3.5) according to the algorithm variables, to determine the list of new positions of the particles.

$$\boldsymbol{p}^{*} = \boldsymbol{p} + \boldsymbol{v}^{*} \tag{4.1}$$

Then getting the cost of the particles $\boldsymbol{cost}$ of the objective function in eq. (4.2).

$$\boldsymbol{cost} = \|\boldsymbol{p} - \boldsymbol{p_g}\| \tag{4.2}$$

4.4.2 Recipients and Donors

The center of PAM regions $\boldsymbol{c^r}$ proposed as the particle's best personal position $\boldsymbol{p^{best}}$ in the swarm, because the particles' positions should be as much closer to the particle personal best position as shown in fig. (4.2). Furthermore, specifying the current fitness level $\boldsymbol{u}$ as it the minimum cost value of the swarm. After that the distances from the particles to the region's center $\boldsymbol{d}$ should be specified to determine positions according to the PAM regions.

Evaluation of kin relationship coefficients $\boldsymbol{k}$ according to each regions is determined by the condition of the particles position if it is far from the best personal particle and its position in the third region, in addition to this the kin relationship coefficient will be as for grandparents and grand offspring and its value is 1/4, and this percentage is quite good for sharing information with particles from the nearest region to improve its performance. Particles in the second region are specified to have the coefficient kin relationship like for full cousins with value of 1/8, where this particles health status is better than the third region's particles so, the sharing of information will be less, and it will also be seeking the nearest donors from the first region to enhance its performance. The first region's particles have no sharing between them because all of them are in the safe zone and near to the optimized particle so no coefficient kin relationship is used for this region.

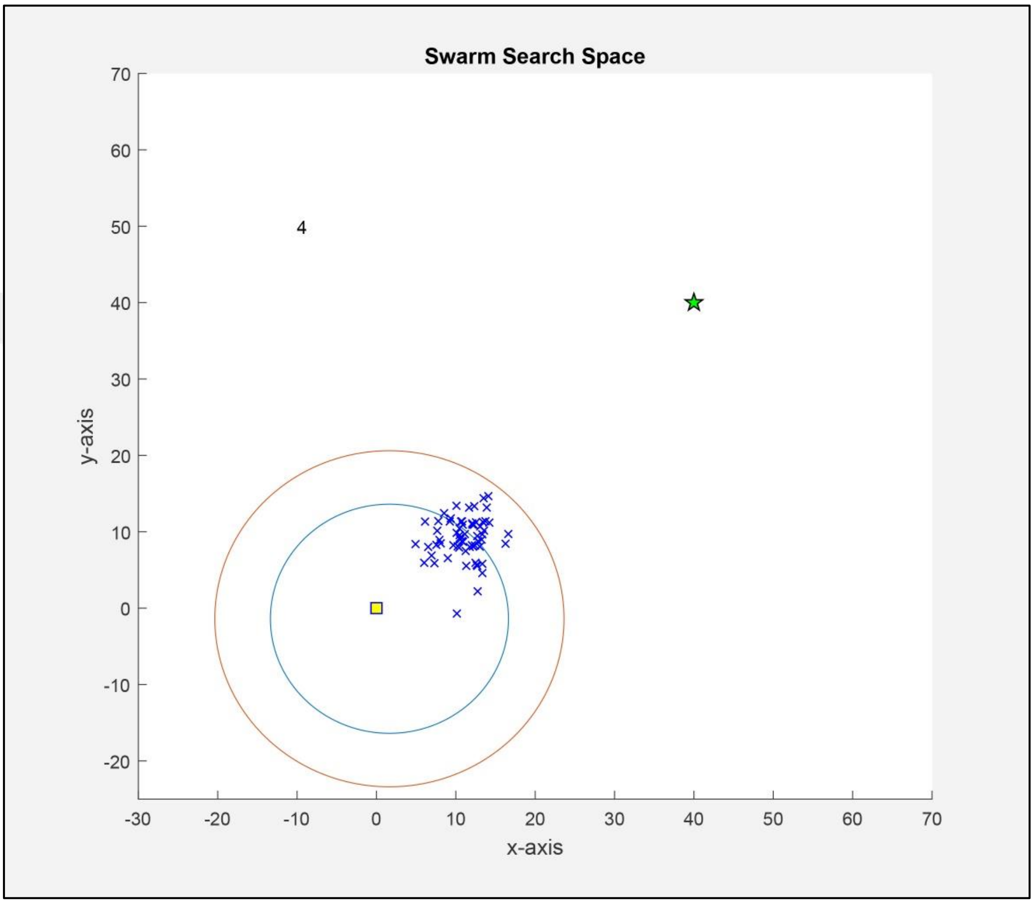

Figure 4.2 Search Space in Iteration 4

4.4.3 Particle's Behaviors Based Regions

Particles will start moving following the shortest path from the start point after they are randomly initialized. Furthermore, all the particles are initialized inside the first region. The system procedure will take these particles as full health status with a value of 100 points each at a moment.

With the consideration of the three regions in the simulation as the health status will change according to the particle's position with reference to these regions. In each region particles are categorized as (donors, recipients and un-active), following are rules of regions on the particles which are inside it:

4.4.3.1 First Region

This region will be the internal one that includes most of the healthiest particles. The particles start with a full value 100 points. When the particles initialized inside or entered this region, the health status will automatically increase with 5 points in each iteration. Because, particles should get back to this region from another regions to retrieve its positive health status. However, this does not mean that the status value will be higher than 100 points, so the maximum value limited to 100 points.

Health information will not be shared between particles in this region because these particles will be near to the optimized particle that is taking the shortest path. So, they will be in the safe zone as donors only for other regions. According to this method, a recipient will not exist, so this region will contain donors and un-active particles.

4.4.3.2 Second Region

This region will contain particles from the second or third iteration according to the random trajectories of the particles. First, when a particle jumps from region one to region two, the health status will decrease by 15 points. That means the particle position has been far from the optimized particle position, at that moment it will losses a part of the control indicator accordingly. Particle's control indicator will continue losing 15 points in each iteration if it remains in the same region.

In this region kinship coefficient $\boldsymbol{k}$ specified as 1/8 after that a determination should execute to the sum of the previous investments $\boldsymbol{\Sigma I}$, expected change of fitness for every potentially recipient $\Delta\boldsymbol{u}$ as eq. (4.3) which is the updated version of eq. (3.2). The expected change of inclusive fitness for the altruist in every kin in investing $\Delta\boldsymbol{u}_{\boldsymbol{inc}}$ as eq. (4.4) which is the updated version of eq. (3.3). According to the new kinship coefficient.

$$\boldsymbol{\Delta u = 1 - exp^{(-a(I+\Delta I))} - u} \tag{4.3}$$

$$\boldsymbol{\Delta u_{inc} = (\Delta u * k) - cost_{alt}} \tag{4.4}$$

With regard to the obtained data, seeking for donors should occur in the first region for the particles that in the second region. If donors found at that moment an update should occur to the positions according to eqs. (4.5) and (4.6), costs according to eqs. (4.7) and (4.8), and health indicator according to eqs. (4.9) and (4.10). By specifying minimum health status value as 20. Otherwise, particles will be out of range of the controllability region.

$$\boldsymbol{p^{d_2}_{recp} = p^{d_2}_{recp} - \Delta u_{inc};} \tag{4.5}$$

$$\boldsymbol{p^{d_1}_{dnrs} = p^{d_1}_{dnrs} - \Delta u_{inc};} \tag{4.6}$$

$$\boldsymbol{cost^{d_2}_{recp} = cost^{d_2}_{recp} - (u * k);} \tag{4.7}$$

$$\boldsymbol{cost^{d_1}_{dnrs} = cost^{d_1}_{dnrs} - (u * k);} \tag{4.8}$$

$$\boldsymbol{b(p^{d_2}_{recp}) = b(p^{d_2}_{recp}) + \sigma/6;} \tag{4.9}$$

$$\boldsymbol{b(p^{d_1}_{dnrs}) = b(p^{d_1}_{dnrs}) - \sigma/6;} \tag{4.10}$$

4.4.3.3 Third Region

This region will have the same procedure that occurred to the previous one regarding the decreasing of the health status indicator and seeking for donors from the nearest region. Mathematically it differs from the previous region’s procedure as explained in the following; like when particles jumped from other regions to the third region, they will lose 30 points from its health status in each iteration.

Kinship coefficient is specified as 1/4 to determine values mentioned before $\boldsymbol{\Sigma I}$,$\boldsymbol{\Delta u}$, and $\boldsymbol{\Delta u_{inc}}$ with reference to the new coefficient $\boldsymbol{k}$ by updating positions from eqs.

