

COMPARATIVE ANALYSIS OF EVOLUTIONARY TECHNIQUES FOR FEATURE SELECTION AND CLASSIFICATION

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CERTIFICATE

This is to certify that **Abhishek Kumar Kanaujia (2k14/ISY/01)** has carried out the major project titled “**COMPARATIVE ANALYSIS OF EVOLUTIONARY TECHNIQUES FOR FEATURE SELECTION AND CLASSIFICATION** ” in partial fulfilment of the requirements for the award of Master of Technology degree in Information Systems by **Delhi Technological University**.

The major project is bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2014-2017. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

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ABSTRACT

Classification problem is the main issues in the large number of features data sets but not all classification algorithms are useful. Here data reduction and feature selection done with the help of (normalize by subtracting mean, covariance, eigenvectors, eigenvalues, significant Principal Components). It reduced the redundant and irrelevant features from the data sets. Feature selection and classification is done by Artificial Neural Networks, its select the relevant features to achieve the better classification performance and reducing the number of feature. This report presents the one comparative study based on Particle Swam Optimization (PSO), Ant Colony Optimization (ACO) and Multiple Objective Particle Swam Optimization (MOPSO) on the train data which in generated by the classification. We investigated PSO-based multi-objective algorithm performed based as compared to single objective PSO and ACO. The MOPSO algorithm presents idea based on non-dominated arrangement into PSO for address the feature selection problems. It accomplished the equivalent results with other two well-known algorithms in most cases.

INTRODUCTION

1.1 Introduction

PSO [1] and [DE] [3] are two stochastic; people based change strategies, which have been associated viably to a broad assortment of issues as dense in [4]

Diverse assortments to both PSO and DE have been made in the before decade to overhaul the execution of these calculations [15]. One class of varieties merges consolidates among PSO and DE, where the benefits of the two methods of insight are joined. The barebones DE (BBDE) is a PSO-DE cross breed number proposed by [14, 18] which joins systems from the barebones PSO [2] and the recombination manager of DE. The subsequent tally butchers the control parameters of PSO and replaces the static DE control parameters with progressively changing parameters to make an in every way that really matters sans parameter, self-adaptable, advancement figuring.

As of late OBL was proposed by [17] and was effectively connected to a few issues [16]. The essential idea of OBL is the thought of an assessment and it's relating inverse gauge all the while to surmise the present competitor arrangement. Inverse numbers were utilized by [16] to improve the execution of DE. Moreover, [20] and [19] utilized OBL to enhance the execution of PSO. In any case, in both cases, a few parameters were added to the PSO that are hard to tune. [19] Utilized OBL amid swarm instatement and in every emphasis with a client determined likelihood. Likewise, Cauchy change is connected to the best Particle to abstain from being catching in nearby optima. Thus, [20] utilized OBL as a part of the introduction stage furthermore amid every emphasis. Be that as it may, a narrowing component is utilized to improve the union pace.

The OBL is utilized to enhance the execution of PSO and BBDE without including any additional parameter. The execution of the proposed techniques is researched when connected to a few benchmark capacities. The examinations led demonstrate that OBL enhances the execution for both PSO and BBDE.

Enhancement is the procedure of selecting the ideal arrangement from the arrangement of option ones. We need to either amplify or minimize the target capacity by computing the estimation of capacity using a few info values from the given scope of qualities. Transformative calculations are by and large generally utilized as a part of enhancement issues. Reproduction, transformation, hybrid, recombination, and so forth, instruments are utilized as a part of such calculations. Populace is shaped by the hopeful solutions of the given issue and in each era development of the population happens by applying fore mentioned instruments. In this report, for streamlining process, FA is utilized which is a simple, viable and powerful worldwide improvement calculation with few control parameters. FA beats numerous other enhancement strategies like GA, PSO and so on. Yang had done a few looks into on FA like FA has been connected to take care of nonlinear configuration issues [22], the seek methodology of FA has been joined with Levy flights to progress its productivity [23], and FA has likewise been reached out to tackle multi target issues [23]. FA has been utilized is a few applications which incorporate basic improvement [24], cross entropy limit choice [25], voyaging salesperson issue [26], grouping [27], picture pressure and so on.

ACO is an excellent framework under the genius of swarm information [49]. ACO are passed on sections. Regardless of the straightforwardness of their basically managed indicate cooperation, By utilizing this association, underground ACO can finish complex undertaking, which increase over the individual uttermost scopes of a single frightful minimal creature. Cases are fulfilling transports, searching for, and division of the work. In which each one of these cases, ants organize their movement. It is a kind of abnormal correspondence between ants using changes of the earth. For example, a looking Ant Colony drop a complex on ground that builds up the probability those different ants takes after a practically identical way.

1.2 Particle Swarm Optimization(PSO)

PSO has appeared to be an effective, enthusiastic and straightforward improvement calculation. The vast majority of the PSO thinks about are experimental, with just a couple of Theoretical investigations that focus on understanding particle directions. The outlines current hypothetical investigations, and extend these examinations to application in mechatronic system, for example, recognizable proof, control pick up and improvement in plan. Trial comes about are given to help the conclusions drawn from the hypothetical discoveries.

PSO is a stochastic population based advancement approach initially distributed by Kennedy and Eberhart in 1995. Since its first production a vast collection of research has been done to

contemplate the execution of PSO, and to enhance its execution. From these examinations, much exertion has been contributed to get a superior comprehension of the union properties of PSO. These examinations focused generally on a superior comprehension of the fundamental PSO control parameters, to be specific the quickening coefficients, dormancy weight, speed clamping and swarm measure. From these exact investigations it can be reasoned that the PSO is delicate to control parameter decisions, particularly the idleness weight, increasing speed coefficients and velocity clamping. Wrong instatement of these parameters may prompt dissimilar or cyclic conduct.

Among existing transformative calculations, the best-known branch is RGA. RGA is a stochastic search methodology in view of the mechanics of regular determination, hereditary qualities and advancement. Contrasted and RGA, PSO has some alluring attributes. IT has memory so information of good arrangements is held by every one of the particles; though in RGA, pervious learning of the issue is disposed of once the populations change. It has useful participation between particles; that is, particle in the swarm shares data among themselves.

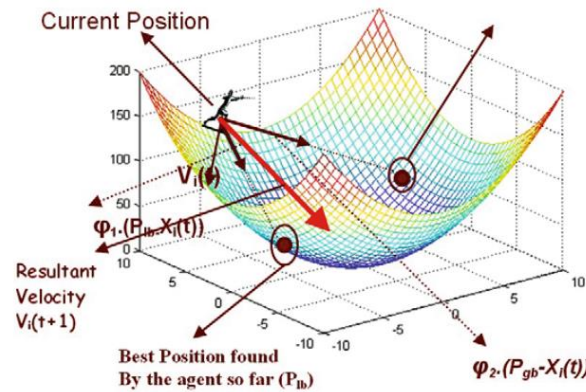


Figure 1.1 showing the particle in PSO

1.3 Opposition Based Population Initialization

In any improvement issue where prior learning is not available, self-assertive presentation is normally used for instating the places of the PSO particles. By using restriction based presentation we may achieve a predominant starting populace when appeared differently in relation to subjective instatement. Right when using restriction based instatement, the swarm of n particles is first self-assertively presented inside the pursuit space. By then the backwards

of each of the n particles in the swarm is delivered. The wellbeing of each molecule (both firsts and the opposite energies) is figured and the n fittest particles are browsed these to fill in as the fundamental populace. Here the $x_i \in [-10, 10]$ and there are 10 particles in the search space. These particles are spoken to by spots. The alternate extremes of these particles are additionally computed and they are spoken to by a cross. As should be obvious, the lower right quadrant of the inquiry space had been disregarded by the first particles. By making the inverse particles we are likewise ready to investigate the lower right quadrant.

Notwithstanding for symmetrical capacities where an underlying particle and its inverse will both have the same wellness, the determination of the fitter particles from the consolidated pool of firsts and their alternate extremes separates the lower wellness population at the earliest reference point. After instatement the reach utilized as a part of the formation of inverse particles changes powerfully (more points of interest in the coming passages) and for the most part a particle and its inverse does not have the same wellness notwithstanding for symmetrical capacities.

OBL theory was coordinated with PSO, and the new variation was named OPSO. [Dhahri and Alimi 2011] proposed the OPSO utilizing the idea of inverse number to make another population during the learning procedure. They joined OPSO with BBFNN. The outcomes demonstrated that the OPSO-BBFNN created a superior speculation execution. [Wang et al., 2012] displayed an improved PSO calculation called GOPSO, which utilized GOBL and Cauchy transformation. GOBL gave a quicker merging and the Cauchy change with a long tail helped caught particles escape from nearby optima. [Dong et al., 2012] proposed a transformative circle location technique in view of a novel chaotic hybrid algorithm (CHA). The strategy consolidated the qualities of PSO, GA, and riotous elements and included the standard speed and position upgrade rules of PSOs, with the thoughts of determination, hybrid, and transformation from GA. The OBL was utilized in CHA for population instatement. What's more, the idea of species was acquainted into the proposed CHA with upgrade its execution in taking care of multi model issues. [Gao et al., 2012] proposed a novel PSO called CSPSO to enhance the execution of PSO on complex multi model issues. In particular, a stochastic inquiry system was utilized to execute the investigation in PSO. [Khan et al., 2012] displayed another discrete PSO way to deal with impel rules from discrete information.