(4.11) and (4.12), costs according to eqs. (4.13) and (4.14), and health indicator according to eqs. (4.15) and (4.16).

$$\boldsymbol{p_{recp}^{d_3}} = \boldsymbol{p_{recp}^{d_3}} - \Delta \boldsymbol{u_{inc}};\tag{4.11}$$

$$\boldsymbol{p_{dnrs}^{d_2}} = \boldsymbol{p_{dnrs}^{d_2}} - \Delta \boldsymbol{u_{inc}};\tag{4.12}$$

$$\boldsymbol{cost_{recp}^{d_3}} = \boldsymbol{cost_{recp}^{d_3}} - (\boldsymbol{u} * \boldsymbol{k});\tag{4.13}$$

$$\boldsymbol{cost_{dnrs}^{d_2}} = \boldsymbol{cost_{dnrs}^{d_2}} - (\boldsymbol{u} * \boldsymbol{k});\tag{4.14}$$

$$\boldsymbol{b}(\boldsymbol{p_{recp}^{d_3}}) = \boldsymbol{b}(\boldsymbol{p_{recp}^{d_3}}) + {}^{\boldsymbol{\sigma}}/_{\boldsymbol{3}};\tag{4.15}$$

$$\boldsymbol{b}(\boldsymbol{p_{dnrs}^{d_2}}) = \boldsymbol{b}(\boldsymbol{p_{dnrs}^{d_2}}) - {}^{\boldsymbol{\sigma}}/_{\boldsymbol{3}};\tag{4.16}$$

Now with the same process, region three recipients will seek donors from the nearest region and by updating the same variables (positions, costs and health indicator) in that moment the minimum health status shouldn't be less than 20 to keep particles

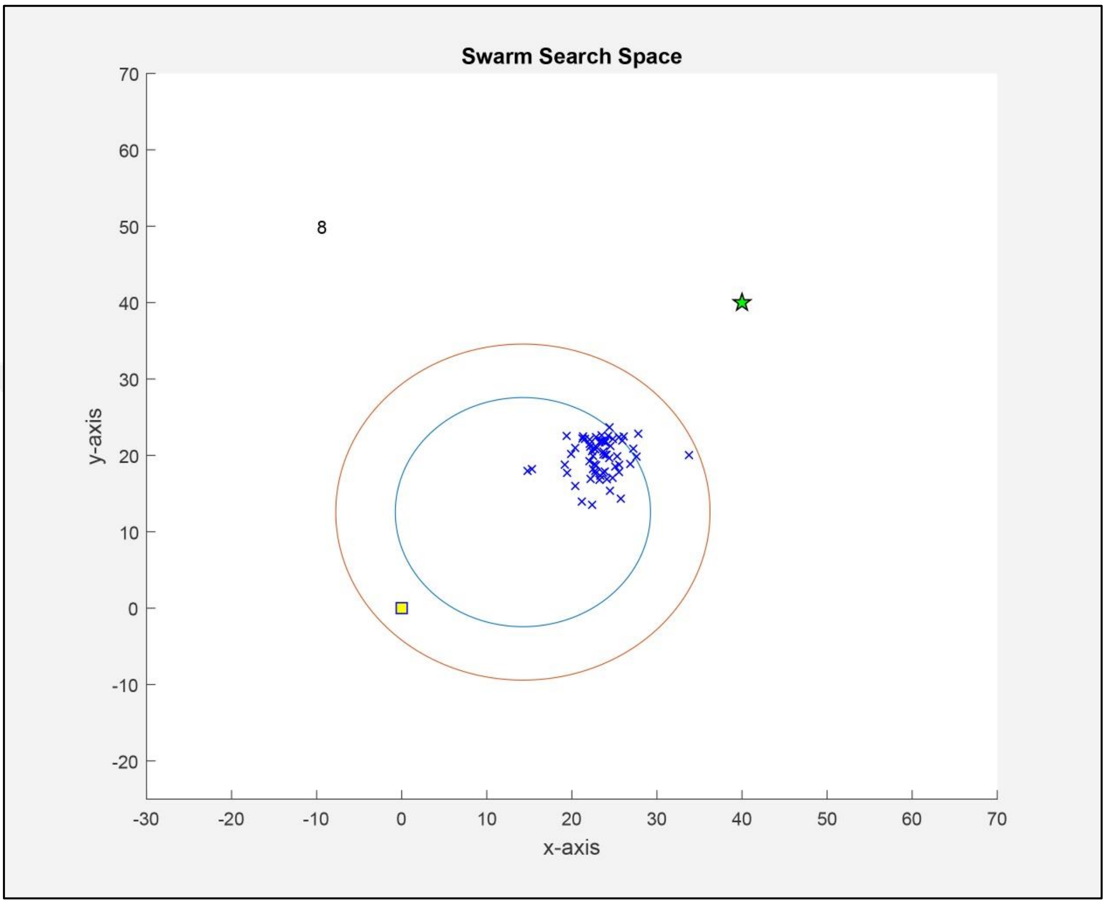

Figure 4.3 Search Space in Iteration 8

under controllability region as shown in fig. (4.3).

4.4.4 Altruistic Investment

The total amount of investment should be updated in each iteration that contains altruistic investment by adding the new total amount of investment to the initial value $\boldsymbol{\Sigma I}$.

4.5 Particles Statements

Find the best personal particle $\boldsymbol{p}^{best}$ and best global particle $\boldsymbol{p}^{gbest}$ in the swarm. In that moment, an update to the velocity vector should occur according to eq. (3.4). Then

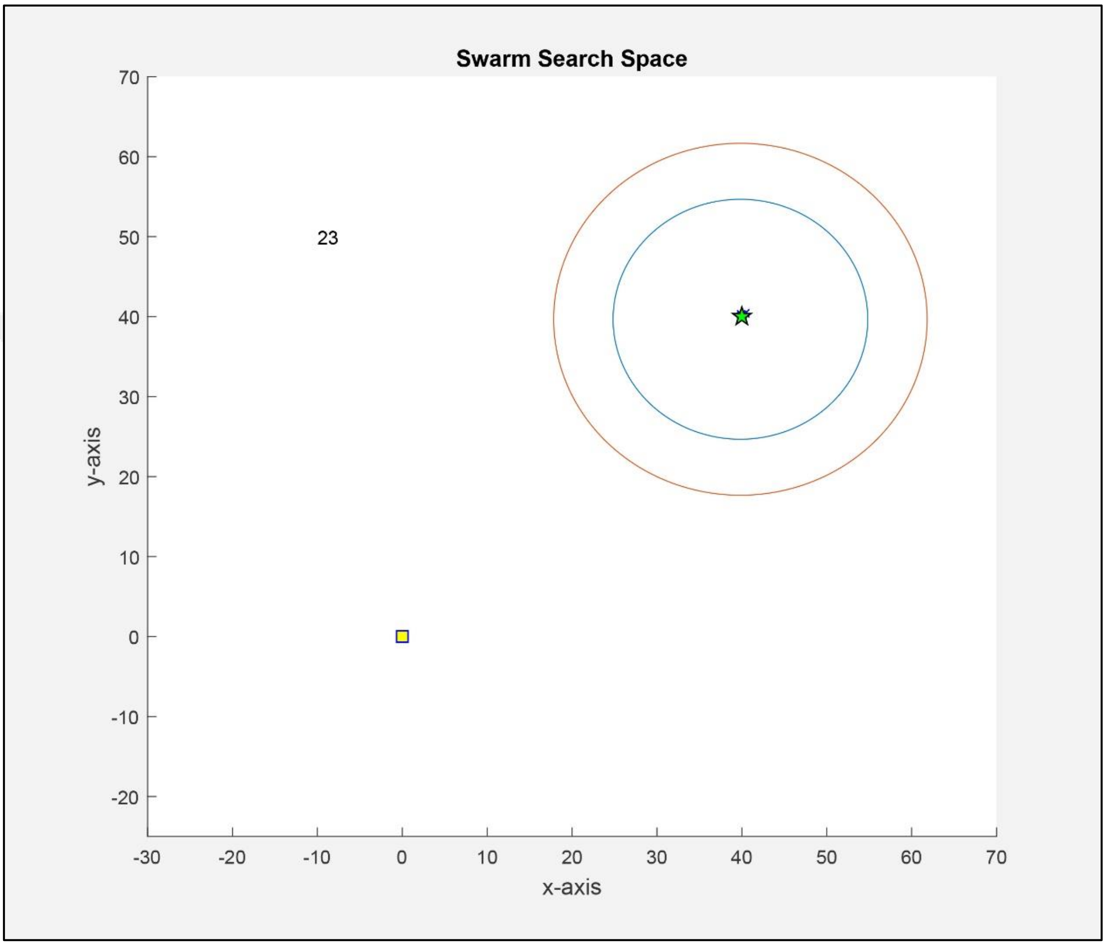

Figure 4.4 Search Space in Iteration 23

iterations execution continue until reaching the goal point as shown in fig. (4.4).

4.6 Proposed Algorithm (RAPSO)

Considering $\boldsymbol{N}$ as the population of the swarm, and by iterate it with the proposed algorithm with a maximum iteration $\boldsymbol{i_{max}}$ with a health indicator representing the controllability of particles or connectivity between them $\boldsymbol{b}$. Inertia weight provided as $\boldsymbol{w}$ is a scale parameter linked to the velocity throughout the earlier time step and a parameter of constriction which helped to guarantee the convergence of the swarm as $\boldsymbol{c}$. The space is categorized in three regions, two circles with deferent radiuses $\boldsymbol{r}^{r}$ and the rest of the space. The unit of investment $\boldsymbol{I}$, the size of investment $\Delta\boldsymbol{I}$ and a fitness cost altruism of one act $\boldsymbol{cost_{alt}}$. Furthermore, $\boldsymbol{p_s}$ is the starting point, and $\boldsymbol{p_g}$ is the ending or goal point. The PAM region's center $\boldsymbol{c^r}$ with a coefficients of relationships for kin $\boldsymbol{k}$ and the rate of health indicator lost from particles entering the third region $\boldsymbol{\sigma}$ with a value of 30 and $\boldsymbol{\gamma}$ with a value of 100 is the maximum rate of health indicator and a minimum rate of health indicator $\boldsymbol{\beta}$ with a value of 20.

The proposed method RAPSO is the extended PSO method with respect to RA to become a global search algorithm that can be constructed as follows:

Algorithm 2: Pseudo-code of Reciprocal Altruism based Path Planning using Particle Swarm Optimization (PSO)

Input: $N, i_{max}, w, c, r^r, I, \Delta I, cost_{alt},\ p_s,\ p_g$;
Procedure:

$p, v, cost, b \leftarrow$ Initialize particles positions randomly, velocity @**zeros**, cost @**high value,** and control indicator @γ;

while $(cost^* \geq min\ (cost))$
- $cost \leftarrow \|p - p_g\|$
- $c^r \leftarrow p^{best}$
- $u \leftarrow min\ (cost)$
- $d \leftarrow \|p - c^r\|$
- Determine $d_1, d_2\ and\ d_3$ according to number of regions
- **if** d_3 is not empty then % exploring particles in region 3
  - set donors, recipients and un-active particles to zeros
  - $b(p_{recp}^{d_3}) \leftarrow b(p_{recp}^{d_3}) - \sigma$;
  - set $k \leftarrow 1/4$
  - finding nearest donors in region 2 to the nearest recipient in region 3
  - **if** $p_{dnrs}^{d_2} \neq 0$ & $p_{recp}^{d_3} \neq 0$
    - compute $\Delta u, \Delta u_{inc}, p_{recp}^{d_3}, p_{dnrs}^{d_2}, cost(p_{recp}^{d_3}), cost(p_{dnrs}^{d_2})$ using Eqs. (4.11), (4.12), (4.13), (4.14), (4.15), (4.16)
    - $b(p_{recp}^{d_3}) \leftarrow b(p_{recp}^{d_3}) + {}^{\sigma}/_{3}$;
    - $b(p_{dnrs}^{d_2}) \leftarrow b(p_{dnrs}^{d_2}) - {}^{\sigma}/_{3}$;
    - **if** $b(p_{recp}^{d_3}) < \beta$ **then;** $b(p_{recp}^{d_3}) \leftarrow \beta$; **end if**
  - **end**
- **elseif** d_2 is not empty then % exploring particles in region 2
  - set donors, recipients and un-active particles to zeros
  - $b(p_{recp}^{d_2}) \leftarrow b(p_{recp}^{d_2}) - {}^{\sigma}/_{2}$;
  - set $k \leftarrow 1/8$
  - finding the nearest donors in region 1 to the nearest recipient in region 2
  - **if** $p_{dnrs}^{d_1} \neq 0$ & $p_{recp}^{d_2} \neq 0$
    - update $\Delta u, \Delta u_{inc}, p_{recp}^{d_2}, p_{dnrs}^{d_1}, cost(p_{recp}^{d_2}), cost(p_{dnrs}^{d_1})$ using Eqs. (4.5), (4.6), (4.7), (4.8), (4.9), (4.10)
    - $b(p_{recp}^{d_2}) \leftarrow b(p_{recp}^{d_2}) + {}^{\sigma}/_{6}$;
    - $b(p_{dnrs}^{d_1}) \leftarrow b(p_{dnrs}^{d_1}) - {}^{\sigma}/_{6}$;
    - **if** $b(p_{recp}^{d_2}) < \beta$ **then;** $b(p_{recp}^{d_2}) \leftarrow \beta$; **end if**
  - **end**
- **else** % exploring particles in region 1
  - $b(p^{d_1}) \leftarrow b(p^{d_1}) + {}^{\sigma}/_{6}$;
  - **if** $b(p^{d_1}) > \gamma$ **then;** $b(p^{d_1}) \leftarrow \gamma$; **end if**
- **endif**
- $I = \Sigma I$
- Calculating the value of fitness of every particle. If the fitness mentioned better the best fitness, then the present fitness as the new best fitness p^{best}.
- Then choosing the global best that it has best value if it compared to swarm p^{gbest}.
- Computer v with regard to Eq. (3.5).
- Updating p with regard to Eq. (4.1).

end while

Output:

Print: “Values of recipients=”, “Values of donors=”; “Values of un-actives =”; “Values of Best cost =”;“Values of health indicator =”; “Values of distances to center =”; “Values of altruism in p08 =”; “Values of altruism in p24 =”; “Values of altruism in p48 =”; “Values of particles regions distribution =”; “Values of reciprocal altruism between first and second regions =”; “Values of reciprocal altruism between second and third regions =”;

CHAPTER 5

RESULTS AND DISCUSSION

Path planning global search space based PSO has been widely discussed in the last decades. This algorithm improved with the reciprocal altruism mechanism that makes the particles keep sharing information to avoid wasted fitness cost in the far positions according to the optimized one.

This technique starts its effect from the starting point to the goal point, by considering keep all particles close to the optimized particle. The two circles that proposed have the same center, but different in radiuses, small and big circles mentioned as the first and second region respectively, and the rest of the space as the third region. Then generate particles randomly, with zero velocities, and the best particle cost in a high value. The health indicator pointing at 100 because of all the particles which started in the first region near to the optimized particle.

The center of PAM regions proposed as it is the particle's best personal position in the swarm, because the particles' positions should be as near as possible to the best personal particle position as possible. The evaluation of kin relationship coefficients according to each region is determined by the condition of the particle's position to conclude the pairs of altruistic investment amount. Particles are categorized as (donors, recipients and un-active) in the search space according to their activity.

All simulations of altruistic distribution produced altruistic investment. In this case the cost of altruism was great enough to offset the modest benefit for recipients. The patterns of distribution of altruism among kin are affected by the changes in the model parameter values from region to another, and because of the procedure that used here, optimized best cost reached in less than 23 iteration as shown in fig. (5.1). Moreover, the other particles takes more than the optimized particle to reach the goal point, therefore the iterations should be increased.

At that moment particles distributed in the space with regard to the cost function and the goal point's position and treat each other. Where the donors particles donated from its health indicator to the particles' health indicator that lost the optimized path in the space to be as recipients' particles.

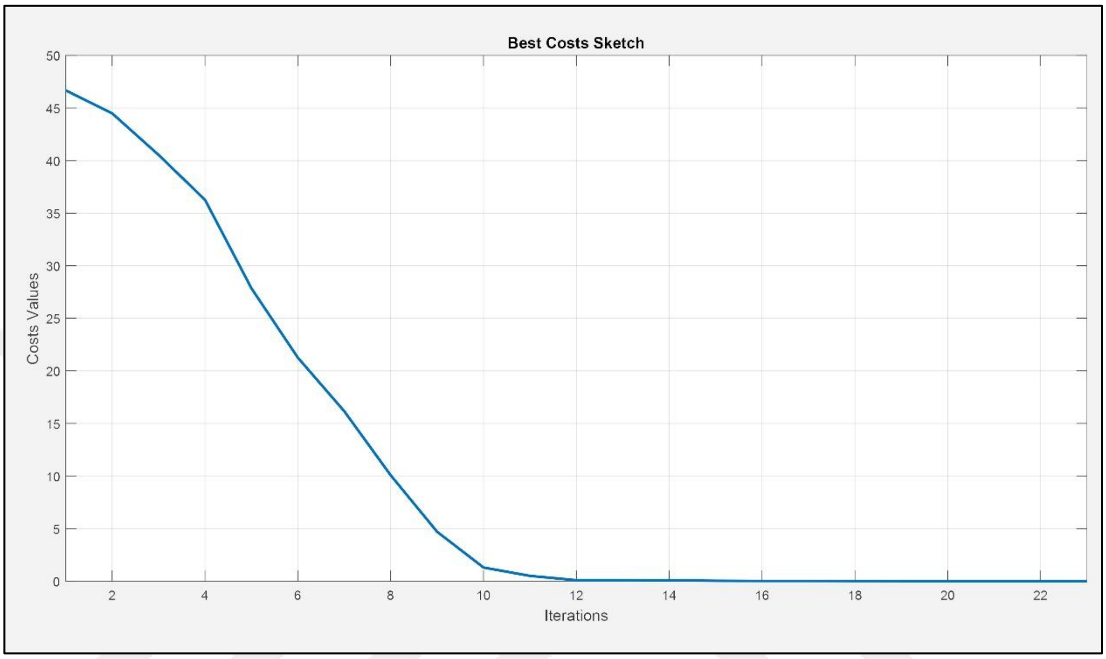

Figure 5.1 Best Costs Sketch

5.1 Iterations Processes

In this thesis, three particles are randomly taken as samples (p08, p24, and p48) to see the particle's status in each iteration as shown on fig. (5.2), iterations processes explained in the following:

5.1.1 First Three Iterations

The health indicators are 100 % for all the particles. Where these particles have started from the first region with full connectivity between each other.