1.4 Initialization Ant colony optimization (ACO)

The proposed approach finds a course of action of connection rules from a planning set to outline a classifier. It doesn't mine all possible connection represents yet only a subset of them. Standard alliance rules mining estimations mine each possible rule, which is computationally exorbitant for far reaching databases. The standards are picked on the start of sponsorship and assurance. Each guideline is in the structure:

IF (Population1 AND Population2 AND ...) THEN class

The proposed approach finds a course of action of connection rules from a planning set to outline a classifier. It doesn't mine all possible connection represents yet only a subset of them. Standard alliance rules mining estimations mine each possible rule, which is computationally exorbitant for far reaching databases. The standards are picked on the start of sponsorship and assurance. Each guideline is in the structure:

The figuring for checking for the standards is ACO based. The intrigue space depicted as a layout, where each middle purpose of the diagram addresses a conceivable estimation of a property. Statutes are found for each class uninhibitedly. A compact arrangement of models is found in the midst of every time of the calculation and embedded in a strategy of essentials held for the picked class stamp. This procedure continues until the point that level of the strategy of standards pick class is additional undeniable than or relating to a base extension edge showed up by the customer. At the point, when rule strategy of the picked class has classy benchmarks to satisfy the base degree edge by then standards are made for another class. The figuring stops when the standards of the aggregate of what classes have been made. The past classifier contains basics of all classes.

Toward the begin of the check, found govern set is void and client portrayed parameters are instate to combine smallest strengthen, least confirmation, least augmentation and number of ants utilized by the calculation. As we mine the association guidelines of each class openly, along these lines the basic walk is to pick a class from the arrangement of leftover classes. The pheromone quality and heuristic quality on relationship between things are instate. The pheromone regards on advancing toward relationship with each a one of a kind small something are setting (0)

that do not satisfy the base reinforce edge with the objective that ants are not prepared to pick these things. The period number "g" is set 1.

Period check control what number of most startling measures of things can be consolidated by an underground terrifying minimal creature in announce some bit of standard which it is building. For example when $g = 2$ an underground bug crawly can combine a most outstanding of two things in its standard antecedent part. This prompts in the primary we mine one-length arrangement coordinates as is commonly said. In the second time we endeavor to have two-length leads at any rate we will all the more then likely be not capable satisfy two-length every so often if the sponsorship of all contender things is underneath very far. Other than we have third, fourth and happening conditions. The most unfathomable estimation of time count is the measure of attributes in dataset beside class property

The count discovers affiliation rules for a class considering sponsorship and sureness measures. In DO WHILE circle each bug crawly creates a standard. Right when all ants have made their models by then help and conviction of each control is figured and those guidelines are picked which meet scarcest sponsorship and sureness limit. By then we sort each and every picked oversee in reducing demand on the start of affirmation and a concise time span later on the familiarize of assistance before attempting with present them in a focal diagram of the picked class. The sort basics are insert one by one in the oversee once-completed of the picked class, as displayed by a standard delineated underneath, until the point that the minute that level of the oversee set is more conspicuous than or relating to a base degree edge coordinated by customer. In the occasion that base degree measure is not met then pheromone qualities are refreshed and later starts.

Thusly benchmarks are working for another class and this system continues until there are no more classes left. After models of the whole of what classes have been made, the real set pruning system tries to oust alarming standards from the discovered lead set and the remaining set is the last classifier. The entire portrayal of estimation is given in next sub locale.

1.4.1 Rule Construction

Each underground ant crawly builds up a lone thing rule in the first. In the second time each ant crawly tries to build up a rule with two things. So additionally we have 3 thing rules in third

time and so forth. Principles with a most outrageous k number of things are made in the k_{th} period, where k is the amount of property in gets ready set excepting the class distinctive.

1.4.2 Pheromone Initialization

The pheromones esteems on all edges are introduced before the begin of WHILE sit tight for each new class. The pheromone gauges on the edges between everything are instated with a comparative measure of pheromone. The basic pheromone is:

$$\tau_{ij} = \frac{1}{\sum_1^a b_i}$$

Where is the total number of properties in orchestrating set in spite of the class trademark and b_i is the measure of possible qualities in the extent of attributes r_i . The pheromone estimations of each a novel little something is set to (0) which don't satisfy a base brace purpose of control. The estimation of zero ensures that those things can't be picked by ants in the midst of statute grouping get ready.

1.4.3 Selection of an Item

An underground insect crawly incrementally consolidates a thing in the envoy some part of the decide that it is building. Right when a thing has been combined into the major at that point there is no other estimation of that property can be consider. The likelihood of choice of a thing for current fragmentary guideline is given blow.

$$P_{ij} = \frac{\eta_{ij}(x)\phi_{ij}(y)}{\sum_{i=1}^a X_i \sum_{j=1}^{b_i} [\eta_{ij}(x)\phi_{ij}(y)]}$$

Where $\eta_{ij}(x)$ is the measure of pheromone related among item i and item j in current period? Plus, $\phi_{ij}(y)$ is the estimation of the heuristic limits on the association among item i and item j for the current picked class? The total number of attributes in get ready dataset is a_n , and x_i is a combined variable that is set to 1 if the property A_i was not used by current underground creepy crawly and for the most part set to 0, and b_i is the amount of possible qualities in the zone of trademark A_i . The denominator is used to institutionalize $\eta_{ij}(x) \phi_{ij}(y)$ estimation of each possible choice with the summation of $\eta_{ij}(x) \phi_{ij}(y)$ estimations of each possible choice. Those things which have higher pheromone and heuristic qualities will probably be picked.

2.1 Existing Approaches

Han and He proposed a changed PSO calculation for noisy issues which use OBL [Han, 2007]. The calculation utilizes three separate expansions to the standard PSO. To start with, the swarm is introduced utilizing opposition based learning, wherein a swarm of n particles is first random instated and the wellness of these particles is assessed. At that point the inverse of the swarm is ascertained and its wellness decided. The n fittest particles from both, the first swarm and its alternate extremes, are chosen and utilized for promote improvement. Second, jumping technique is utilized which, in view of a predefined likelihood, makes the inverse of the swarm amid a portion of the cycles. The inverse is consolidated with the first swarm and n best particles are chosen for the following cycles and whatever is left of the particles are disposed of. Third, every Iteration distinction posterity and inverse of the worldwide best particle is made. The distinction posterity is made by including a rate of the contrast between two randomly chose swarm particles in the worldwide best particle. The particle having better wellness from these three particles (distinction posterity, worldwide best, and inverse of worldwide best) is chosen as worldwide best for the following emphasis and the other two are disposed of. The creators have demonstrated that their OPSO displays better execution when contrasted with standard PSO on loud optimization issues.

Wang and Liu [Wang, 2007] proposed a technique which utilizes OBL in an indistinguishable way from proposed by [Han, 2007] however rather than correlation of worldwide best with its inverse and the distinction posterity in every iteration, they apply a dynamic Cauchy transformation on the worldwide best particle. The worldwide best particle is supplanted by the transformed worldwide best if the wellness of the changed particle is superior to its wellness. The creators test their strategy on both unimodal and multimodal issues and contrasts the outcomes and those of standard PSO. The outcomes demonstrate that the proposed OPSO with Cauchy transformation shows better execution.

Wu et al. [Wu, 2008] have OBL in the comprehensive learning PSO created by [Liang, 2006]. The strategy utilized for OBL instatement is the same as that utilized by [Han, 2007] and [Wang, 2007]. In the first exhaustive learning PSO the particle position refresh condition has

been changed with the end goal that each measurement of a particle can gain from the comparing measurement of some other particle's best cost. For this reason wellness of two arbitrarily picked particles are contrasted and the particle and the better wellness is held. In OBL choice, two particles are random chosen from the population and their contrary energies are made. The individual bests of these particles and their alternate extremes contend and the best fitness value.

Omran [Omran, 2009] has incorporated OBL in a PSO and differential development crossover calculation called Barebones DE. In this approach the particle having most noticeably bad wellness in every cycle is supplanted by its inverse particle. OBL is just connected to one particle rather than the entire swarm and is additionally not utilized at the initialization.