5.1.2 Fourth Iteration

The first sample (p08) started losing the optimized path which went outside the first region shown when its loss 10 points from its indicator in fig. (5.2), and looks like it found a mate to donate from, therefore it has been a recipient at that moment.

(p24) and (p48) in fig. (5.2) are un-active in the fourth iteration so there is no altruism happening with them.

Distribution of particles show that all the 64 particles are inside the first region in the first three iterations in fig. (5.3), and there are two particles that jumped to the second region in the fourth iteration. Therefore, altruism is highly recommended here to treat this situation.

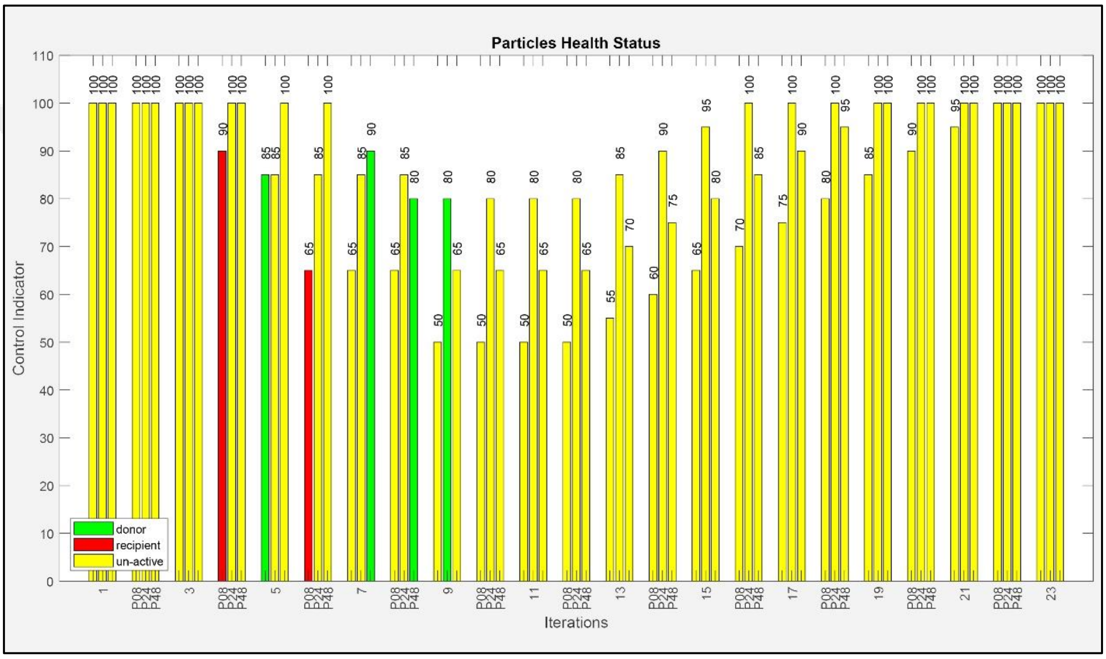

Figure 5.2 Particles Health Status

The altruism in the mentioned iteration can be shown in fig. (5.4) that there are two donors from region 1 and there is one recipient in region 2 meaning that there are two donors for (p08) and noticed in the same figure, there are no recipients in this iteration except one and (p08) noticed as a recipient in fig. (5.2) meaning that (p08) is the recipient that mentioned before.

So, there is an altruistic investment for just one recipient from two donors. In this case, there is one recipient particle and another un-active particle in region 2 and two donors and 60 un-active particles in region 1 and no particles in region 3.

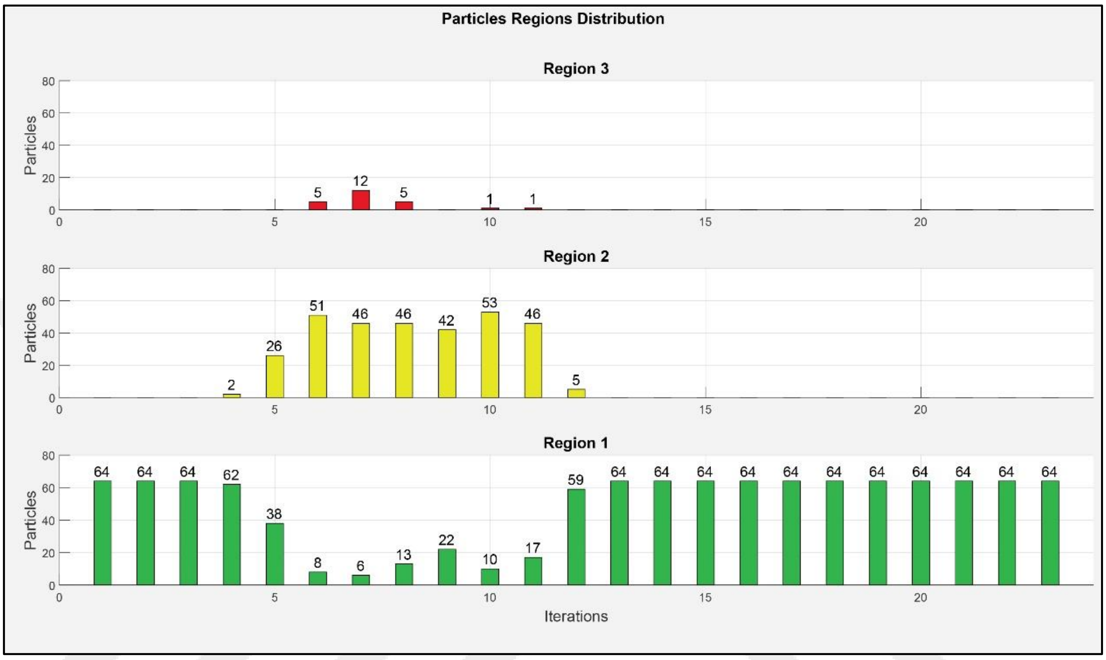

Figure 5.3 Particles Regions Distribution

In fig. (5.5) noticed clearly which is related to the behavior of (p08) in each iteration, the distance from the position of (p08) to the center did not change in the first three iterations as mentioned above. Were (p08) was as un-active particle. But, it is changed in the fourth one from 17 to 7 meaning that altruism is happening in this situation and the particle's position changed to be nearer to the optimized particle than its original position in the third iteration.

5.1.3 Fifth Iteration

26 Particles found were jumped to region 2 as shown in fig. (5.3). Moreover, altruistic investment was occurring with these particles as 20 particles were donors from region 1 to two particles from region 2 to be as a recipients and stills 24 and 18 un-active particles in region 2 and 1 respectively that shown in fig. (5.4).

In this iteration, fig. (5.2) shown that (p08) is a donor while it was a recipient in the previous iteration, and this is the real mean of the reciprocal altruism that happen between particles, and whenever it can donate it will do that with particles that helped it before according to the kinship strategy. Even though its indicator is not full as is 85, one of its neighbors or in another word its supporters needs its help to get back its health status. Altruistic investment happened with (p08) shown in fig. (5.5) to clarify the changing in its distance to the center from 15 to 19, and this is because it is a donor now and has shared information with a colleague by this altruistic value.