While [Wu, 2008] joins OBL in comprehensive learning PSO and [Omran, 2009] does it on barebones DE our attention is on ordinary PSO calculation. We use an indistinguishable OBL from is finished by [Han, 2007], [Wang, 2007] and [Wu, 2008]. Moreover our jumping technique is not at all like that of [Han, 2007] and [Wang, 2007] on the grounds that we make the inverse of a particle and after that contrast the inverse wellness and the particle's close to home best wellness (rather than the wellness of the present position of the particle). We don't make the distinction posterity of worldwide best as is finished by [Han, 2007] or Cauchy transformation of worldwide best as is finished by [Wang, 2007]. Moreover, our development is the presentation of the thought of opposite velocity.

[Wang, Hui, et al. [5]] This paper shows an OPSO to get faster the convergence of PSO and keep away from untimely joining. This technique utilizes OBL for every particle and applies an element Cauchy change on the best particle. Exploratory results and applies an element Cauchy change on the best particle. Exploratory results on some understood benchmark improvement problems have demonstrated that OPSO could effectively manage those difficulty multimodal capacities while keeping up quick search speed on those basic unimodal capacities in the enhancement.

[Jabeen, Hajira, ZuneraJalil, and Abdul RaufBaig [6]] Here author present a new algorithm for the initialization population in the standard PSO that also called asOPSO. The enhancements of the proposed initialization assign algorithm are compared with the existing PSO variants with the various benchmark functions. The tentative results make known that OPSO outperforms the existing approaches to a large extent.

[Wang, Hui, et al., [7]] Here author shows the improved PSO calculation called GOPSO, which utilizes GOBL and Cauchy change to defeat this problem. GOBL can give a quicker convergence, and the Cauchy transformation with a long tail helps caught particles escape from neighborhood optima. The proposed approach utilizes a comparative plan as ODE with opposition-based population initialization and generation jumping using GOBL. Trials are directed on a thorough arrangement of benchmark capacities, including pivoted multimodal problems and moved substantial scale problem. The outcomes demonstrate that GOPSO acquires promising execution on a dominant part of the test problem.

[Tang, Jun, and Xiaojuan Zhao [8]] In this paper, an improved OPSO, called EOPSO, is planned by combing an upgraded OBL and the normal PSO. The improved opposition give preparations more nearly to the worldwide ideal than the customary opposite arrangements. Trial studies on 4 unimodal capacities and 4 multimodal capacities demonstrate that the EOPSO does not just surpass the standard PSO and opposition construct PSO in light of test capacities, additionally indicates speedier meeting rate.

[Imran, Muhammad, RathiahHashim, and Noor ElaizaAbd Khalid [9]] PSO is a perceived calculation for reformation problems, however experiences untimely convergence. Here the authors shows an OPSO to quicken the merging of PSO and in this meantime, maintain a strategic of distance from early joining. The proposed OPSO technique is combined with the understudy T change.

PSO is a stochastic calculation, utilized for the streamlining issues, proposed by Kennedy [10] in 1995. Results from the analysis performed on the standard benchmark capacities demonstrate a change on the execution of PSO.

[Han, Lin, and Xingshi He., [11]] It utilizes resistance based information for the swarm introduction, bouncing, era. Here likewise enhanced swarm's best part with typically utilized benchmark capacities is in work for the investigational check, and results demonstrate the notice capably new calculation beats PSO regarding the joining speed and worldwide inquiry capacity.

[Shahzad, Farrukh, et al. [12]] Probabilistic opposition based learning for particles have been utilized as a part of the proposed technique which utilizes speed clipping to control the velocity and course of particles. Tests have been performed upon different surely understood benchmark improvement problems and results have demonstrated that OVCPSO can manage difficulty

unimodal and multimodal enhancement problems proficiently and adequately. The calls NFC are fundamentally not exactly other PSO variations i.e. Fundamental PSO with latency weight, PSO with dormancy weight and speed bracing (VCPSO) and OPSO with Cauchy Mutation (OPSOCM).

[Verma, Om Prakash, Deepti Aggarwal, and Tejna Patodi [13]] Here author concludes the proposed advanced firefly algorithm provides better and more effective result as compared to the FA. But the time complexity of the advanced FA is also showing a comparison with the original FA. FA used with the opposition algorithm then it improves initialization of fireflies so that it's converging faster.

3.1 Proposed Method

We depict OPSO calculation [Rashid, 2010b]. This calculation varies from the standard PSO in that it consolidates opposition based figuring out how to improve PSO's execution. The PSO is changed to exploit OBL based speed and velocity. Opposition based introduction is utilized when the particles of the swarms are being instated. Opposition based era hopping is arbitrarily connected amid the execution of the calculation. At whatever point opposition based era bouncing is connected, we additionally apply opposition based speed count.

Characterization is a vital assignment in machine learning and information mining, which means to order each instance in the informational index into various gatherings in light of the data described by its components. Without earlier information, it is troublesome to determine which highlights are valuable. Thus, an extensive number of highlights are generally acquainted with the informational collection, which includes relevant, superfluous, and excess components. In any case, irrelevant and excess components are not helpful for grouping, and they may even decrease the characterization execution due to the large look space known as "the scourge of dimensionality" [33].

Highlight choice can address this issue by choosing only relevant highlights for arrangement. By disposing of/reducing irrelevant and excess components, include choice could reduce the number of elements, abbreviate the preparation time, rearrange the learned classifiers, and additionally enhance the characterization performance [34] [35].

Highlight determination is a troublesome undertaking in light of the fact that there can be complex collaboration among highlights. An independently relevant (redundant or unessential) component may wind up plainly excess (relevant) when cooperating with different elements. Therefore an ideal component subset ought to be a gathering of complementary features that traverse over the different properties of the classes to appropriately separate them. The element determination undertaking is challenging additionally in view of the vast pursuit space. The size of the pursuit space increments exponentially as for then number of accessible components

in the informational index [36], Hence, an exhaustive inquiry is for all intents and purposes unimaginable much of the time.

Keeping in mind the end goal to tackle this issue, an assortment of hunt methods have been connected to include choice, for example, greedy search based (SFS) [37] and (SBS) [38]. In any case, these element selection approaches still experience the ill effects of an assortment of issues, such as stagnation in neighborhood optima and high computational cost.

Keeping in mind the end goal to better address highlight choice issues, an efficient worldwide inquiry method is required. EC strategies are outstanding for their worldwide accessibility. PSO [39], [40] is a relatively recent EC strategy in view of swarm insight. Compared with other EC calculations, for example, (Gas) and (GP), PSO is computationally less expensive and can join all the more rapidly. In this manner, PSO has been utilized as a successful strategy in many fields, including feature determination [35] [41] [42].

For the most part, highlight determination is a multi-target issue. It has two principle destinations, which are to amplify the classification performance (limit the order mistake rate) and to limit the quantity of components. These two objectives are normally clashing, and the ideal choice needs to be made within the sight of a tradeoff between them. Treating feature choice as a multi-target issue can get a set of no commanded include subsets to meet diverse requirements in genuine applications In spite of the fact that PSO, multi-objective optimization and highlight determination have been independently investigated frequently, there are not very many examinations on multi-objective feature choice. In the meantime, existing component selection algorithms experience the effects of the issues of high computational cost and PSO is contended computationally more affordable than other EC systems. What's more, the utilization of PSO for multi-objective feature determination has not been explored.

This report communicates to the first circumstance when that PSO has been applied to multi-target include determination. This will require novel techniques to be presented as there is not any more a single basis worldwide arrangement yet an arrangement of answers for meet different requirements.

3.2 Opposition Based Population Initialization

In any upgrade issue where prior data is not open, discretionary presentation is ordinarily used for instating the spots of the PSO particles. By using resistance based presentation we may finish a prevalent starting populace when appeared differently in relation to optional presentation. While using resistance based presentation, the swarm of n particles is first aimlessly instated inside the interest space. By then the opposite of each of the n particles in the swarm is delivered. The wellbeing of each molecule (both firsts and the opposite energies) is as curtailed and the n fittest particles are looked over these to fill in as the basic populace.

Here the $\xi \in [-10, 10]$ and there are 10 particles in the hunt space. These particles are spoken to by spots. The alternate extremes of these particles are likewise computed and they are spoken to by a cross. As should be obvious, the lower right quadrant of the hunt space had been overlooked by the first particles. By making the inverse particles we are additionally ready to investigate the lower right quadrant.

Notwithstanding for symmetrical capacities where an underlying particle and its inverse will both have a similar wellness, the determination of the fitter particles from the joined pool of firsts and their contrary energies winnows the lower wellness population at the earliest reference point. After instatement the range utilized as a part of the formation of inverse particles changes powerfully (more points of interest in the coming sections) and more often than not a particle and its inverse does not have a similar wellness notwithstanding for symmetrical capacities.

The PSO has been effectively connected to improvement different constant nonlinear capacities by and by. For example, we utilizing the PSO calculation a novel configuration strategy for the self-tuning PID control in a slider-wrench instrument framework, and we propose a viable technique for peculiarity control of a completely parallel robot controller utilizing the PSO and (GP) Kennedy and Eberhart presented the idea of capacity streamlining by method for a particle swarm. Assume the worldwide ideal of a n -dimensional capacity is to be found. The capacity might be scientifically spoken to as:

$$f(p_1, p_2, p_3, \dots, p_n) = f(\vec{P}) \quad (1)$$

Where p is the partial variable vector, which really speaks to the arrangement of autonomous factors of the given capacity, the assignment is to discover such a p , that the capacity esteem $f(p)$ is either a base or a most extreme meant by f^* in the pursuit go. In the event that the segments of p accept genuine esteems then the undertaking is to find a specific point dimensional hyperspace which is a continuum of such focuses.

$$F(p_1, p_2) = f(P) = p_1^2 + p_2^2, \quad (2)$$

In the event that p_1 and p_2 can expect genuine esteems at exactly that point by investigation it is truly certain that the worldwide minima of this capacity is at $p_1 = 0, p_2 = 0$, i.e., at the cause $(0, 0)$ of the inquiry space and the base esteem is $f(0, 0) = f^* = 0$. No other point can be found in the p_1 – p_2 plane at which estimation of the capacity is lower than $f^* = 0$. Presently the instance of finding the optima is not all that simple for a few capacities (an illustration is given underneath):

$$f(p_1, p_2) = p_1 \sin(4\pi p_2) - p_2 \sin(4\pi p_1 + \pi) + 1 \quad (3)$$

This capacity has different pinnacles and valleys and an unpleasant wellness scene. To find the worldwide optima rapidly on such a harsh surface calls for parallel hunt procedures. Here numerous specialists begin from various beginning areas and continue investigating the inquiry space until a few (if not all) of the operators achieve the worldwide ideal position. The specialists may impart among themselves and offer the wellness work esteems found by them.

3.3 Proposed Algorithms

PSO Algorithm

1 begin

2 Time series data classified train and test by ANN

Initialization of PSO Parameter;

Step 1: position and velocity of the particles: $P_i(0)$ and $V_i(0)$

Step 2: Output: best cost of the particle

Begin

Step 3: While PSO condition terminate do

Begin

Step 4: for $i = 1$: particles

Step 5: fitness function: $= f(P_i)$;

Step 6: Update position and g best

Step 7: calculate $V(i)$ of the particle using equations (1);

Step 8: Update the $P(i)$ of the particle;

Step 9: Increase particle number;

Step 10: end while

Step 11: end

OPSO Algorithm

We have successfully completed two modifications inside established PSO. After the random notation of swarm particles within a search space after that create opposite particles based on opposition based population system described previous.

1 begin

2 Time series data classified train and test by ANN

Initialization of OPSO Parameter;

Step 1: n = size of population;

Step 2: P = current population value;

Step 3: OP = opposition value of P ;

Step 4: $P_j \in [a P_j, b P_j]$

Step 5: P_o = inverse likelihood;

Step 6: best fitness value = best cost value by all particles

Step 7: optimum value

Step 8: for $i=1:\max_iter$

Step 9: While (best value > optima & $i \leq \max_iter$)

If($\text{rand}(0,1) < P_o$)

Step 11: Update the limits $[a P_j, b P_j]$ in current population

For $i = 1$ to n

Step 12: opposition particle OP_i ;

Step 13: speed opposition particle OP_i ;

End for

Step 14: Calculate best value for every particle in OP;

Step 15: Select best fitness in P and OP as another

Step 16: Current population;

Step 17: p best, Else

Step 18: For each particle P_i

Step 19: particle speed;

Step 20: particle position;

Step 21: update best value of particle P_i ;

Step 22: Update p best, g best

End for

End if

End while

End

MOPSO Algorithm

=====

1 begin

2 Time series data classified train and test by ANN

Initialization of MO PSO Parameter;

3 initialize the set of leaders Leader Set and Archive

4 crowding distance of each particle in Leader Set;

5 while Max_iter is not reached do

6 for particle do

7 g best from Leader Set for each particle on the crowding distance;

8 update the velocity and position of particle i

9 apply mutation operators;

10 estimate two objective values for every particle

11 update the p best of every particle;

12 end

13 categorize the non dominated particles to Leader Set;

14 end

17 Measure the classification error rate on the test set;

18 Return the best solutions and train and test classification error rates;

19 end

3.4 ANT COLONY OPTIMIZATION (ACO)

ACO [43] [44] [45] is a population based meta heuristic, used to discover ideal answer for troublesome upgrade issue. The subterranean insect based meta heuristic comprises of three phases i.e. introduction, development and input. The essential stage i.e. instatement arrange includes the parameters settings, for example, the quantity of provinces and the quantity of ants. The development organize taken after by input arrange includes the development of way on the premise of pheromone focus while the criticism arrange manages the extraction and the fortification of ants voyaging encounters obtained amid the past looking way. Every insect has the accompanying attributes:

- It choose the city to run a likelihood which is component of city separate and the measure of trail introduce on inter facing edge.
- To constrain subterranean insect to make lawful visits. Urban areas which are as of now gone by are refused until the point that a visit is finished.
- When visit is finished it lay a substance called pheromone on each edge (i,j).

It is meta-heuristic algorithms that have a stage of dispersed calculation, autocatalysis with positive criticism, and down to earth realism to locate a best answer for the combinatorial improvements issues. This ACO calculation tries to limit the insect's execution and has recognized much thought and fused in different upgrade issues, for example, arrange directing, quadratic task, and voyaging sales representative and asset dissemination issues [46].

This perform was detailed as A. S by Dorigo et al. [47]. Taking into account the AS algorithm the ACO calculation was proposed [48]. In ACO calculation, the enhancement problems is detailed as a diagram $G = (C; L)$, where C is the arrangement of parts of the problems, and L is the arrangement of conceivable associations or moves among the components of C.

The arrangement is communicated as far as possible ways on the chart G, regarding an arrangement of given limitations. The quantity of occupants in administrators all around all in all tackles the issue under idea using the graph portrayal. In spite of the way that each able arrangement is prepared for finding a game plan, extraordinary quality game plans can create as a delayed consequence of total joint effort among ants. The Pheromone lines are encoding a long memory about whole ant. Its quality depends on upon the issue description and progression objective.

Total number of population N, $\tau_{ij}(T)$ be the power of pheromone (i,j) at time T

$$\tau_{ij}(T+N) \leftarrow (1-\lambda)\tau_{ij}(T) + \Delta\tau_{ij}(T+N) \quad (1)$$

Where, λ = coefficient of evaporation,

$$\Delta\tau_{ij}(T+N) = \sum_{k=1}^N \Delta(\tau_{ij}^k) \Delta\tau_{ij}(T+N) \quad (2)$$

$$\Delta(\tau_{ij}^k) = \begin{cases} 0; & \text{if ant does not travel edges } ij \\ \frac{K}{L_k}; & \text{Otherwise} \end{cases}$$

Now,

Where, L_k is the cost of populace found by ants k and here K is consistent. The measure of pheromone which ants credit on an edge which is conversely relative to populace length L_k , Assume, ants at populace i move to populace j with likelihood

$$P \propto \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum [\tau_{ih}]^\alpha [\eta_{ih}]^\beta} \quad (3)$$

Where $\left[\eta_{ij}\right]^{\beta}$ is the perceivability which is conversely corresponding to cost (i,j) and "P" is the arrangement of permitted populace which implies these populaces are consider which won't

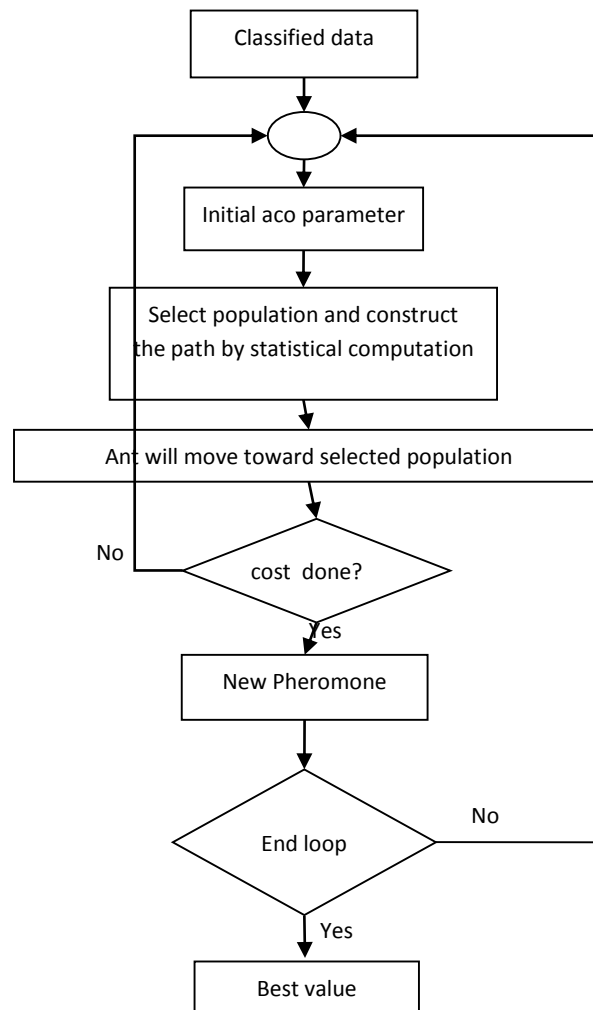


Figure 3.1 Flow Chart of ACO

close circle rashly.