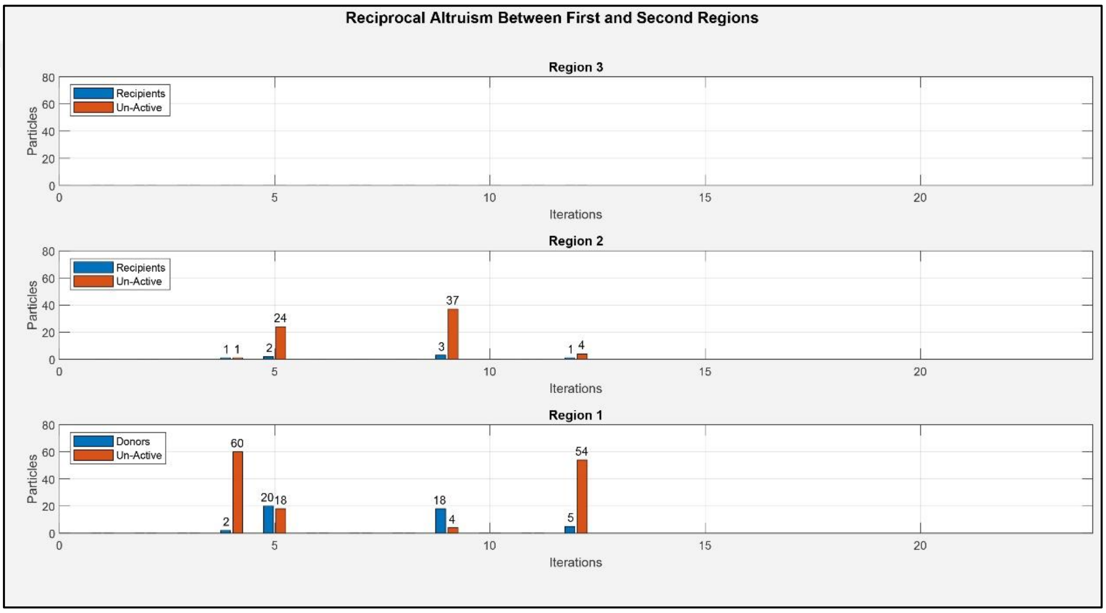

Figure 5.4 Reciprocal Altruism between First and Second Regions

(p24) also losses 15 points from its indicator which means that it has moved to the second region in this iteration, but it is un-active according to fig. (5.2). (p48) still has a full health indicator which means it is still in the first region and maintains its path near to the optimized one.

According to the results from the fifth iteration, there is no altruism investment found that happening between regions 2 and 3, however it is between regions 1 and 2.

5.1.4 Sixth Iteration

Particles distributed in the search space as 8 particles in the first region and 51 particles in the second region and 5 particles in the third one. So, the conclusion is the particles decrease in the first region and the opposite is happening in the second region. Furthermore, 5 of the particles jumped to the third region as in fig. (5.3).

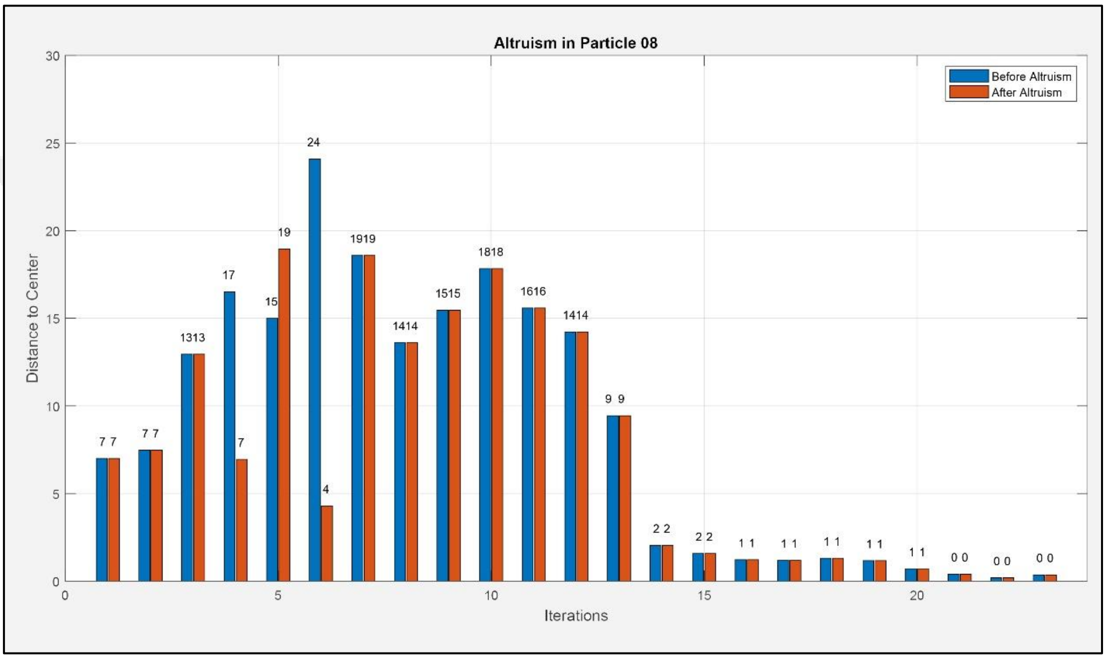

Figure 5.5 Altruism in Particle 08

There is no altruistic investment happening between regions 1 and 2 as shown in fig. (5.4), however it is happening in regions 2 and 3 as shown in fig. (5.6). As the 8 particles in region 1 are un-active, there are 5 of region 2 which behave as donors to one recipient in region 3 according to the kinship relationships behavior. In addition to that, yet 46 and 4 in regions 2 and 3 respectively are still un-active.

In fig. (5.2) noticed that (p08) health indicator decreased to 65 in this iteration as compared to the previous one. (p08) is a recipient now, it is possible that the reason for finding a donor is that particle being donor before that. Furthermore, the amount of investment in fig. (5.5) changed the position of the particle to be in a better position according to the optimized particle as the distance decreased from 24 to 4.

(p24) and (p48) noticed in fig. (5.2) that they maintain their level as 85 and 100 respectively. The interesting point about (p48) is that it remains still in the first region and also close to the optimized path and particle, and this is a good behavior. As compared with others, its distance to the center of the graph can be shown in fig. (5.7).

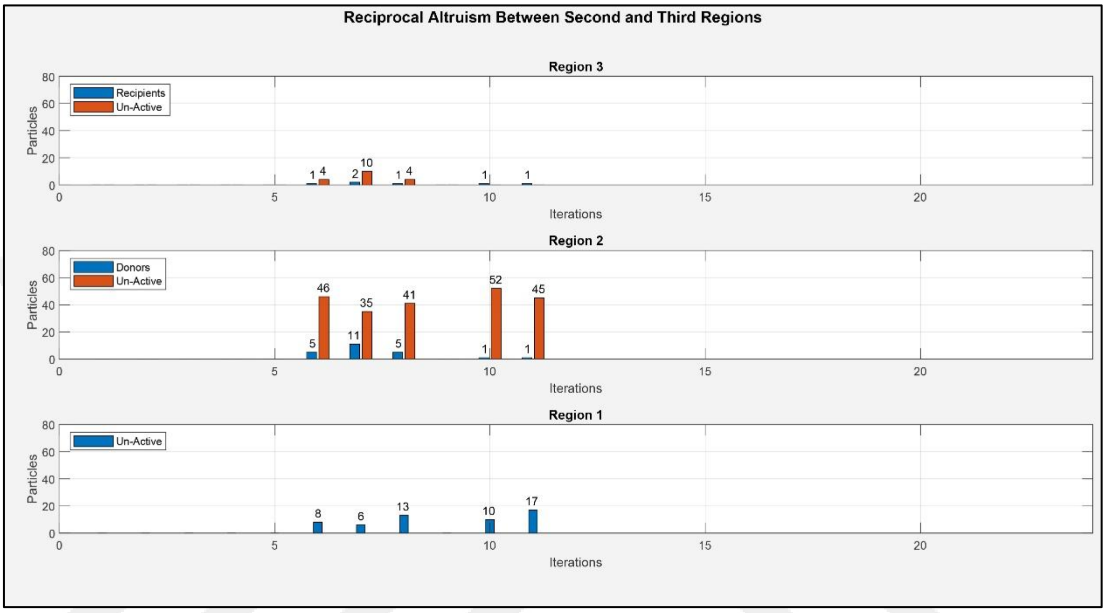

Figure 5.6 Reciprocal Altruism between Second and Third Regions

5.1.5 Seventh Iteration

There is not much change noticed in this iteration, and it seems it has been worse than before because in fig. (5.3), it is shown that there are only 6 particles in the first region. 46 Particles in the second region that their quantity decreased as compared to the sixth iteration. On the other hand, particles in the third region increased to 12 and this is the worst situation and should be handled to increase the health status of the particles in order to keep them near to the optimized region.

In addition, there is no altruism between region 1 and 2 in this iteration, however it exists between regions 2 and 3 as shown in fig. (5.6) that the 6 particles that mentioned before in the first region are all un-active. The 46 particles in the second region has 11 particles as donors and 35 particles are un-active, and the 12 particles in the third region has two particles as recipients and 10 particles as un-active.