3.5 Software Requirement

➤ MATLAB Version R2013a

3.5.1 MATLAB

- MATLAB is a scientific device for specific particular organizes computation, network, and condition, straight and non-direct programming simple to-utilize circle conditions here issues and results are passed on in standard sensible documentation.
- Data Examination, Procurement, Examining & Conception
- Engineering diagram and rational plans

- Analyze of algorithmic illustrating and improvement
- Numerical capacity and Computational capacities
- Simulate issues prototyping and displaying
- Function programming using GUI building condition

Using MATLAB, we can take care of linear and nonlinear problems and its fast solver with predictable programming languages, for instance, C, C++, and FORTRAN

Chapter 4

EXPERIMENTAL RESULTS

4.1 Result Analysis

4.1.1 Data classification

Here used data is download from the UCI website, for the superior performance of PSO, OPSO, MPSO and ACO specially on the data sets with large numbers of description.

Table 4.1 ANN Classification on heart dataset	
Layer and Neurons	Min-Error
1 & 15	9.1793
2 & 25	8.8906
3 & 25	8.7697
4 & 25	8.7504
5 & 1	8.6351

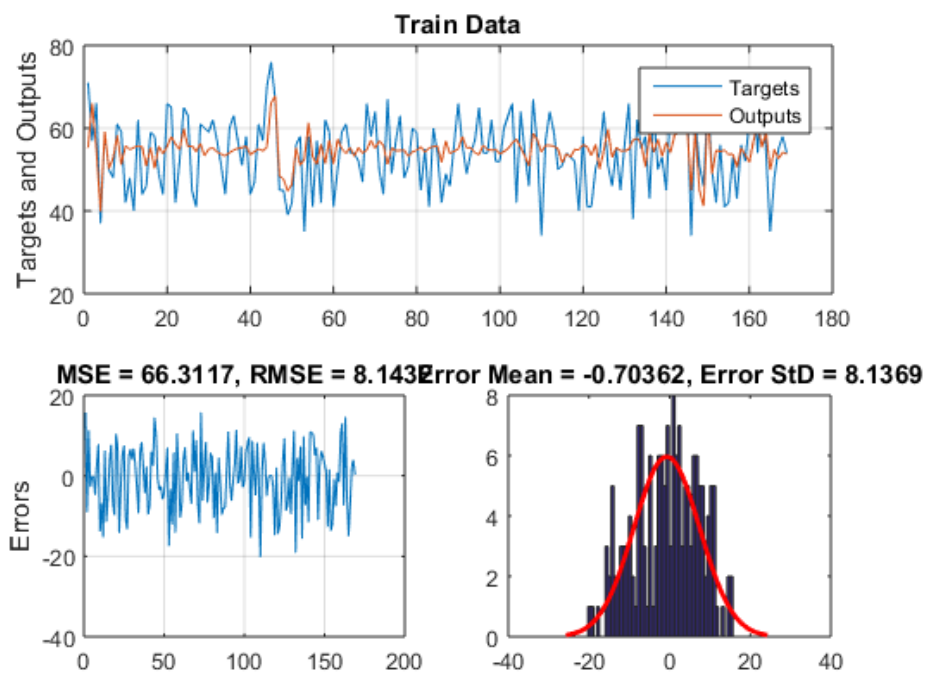


Figure 4.1 Prepare information with ordered execution.

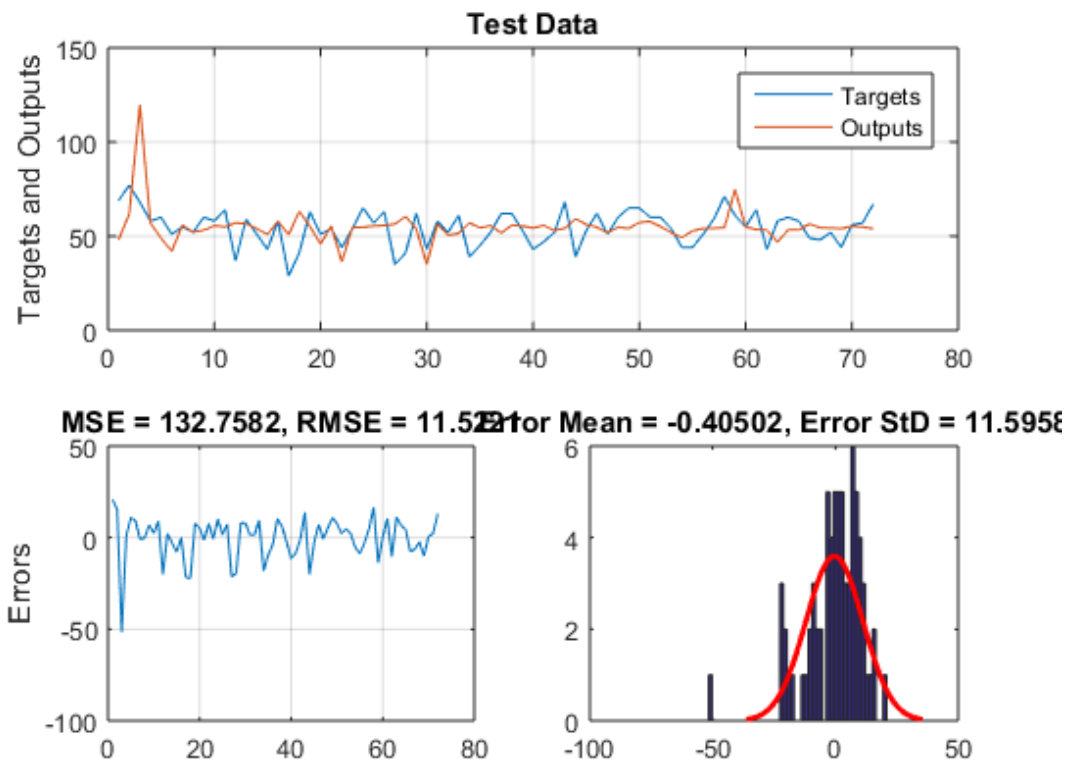


Figure 4.2 Test data with classified performance.

Demonstrates the examination amongst PSO and OPSO for function f1 to f2, where "Mean Best" estimation of the mean best function esteems found inside last era, and "StdDev" stands for the standard deviation, indicates best esteem and most exceedingly awful esteem accomplished utilizing different algorithms more than 50iteration individually. Clearly OPSO performs superior to standard PSO. Figure indicates performance comparison between standard PSO and OPSO.

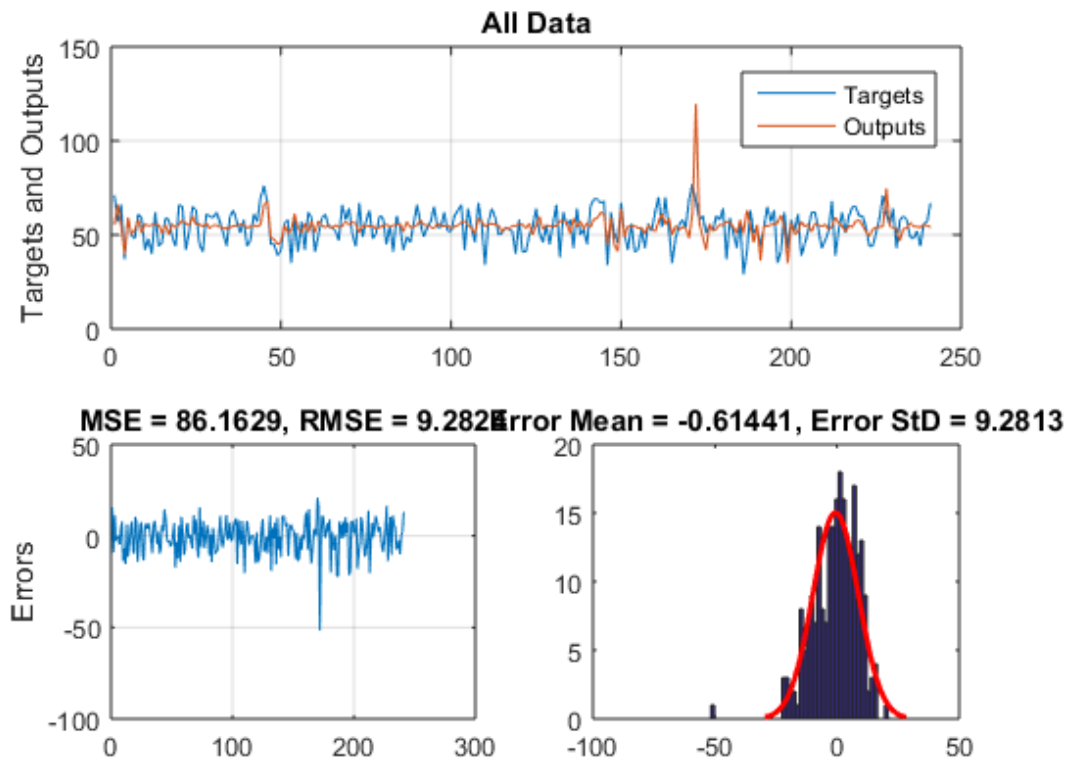


Figure 4.3 Train and test combine data with classified performance.

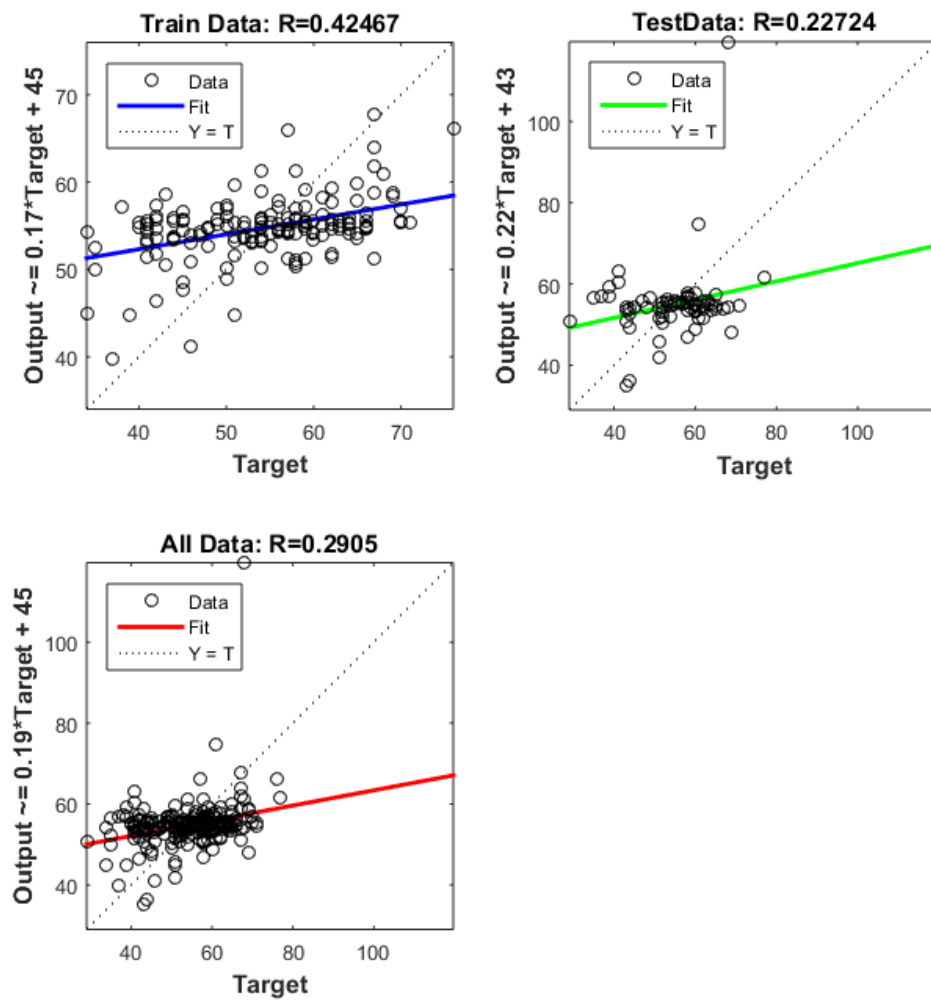
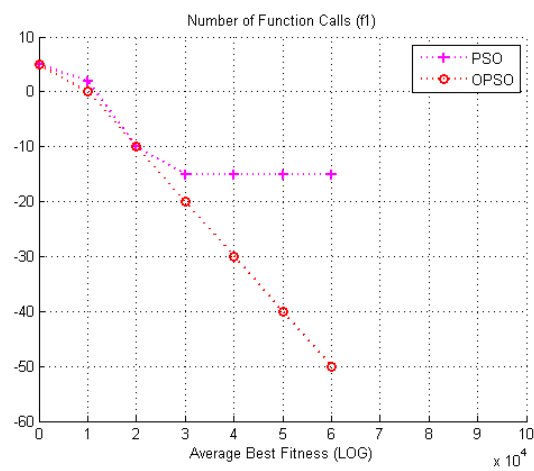


Figure 4.4 degeneration plot is represent all three data.



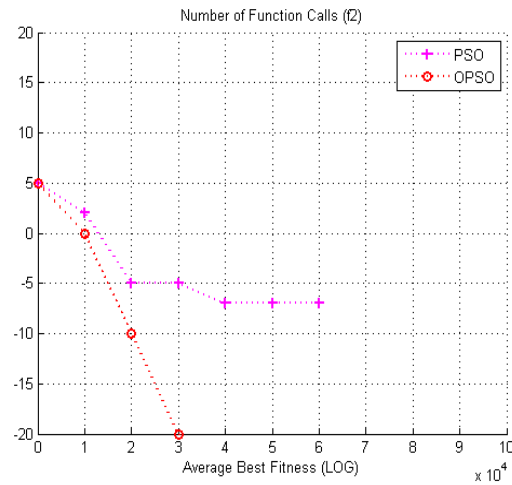


Figure 4.5 showing the performance comparison between PSO and OPSO. Horizontal axis showing average number of function calls and vertical axis is the average.

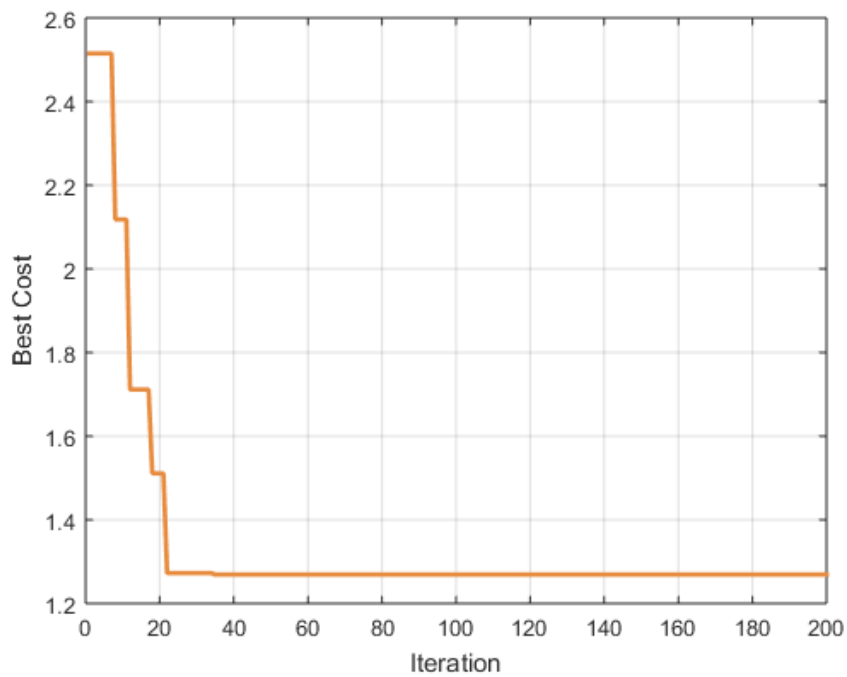


Figure 4.6 showing the best cost opposed to iteration in the PSO.

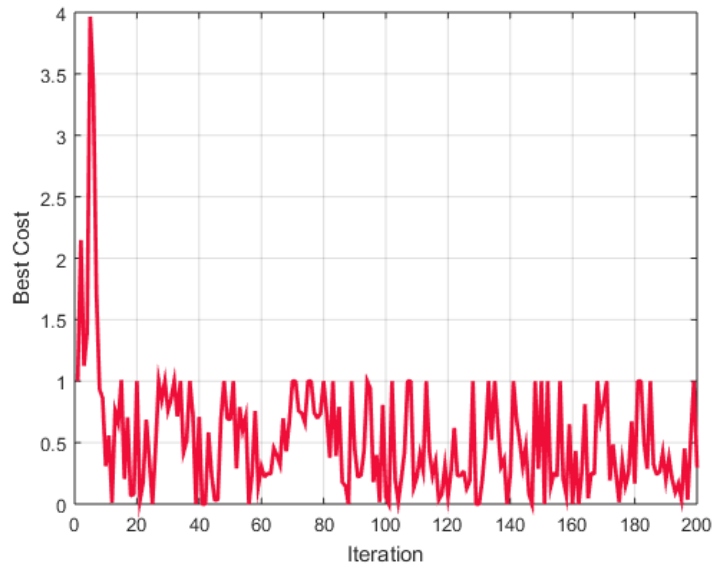


Figure 4.7 showing the best cost versus iteration in the MOPSO.