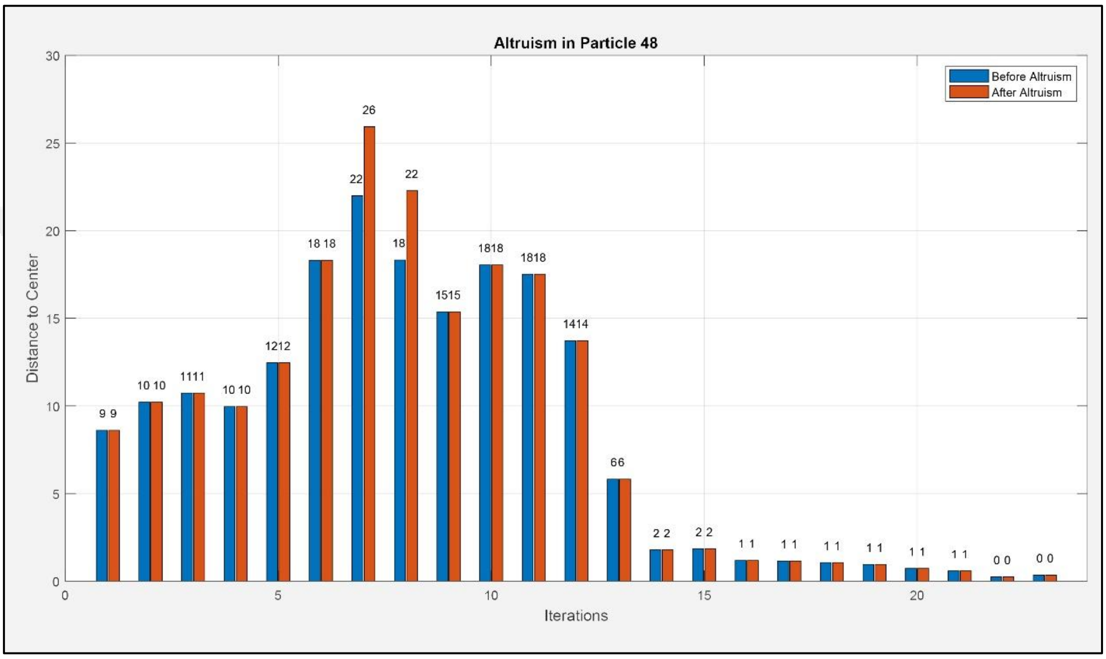

Figure 5.7 Altruism in Particle 48

In the same iteration, also noticed that (p08) has maintained its health indicator as shown in fig. (5.2) as 65, and it is also shown as un-active. Furthermore, it has maintained its position as well as shown in fig. (5.5) with a value of 19 before and after altruistic investment.

(p24) has not changed as shown in fig. (5.2), therefore its health indicator value still as 85. (p24) distance to the center as shown in fig. (5.8) maintains its value in all iteration from the beginning until this one, however, it has reached its peak in this iteration with a value of 21.

(p48) losses 10 points from its health indicator in this iteration after maintaining its value for 6 iterations, and is still one of the good performing particles. The proof for this is that it is a donor now, even when loss from its health indicator still donate as shown in fig. (5.2). from the observation carried out on the altruistic investment effect in fig. (5.7), the distance value found that is changed from 22 value before altruism to 28 value after altruism.

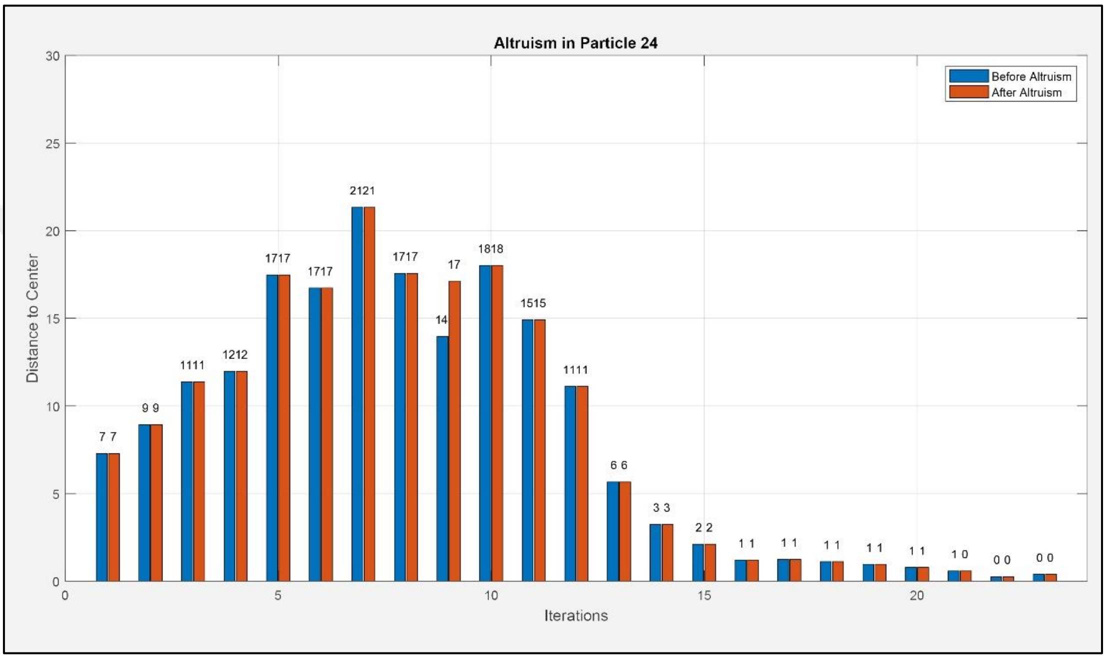

Figure 5.8 Altruism in Particle 24

5.1.6 Eighth Iteration

In fig. (5.3) found that the 64 particles distributed in the search space as 13 particles in the first region. Particles in the first region increased as compared with the previous iteration, proving the behavior of the particles improved to be better than before. 46 Particles in the second region which is the same number from the previous iteration, and the third region decreased by 5 particles which is a positive status for the mentioned region.

There is no altruism between regions 1 and 2 in this iteration as also shown in fig. (5.4), because there are particles in the third region, and the proposed algorithm focuses on the farther away particles as they are more important than the others. In fig. (5.6) clearly shows that the altruistic investment is happening. Furthermore, there are

13 particles noticed in the first region as un-active, 5 donors and 41 un-active particles in the second region and at last one recipient and 4 un-active particles found in the third region. Moreover, the number of particles is decreasing as compared to the previous iteration which mean that the status of the particles' connectivity is positive and is going to be better if the connectivity behavior continued.

In this iteration (p08) has no changes as its health indicator noticed in fig. (5.2) which is still the same value as 65 and un-active particle. Furthermore, (p08) distance to the center is also still the same before and after altruism as 14 that shown in fig. (5.5).

(p24) status has no unique deference from (p08) as it has the same health indicator in fig. (5.2) and same distance to the center as shown in fig. (5.8).

(p48) decreased by 10 points from its health indicator in fig. (5.2) but is still one of the healthy particles if compared to others taking in consideration that it has been a donor in this iteration. The effect of the altruistic investment noticed in fig. (5.7) with the changing of its value from 18 before altruism to 22 after altruism. It was also noticed in the same figure that its distance changed from 28 to 18 before altruism in this iteration which belongs to the updating of its position according to the velocity in each iteration.

5.1.7 Ninth Iteration

It was noticed that the particles increased in the first region in fig. (5.3) to 22 and decreased to 42 in the second region, and there are no particles in the third region, therefore that obviously is a healthy state now.

Altruistic investment is happening between regions 1 and 2 as shown in fig. (5.4), which clarifying that there are 18 donors and 4 un-active particles in the first region and 3 recipients and 37 un-active particles from the second region. In addition to that, most of the reciprocation particles have moved to the optimized zone and have started to behave in a positive way.

There is no altruism between regions 2 and 3, because as mentioned above that there are no particles in that region as shown in fig. (5.6).

Particle health indicator in fig. (5.2) shows that (p08) decreases from 65 to 50 and this means it is far from the optimized path. In addition to that, (p08) currently being in an un-active state. The distance of (p08) position to the center remains the same as shown in fig. (5.5) as its value does not change which remaining at 15 before and after altruism.

(p24) losses 5 points from its health indicator if it compared to the previous iteration as shown in fig. (5.2). Therefore, (p24) has been 80 instead of 85 but is still in a healthy state as compared to others also due to it being a donor in this iteration as shown in fig. (5.8). the distance of (p24) position to center value was 14 before altruism and became 17 after that.