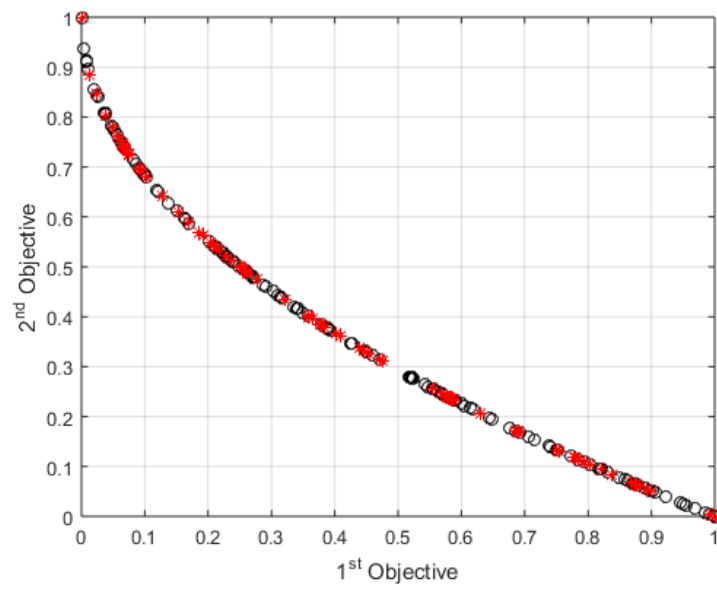


Figure 4.8 showing the Population (black) versus Repository (Red) in the MOPSO.

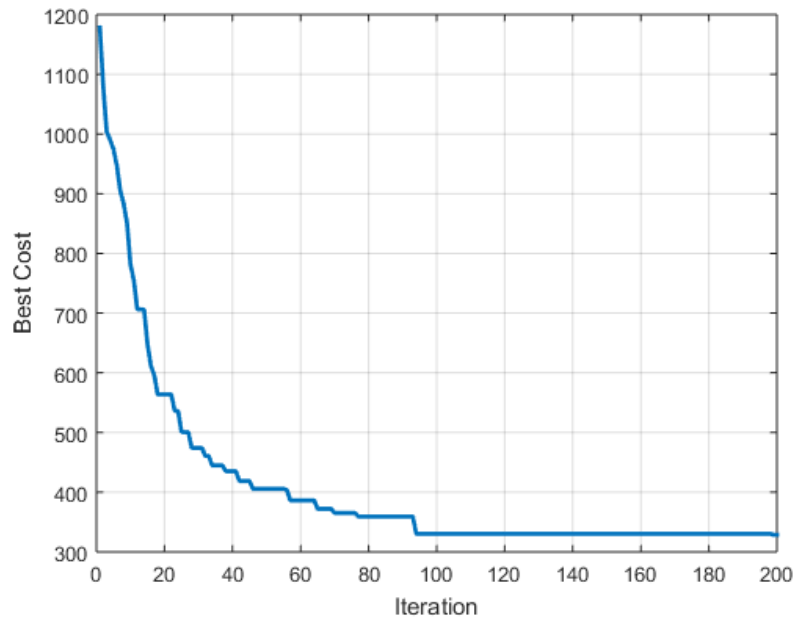


Figure 4.9 demonstrating the best cost versus cycle in the ACO.

Above chart is plot between best cost versus number of emphasess. Above chart is plainlyobvious the most extreme best cost is coming 1155.22 in just 200 emphasess.

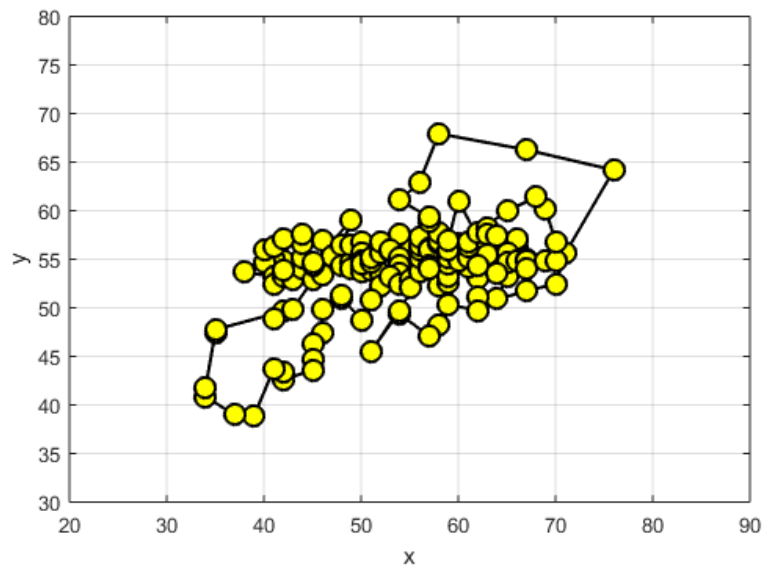


Figure 10: Result of optimzation using ACO

In above figure yellow dabs demonstrates area of cordinates of the populace. The way all the populace are associated with each different shows streamlined way.

Table 4.2 Comparison performance with attribute reduction on heart dataset

Parameter	PSO	MOPSO	OPSO
Iteration	1000	1000	1000
Accuracy	85.2	88.3	86.5
Specificity	82.6	84.9	82.6
Sensitivity	88.1	93.3	80.6

Table4.3 Simulation metrics

	ACO	PSO	MOPSO
Total no. of iterations	200	200	200
Total Population	50	50	50
Best. Cost	316.2719	0.59823	0.000113

The possibility of OPSO is to utilize an OBL technique and an element Cauchy transformation administrator to offer assistance stay away from neighborhood optima and quicken the union of PSO. By evaluating positions and the inverse positions, and applying a Cauchy mutation on the best particles founded by all particles so far in every era, OPSO could discover preferable arrangements over PSO.

ACO is Meta heuristics approaches for take care of hard combination of improvement issues. The huge nature of guidelines helps in better basic management. On the premises of the affiliation control mining and Apriority calculation, other calculations are projected in light of ACO calculation to improve the consequence of affiliations run mining. ACO enhanced the outcome produced by Apriority Algorithm presenting probabilistic plan.

Relative examination likewise demonstrates that MOPSO and OPSO approach is superior to anything PSO as time taken in preparing of the calculations on Heart dataset. As it can be seen that the MOPSO and OPSO procedure was discover exceptionally valuable from current systems, however same time there is degree for progression in the proposed way to deal with oversee stretch out accordingly to oversee handle arrangement of condition and data. Proposed reasoning which execute on organized dataset which is delivered by the Artificial Neural Networks by using a twofold rivalry determination in view of the swarming division and the gathering bungle rates of the game plans in Archive on the Train Data Set.

In all above trial comes about we reason that insect settlement streamlining produces the best arrangement of 316.2719in only 181 emphases out of 200 cycles taken. The reproduced MOPSO produces the 0.00011306 outcome in 36 cycles out of 200 emphases while the PSO calculation creates high cost of 0.59823in150 emphasis. In this way MOSO is the best calculation in regard of best arrangement versus number of emphasis.

REFERENCE

- [1] Kennedy, J. (1999). Small Worlds and Mega-Minds: Effects of Neighborhood Topology on Particle Swarm Performance. Proceedings of the IEEE Congress on Evolutionary Computation, Vol. 3, pp. 1931-1938.
- [2] Kennedy, J. (2003). Bare Bones Particle Swarms. Proceedings of the IEEE Swarm Intelligence Symposium, pp. 80-87.
- [3] Kennedy, J. & Eberhart, R. (1995). Particle Swarm Optimization. Proceedings of the IEEE International Joint Conference on Neural Networks, pp. 1942-1948.
- [4] Kennedy, J. & Mendes, R. (2002). Population Structure and Particle Performance. Proceedings of the IEEE Congress on Evolutionary Computation, pp. 1671-1676, IEEE Press.
- [5] Wang, Hui, et al. "Opposition-based particle swarm algorithm with Cauchy mutation." Evolutionary Computation, 2007. CEC 2007. IEEE Congress on. IEEE, 2007.
- [6] Jabeen, Hajira, ZuneraJalil, and Abdul RaufBaig. "Opposition based initialization in particle swarm optimization (O-PSO)." Proceedings of the 11th Annual Conference Companion on Genetic and Evolutionary Computation Conference: Late Breaking Papers. ACM, 2009.
- [7] Wang, Hui, et al. "Enhancing particle swarm optimization using generalized opposition-based learning." Information Sciences 181.20 (2011): 4699-4714.
- [8] Tang, Jun, and Xiaojuan Zhao. "An enhanced opposition-based particle swarm optimization." Intelligent Systems, 2009. GCIS'09. WRI Global Congress on. Vol. 1. IEEE, 2009.
- [9] Imran, Muhammad, RathiahHashim, and Noor ElaizaAbd Khalid. "Opposition based particle swarm optimization with student T mutation (OSTPSO)." Data Mining and Optimization (DMO), 2012 4th Conference on. IEEE, 2012.
- [10] Kennedy, James. "Particle swarm optimization." Encyclopedia of machine learning. Springer US, 2011. 760-766.
- [11] Han, Lin, and Xingshi He. "A novel opposition-based particle swarm optimization for noisy problems." Natural Computation, 2007. ICNC 2007. Third International Conference on. Vol. 3. IEEE, 2007.