(p48) maintains a healthy indicator level as shown in fig. (5.2) at 65 from four iterations until this iteration. Therefore, (p48) is un-active which fig. (5.7) ensured that as it maintains its distance level at 15.

5.1.8 Tenth Iteration

10 Particles noticed in the first region, and 53 particles in the second region and one particle in the third region as shown in fig. (5.3). As previously discussed, the proposed algorithm focused on the distant particles more than the others because that there are particles in the third region, even though it is just one particle. Moreover, the algorithm will neglect the altruistic investment between 1 and 2 regions as shown in fig. (5.4) which shows that no altruism happened. Furthermore, altruism will happen in between regions 2 and 3 as shown in fig. (5.6). It is clear that 10 un-active particles in the first region. In addition to that, one donor and 52 un-active particles in the second region and one recipient in the third region to implement the altruistic investment.

The particles' (p08, p24, and p48) health indicator in fig. (5.2) viewed a stable iteration for all. (p08, p24, and p48) have the same health indicators as compared to the previous iteration which is 50, 80, and 85 and same distance to center as 18, 18, and 18 as shown in figs. (5.5, 5.8, 5.7) respectively. However, the equal distances to center doesn't mean all of these particles have the same position.

5.1.9 Eleventh Iteration

17 Particles in the first region noticed, 46 particles in the second region, and one particle in the third region as shown in fig. (5.3).

Altruistic investment didn't happen between regions 1 and 2 in this iteration because there are particles in the third region as shown in fig. (5.4) and fig. (5.6). Moreover, there are 17 particles in the first region being as un-active particles, and one donor. Furthermore, 45 un-active particles in the second region. One recipient particle in the third region.

The selected particles (p08, p24, and p48) in fig. (5.2) are not effected and therefore possess the same values as the previous iteration. The distances to the center were stable as 16, 15, and 18 as shown in figs. (5.5, 5.8, 5.7) respectively.

5.1.10 Twelfth Iteration

In this iteration, the healthy status appeared as shown in fig. (5.3), where 59 particles in the first region, and 5 particles in the second region, and no particles in the third one.

Altruistic investment happened between regions 1 and 2 as shown in fig. (5.4), where there are 5 donors, and 54 un-active particles in the first region. One recipient, and 4 un-active particles in the second region. The amount of the un-active particles noticed according to kinship relatedness algorithm. There is no altruistic investment between region 2 and 3 as shown in fig. (5.6).

The health indicators for all the selected particles have stable status and remain as the previous iteration as shown in fig. (5.2). Furthermore, distances to the center are stable in addition to no altruistic investment effect on them as clarified in figs. (5.5, 5.8, 5.7).

5.1.11 Thirteenth Iteration

All particles returned to the first region as shown in fig. (5.3), and no particles in the second and third regions. As a result, there is no altruistic investment in both second and third regions as shown in fig. (5.4) and fig. (5.6).

Health indicators are gaining back their health status's values incrementally which is a positive status of the selected particles (p08, p24, and p48). Indicator values increased by 5 point each as shown in fig. (5.2) according to its returns to the optimized zone.

Moreover, distances have decreased a lot from the center as shown in fig. (5.5, 5.8, 5.7).

5.1.12 Rest of Iterations

All particles are allocated in the optimized zone from the thirteenth to the twenty third iteration as shown in fig. (5.3), and so there is no more altruistic investment accordingly in the mentioned iterations neither between regions 1 and 2 nor between regions 2 and 3.

The particles (p08, p24, and p48) health status as in fig. (5.2) shows positive increment. Where the example particles indicators increased by 5 points each, in each iteration for all according to the first region rule of gaining health status whenever the particles inside this region. In addition to that, until all of the particles have reached a full health indicator and these particles remain in this region to the last iterations.

All the particles distances to center have been decreased, and for each next iterations the particles will be closer to the optimum position until reaching the target point in the last iterations as figs. (5.5, 5.8, 5.7).

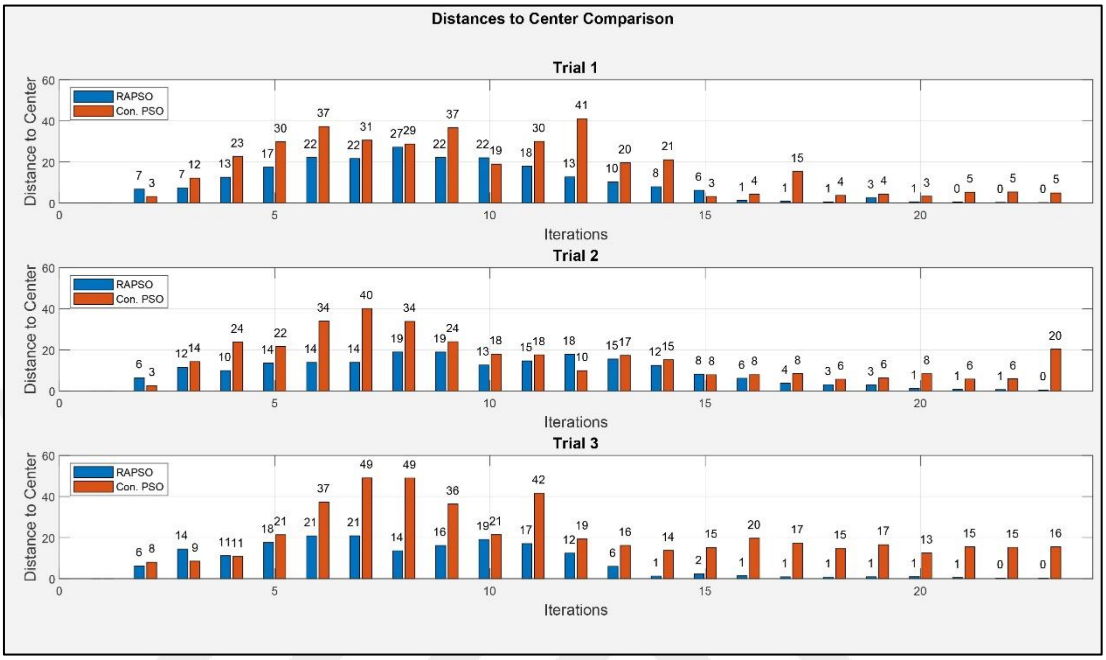

Figure 5.9 Distances to Center Comparison

5.2 Comparison between RAPSO and Conical PSO

5.2.1 Distance to Center

RAPSO has an improved method of the conical PSO. Furthermore, it has a solution to the original method's problems to achieve the goal point in an effective manner. Some tests and comparisons between the two methods made, and will explained next.

RAPSO and Conical PSO methods examined three times in a 23 iteration, to calculate the farther particle from the optimized particle in the swarm. In fig. (5.9) found that the peeks of RAPSO are increasing in a converging manner in each trial. On the other hand, the peeks is not increasing with the conical PSO method. Where the increasing in the conical PSO sometimes is converging but not in a unique manner, and most of the time there are some randomly jumps. According to the jumps, there is no unique

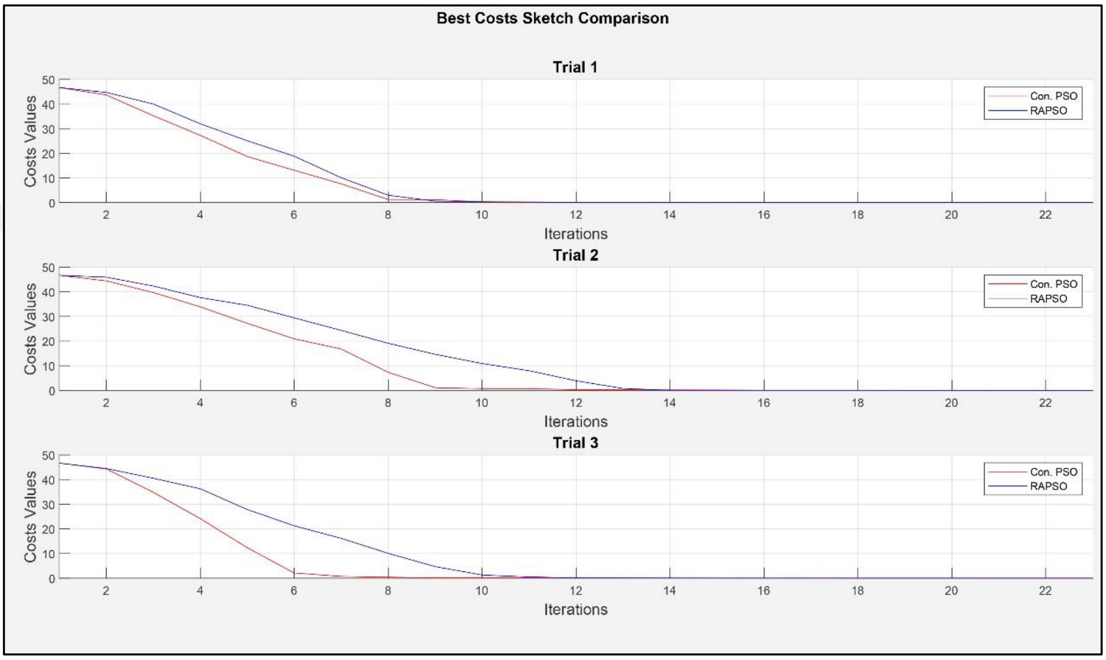

Figure 5.10 Best Costs Sketch Comparison

converging in the Conical PSO method.

The peeks of distances to the optimized particle of the RAPSO are near to be systematically decrement, until goes to zeros even before the 23 iteration by three simulations. Furthermore, in the conical PSO the peeks are not a unique decrement as mentioned before. Moreover, there are some jumps in all three tests also it is not reaching the goal point or optimized particle in 23. The peeks of the conical PSO will reach the goal point but in more than 23 iterations. As a result, the RAPSO has effective rules and conditions to manage its particles, and make it more systematically by reaching the goal point in the shortest path and time, with a unique moving particles which are connected between each other’s.

None of RAPSO peaks reached 30 in the three simulations. However, in the conical PSO peaks reached more than that value in a high percentage, also which is a proof of the managing condition of RAPSO with the particles and how to control it.

The best costs values of the RAPSO method have decreased, until being in the optimum cost between the iterations 10-13 and further as shown in fig. (5.10). Furthermore, in the conical PSO sometimes being visualized to reach the optimum cost before the RAPSO. Which is the treatment of gathering and connecting of the particles between each other's in RAPSO may effect some limitations to make the swarm more stable of its movement to reach the end point with error reduction.

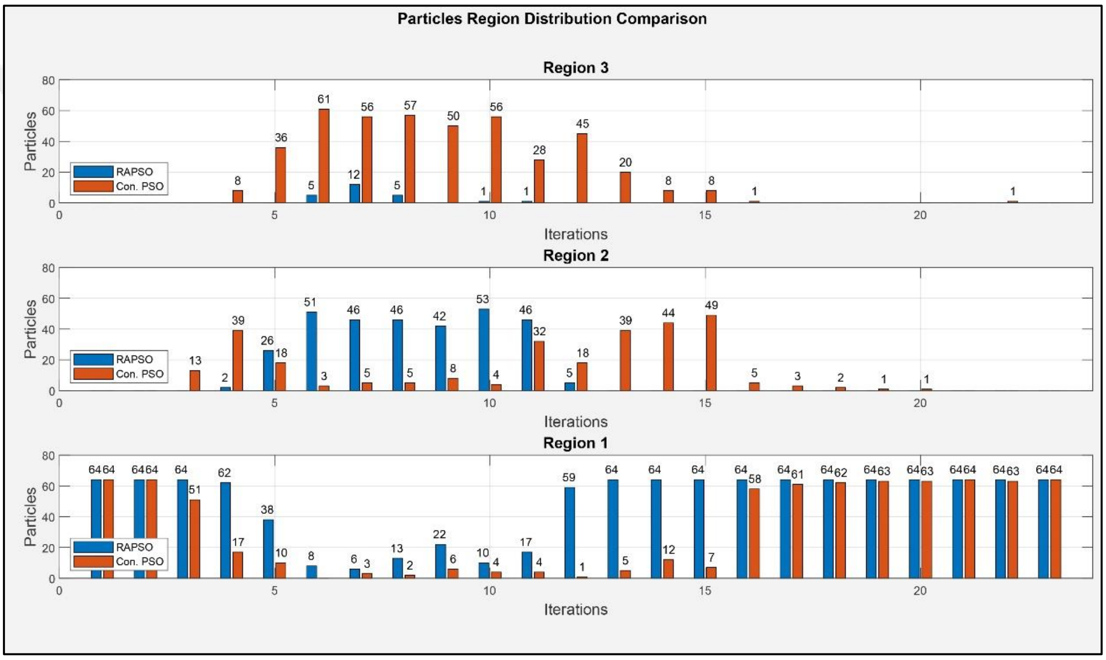

Figure 5.11 Particles Regions Distribution Comparison

The last comparison between RAPSO and conical PSO is the particles positions with reference to the regions as shown in fig. (5.11). the deference between them can be noticed (e.g., the particles in the first region of the conical PSO started jumping to other regions before the RAPSO's particles. Moreover, the particles of the conical PSO reached zero, and it is not the RAPSO's particles. The RAPSO's particles gathered again from iteration 13, and it is not of the conical PSO because it is not stable, also, one particle of the conical PSO noticed in the third region in the twenty second iteration. Particles of the RAPSO in the third region in all the iterations did not reach more than 12, but in conical PSO it reached more than 49 in five iterations.)

RAPSO particles in the second region existed in 9 iteration and in the third region in just 5. However, in the conical PSO gathered in the second region in 18 iteration and in the third region in 14 and that proves the good performance and behavior of the RAPSO if it is compared to the conical PSO.

5.2.2 Time Consuming

With experimenting both algorithms RAPSO and Conical PSO in eight trials, by taking same quantity of particles as mentioned before 64, and same search space, starting and ending points to reach the optimum approach. In table (5.1) the time consuming to reach the optimum point by the Conical PSO is in the range of 0.02 – 0.07, and iterations are in the range of 37 – 57. Furthermore, the time consuming to reach the optimum point by the RAPSO is in the range of 0.07 – 0.11, and iterations are in the range of 23 – 29. It is clear that the Conical PSO is taking less period as compared to the RAPSO. However, the iterations in Conical PSO are more than the ones of RAPSO as noticed in fig. (5.9). The RAPSO reached the optimum point in 23 iterations, furthermore in the Conical PSO did not reach the optimum point in the three trials. The proposed approach explicitly concentrates on error reduction instead of less time-consuming. As much RAPSO is more time-consuming, that means more error reduced.

Table 5.1 Time Based Performance Comparison

No.	Conical PSO		RAPSO	
	Time	Iterations	Time	Iterations
1	0.025660	42	0.072103	26
2	0.029219	44	0.077625	27
3	0.031302	37	0.082816	26
4	0.034536	46	0.093720	27
5	0.039994	44	0.094886	26
6	0.054151	50	0.095946	26
7	0.054706	57	0.107398	29
8	0.071367	43	0.112236	23

CHAPTER 6

CONCLUSION AND FUTURE WORK

A novel optimization algorithm with explicit reciprocal altruism is proposed for working on path planning, namely Reciprocal Altruism Particle Swarm Optimization (RAPSO). RAPSO can quickly find the particles that they are far from the optimized path to treat them after evaluating its scenarios according to a kinship relationship by changing two conditions of those particles. First, enforce the distant particle to come closer to the optimized one. Secondly, the health indicator is updating itself based upon its distance from the optimized path. Also, utilizing the healthy particles of the search space to guide them to the promising point and avoid wasting fitness area. In the proposed algorithm, the swarm is categorized into recipients, donors and un-active swarms in the space, which they were configured to treat and complete each other during the search process. Furthermore, the space is also determined to be categorized into three regions as two circles have the same center which is represented by the optimized particle. This means that the first region is the safe and optimized one and doesn't have altruistic investment. The bigger circle than the first region is the second region, and has the same center as mentioned above. The second region has a specific kinship relatedness factor, which is effect on the amount of information shared. Where the information shared by the reciprocal altruism algorithm of the current region particles with another's from deferent regions like the third region. The third region is the rest of the space which is out of these two circles. Reciprocal altruism is represented between particles from different regions, like recipients in the third region should get help from donors from the second region. Moreover, the recipients from the second region helped by donors from the first region. The difference between the two processes mentioned previously is the amount of altruistic investment. In addition to that, the increased amount of investment which will occur between the second and third regions. As a result, particles in the third region needs help more than the particles in the second region. As particles in the third region are farther away as compared to the particles in the second region, according to the distance from the optimized particle. Moreover, by depending on the kinship relatedness to choose the particles mates, and the total of previous investments to increase the altruistic investment accordingly. RAPSO ensures better connectivity and information sharing by the health indicator and optimized movement of the swarm. Furthermore, it explicitly concentrates on error reduction instead of less time-consuming. The performance of the proposed approach shows that reciprocal altruism has played its role effectively in order to control the movement of the swarm along the optimized path. The simulation results proved that RAPSO outperforms the conical PSO algorithm both in terms of error reduction and close connectivity. Future work is summarized in three points; first, the recipient's quantities should be more as if it compared to the donors, and improvements most execute with the kinship relatedness coefficient to ensure a wide range of recipient's altruism. Second, controllability lost from particles went far with less than a 20% health status. Third, fixed or dynamic environment should be considered in the search space.

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