- [12] Shahzad, Farrukh, et al. "Opposition-based particle swarm optimization with velocity clamping (OVCPSO)." *Advances in Computational Intelligence*. Springer Berlin Heidelberg, 2009. 339-348.
- [13] Verma, Om Prakash, Deepti Aggarwal, and Tejna Patodi. "Opposition and dimensional based modified firefly algorithm." *Expert Systems with Applications* 44 (2016): 168-176.
- [14] Omran, M., Engelbrecht, A. & Salman, A. (2007). Differential evolution based on particle swarm optimization. *Proceedings of the IEEE Swarm Intelligence Symposium*, pp. 112- 119.
- [15] Price, K.; Storn, R. & Lampinen, J. (2005). *Differential Evolution: A Practical Approach to Global Optimization*, Springer.
- [16] Rahnamayan, S.; Tizhoosh, H. & Salama, M. (2008). Opposite-based Differential Evolution. *IEEE Trans. On Evolutionary Computation*, Vol. 12, No. 1, pp. 107-125.
- [17] Tizhoosh, H. (2005). Opposition-based Learning: A New Scheme for Machine Intelligence. *Proceedings Int. Conf. Comput. Intell. Modeling Control and Autom*, Vol. I, pp. 695-701.
- [18] Tizhoosh, H. (2005). Opposition-based Learning: A New Scheme for Machine Intelligence. *Proceedings Int. Conf. Comput. Intell. Modeling Control and Autom*, Vol. I, pp. 695-701.
- [19] Wang, H.; Liu, Y.; Zeng, S.; Li, H. & Li, C. (2007). Opposition-based Particle Swarm Algorithm with Cauchy Mutation. *Proceedings of the IEEE Congress on Evolutionary Computation*, pp. 4750-4756.
- [20] Han, Lin, and Xingshi He. "A novel opposition-based particle swarm optimization for noisy problems." *Natural Computation, 2007. ICNC 2007. Third International Conference on*. Vol. 3. IEEE, 2007.
- [21] Yang, Xin-She. "Firefly algorithm, Levy flights and global optimization." *Research and development in intelligent systems XXVI*. Springer London, 2010. 209-218.
- [22] Yang, Xin-She. "Firefly algorithm, stochastic test functions and design optimisation." *International Journal of Bio-Inspired Computation* 2.2 (2010): 78-84.
- [23] Yang, Xin-She, and Xingshi He. "Firefly algorithm: recent advances and applications." *International Journal of Swarm Intelligence* 1.1 (2013): 36-50.
- [24] Gandomi, A. H., Yang, X. S., & Alavi, A. H. (2011). Mixed variable structural optimization using firefly algorithm. *Computers & Structures*, 89(23–24), 2325–2336.

- [25] Horng, M.-H., & Liou, R.-J. (2011). Multilevel minimum cross entropy threshold selection based on the firefly algorithm. *Expert Systems with Applications*, 38(12), 14805–14811.
- [26] Jati, K. G., & Suyanto (2011). Evolutionary discrete firefly algorithm for travelling salesman problem. *Adaptive and Intelligent Systems*, 6943, 393–403
- [27] Senthilnath, J., Omkar, S. N., & Mani, V. (2011). Clustering using firefly algorithm: performance study. *Swarm and Evolutionary Computation*, 1(3), 164–171.
- [28] H. Dhahri and A. M. Alimi, “Opposition-based particle swarm optimization for the design of beta basis function neural network,” in *Proceedings of the International Joint Conference on Neural Networks (IJCNN '10)*, pp. 1–8, 2010.
- [29] H. Wang, Z. Wu, S. Rahnamayan, Y. Liu, and M. Ventresca, “Enhancing particle swarm optimization using generalized opposition-based learning,” *Information Sciences*, vol. 181, no. 20, pp. 4699–4714, 2011. [View at Publisher](#) • [View at Google Scholar](#) • [View at MathSciNet](#) • [View at Scopus](#)
- [30] N. Dong, C.-H. Wu, W.-H. Ip, Z.-Q. Chen, C.-Y. Chan, and K.-L. Yung, “An opposition-based chaotic GA/PSO hybrid algorithm and its application in circle detection,” *Computers & Mathematics with Applications*, vol. 64, no. 6, pp. 1886–1902, 2012. [View at Publisher](#) • [View at Google Scholar](#) • [View at Scopus](#)
- [31] W. F. Gao, S. Y. Liu, and L. L. Huang, “Particle swarm optimization with chaotic opposition-based population initialization and stochastic search technique,” *Communications in Nonlinear Science and Numerical Simulation*, vol. 17, no. 11, pp. 4316–4327, 2012.
- [32] N. K. Khan, A. R. Baig, and M. A. Iqbal, “Opposition-based discrete PSO using natural encoding for classification rule discovery,” *International Journal of Advanced Robotic Systems*, vol. 9, 2012.
- [33] I. A. Gheyas and L. S. Smith, “Feature subset selection in large dimensionality domains,” *Pattern Recognit.*, vol. 43, no. 1, pp. 5–13, Jan. 2010.
- [34] M. Dash and H. Liu, “Feature selection for classification,” *Intell. Data Anal.*, vol. 1, no. 1–4, pp. 131–156, 1997.
- [35] A. Unler and A. Murat, “A discrete particle swarm optimization method for feature selection in binary classification problems,” *Eur. J. Oper. Res.*, vol. 206, no. 3, pp. 528–539, Nov. 2010.
- [36] I. Guyon and A. Elisseeff, “An introduction to variable and feature selection,” *J. Mach. Learn. Res.*, vol. 3, pp. 1157–1182, Mar. 2003.

- [37] A. Whitney, "A direct method of nonparametric measurement selection," *IEEE Trans. Comput.*, vol. C-20, no. 9, pp. 1100–1103, Sep. 1971.
- [38] T. Marill and D. Green, "On the effectiveness of receptors in recognition systems," *IEEE Trans. Inf. Theory*, vol. IT-9, no. 1, pp. 11–17, Jan. 1963.
- [39] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Netw.*, 1995, vol. 4, pp. 1942–1948.
- [40] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in *Proc. IEEE Int. CEC*, 1998, pp. 69–73.
- [41] Y. Liu, G. Wang, H. Chen, and H. Dong, "An improved particle swarm optimization for feature selection," *J. Bionic Eng.*, vol. 8, no. 2, pp. 191–200, Jun. 2011.
- [42] A. Mohemmed, M. Zhang, and M. Johnston, "Particle swarm optimization based AdaBoost for face detection," in *Proc. IEEE CEC*, 2009, pp. 2494–2501.
- [43] Sivagaminathan, Rahul Karthik, and Sreeram Ramakrishnan. "A hybrid approach for feature subset selection using neural networks and ant colony optimization." *Expert systems with applications* 33.1 (2007): 49-60.
- [44] Aghdam, Mehdi Hosseinzadeh, Nasser Ghasem-Aghaee, and Mohammad Ehsan Basiri. "Text feature selection using ant colony optimization." *Expert systems with applications* 36.3 (2009): 6843-6853.
- [45] Al-Ani, Ahmed. "Feature subset selection using ant colony optimization." *International journal of computational intelligence* (2005).
- [46] Huang, Cheng-Lung. "ACO-based hybrid classification system with feature subset selection and model parameters optimization." *Neurocomputing* 73.1 (2009): 438-448.
- [47] Nemati, Shahla, et al. "A novel ACO–GA hybrid algorithm for feature selection in protein function prediction." *Expert systems with applications* 36.10 (2009): 12086-12094.
- [48] Chen, Yumin, Duoqian Miao, and Ruizhi Wang. "A rough set approach to feature selection based on ant colony optimization." *Pattern Recognition Letters* 31.3 (2010): 226-233.
- [49] A. Abraham, C. Grosan, and V. Ramos, "Swarm Intelligence in Data Mining," *Studies in Computational Intelligence*, Vol. 34, pp. 1-20, Springer 2006.