HEURISTIC OPTIMIZATION USING GENE NAVIGATION WITH THE GRAVITATIONAL SEARCH ALGORITHM

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Abstract: *Automation is the effective model to reduce the human workload and to increase the accuracy of working process. It is mainly involved by utilizing the architecture of the Artificial Intelligence (AI). AI is primarily developed by using the optimization to reduce the time of the workload. Optimization is the process of identifying the best solution from the large combination of solution sets. The best solution is selected by validating the objective value of the solution set using the objective function. Without explicit programming, creating the ability of learning to the machine is known as machine learning. The machine learning required to solve the various problems raises in the power electronics application. This work mainly involved to perform the pattern matching process using the CCD sensor. And also there is need to identify the optimal position of the CCD sensor in the agriculture region. The knowledge processing exhibits the higher significance in machine learning to the pattern matching and optimal placement. Genetic optimization is the heuristic approach used in the search process, which executes the natural selection in the evolutionary process. The Gravitational Search Algorithm (GSA) is the optimization model based on the law of gravity and interaction between the mass. In this paper, unique solution is designed with the genetic algorithm by merging with the GSA to identify the optimal placement position of CCD sensor to identify the Crop disease. The performance evaluation of GA and proposed GA-GSA is conducted using the Matlab, and the evaluation exhibits that the proposed solution achieves better performance in terms of number of iterations and computational complexity.*

Keywords: *Genetic Algorithm, Gravitational Search Algorithm, Heuristic, Machine Learning, Non-Polynomial, Optimization.*

1. Introduction.

Automation is the evolution of developing the machine with the set of steps repeatedly operating with kind of cognitive ability [5,14]. Mathematical optimization is the technique which processes the function of several inputs under the set of constraints either by using the linear programming or by using the system analysis to select the best set of solution. The selection of best combination is identified in maximum or minimum based on the problem category. Mainly optimization is used to determine the best combination among all possible combinations, by applying reduction in the number of iterations which avoids the processing of entire solution sets. Optimization is primarily used to perform the search process in the heuristic and meta-heuristic model.

In the linear programming model, the optimization is achieved by using the linear equality and linear inequality constraints. It produces the feasible region using the real-valued affine function which takes the input as a variable subject to the defined constraints. In the defined set of domain including the various types of the objective function, the identification of "best available" solution is obtained as an outcome of the optimization in the linear programming model. The tradeoff in the optimization algorithm is to reduce the value set of the mathematical function by using the minimal valued function based on the related variables in the problem. The optimization solutions are mainly characterized under the machine learning [7,15] approaches in terms of the cost function. The machine learning is primarily used to identify the features of the input data during the classification process with the repeated attempts.

The predictive value of the linear optimization problem [17] is termed as a small set of features that possess the greatest related value in the prediction. The efficiency of the machine algorithm is represented by using the local search process which either identifying the local minima or local maxima to the linear optimization objective. These machine learning algorithms initiate the solution identification either from the random set of solution or from the set of initial values that are related to problem constraints.

From the set of initial solution, the possible combination of solution is determined by the direction of the convergent point from the current initial solution. The convergence point of the problem relates to the solution in the local region with local minima of the objective values. The local minima are the point of the solution which has least neighborhood in the current domain. But the solution is not classified as the global best solution to solve the problem objective. Once the local best solution is normalized under the global best criteria with the required objective maximization, then it is represented as the global solution to the problem domain.

In other words, the local minima can be the global minima [10] if and only if the function is convex and the desired objective is slopped everywhere in the domain of the objective maximization. The iteration reduction in optimization model is found in the form of min-max modeling of the computation with the multi-heuristic objective of the problem. In the multi-heuristic optimization, the objective value of the current solution is identified with the number of input constraints which levies the solution linearity.

Gravitational Search Algorithm is the [12] heuristic optimization model which is inspired from the Newton law of gravity and it is clustered under the population approaches. GSA mainly utilizes [2] the gravity rules for exploring the exploiting the solution to the problem. It mainly computes the force between two masses which is evolved based on the distance with respect to the gravity rule. The GSA evolves the classification of heaviest mass objects in the search space with the gravitational fitness function. It mainly navigates the solution space in the search space by adjusting the gravitational and inertial masses.

In this work, multi-heuristic optimization algorithm is designed to decrease the navigation of solution space in the search space using the Genetic algorithm [3] classified under the machine learning which combined with the Gravitational Search model. The process of fitness function design is completed with the Gravitational force between the selected solution set as well as the mass & the acceleration of the selected points in terms of genes in the solution set. The relativity between the each gene in the solution set is represented in the form of mass and acceleration to solve the problem.

2. Related Work

Optimization is mainly used for the decidable problem under the category of non-polynomial input variants. The selection of best solution using the fitness function with from the large set of solution is handled by using the optimization methodology. Under the category of the NP-complete problem with the various complex and linear computations, large set of effective solution is identified and the selection operator is applied with the linear objective under the supervised learning operation. The optimization under the Machine learning is operated with the two primary phases, namely (i) Large set solution formation and (ii) Selection of the best solution.

These two phases are sub-categorized into following phases,

1. Creating the initial solution set
2. Computation of Objective value (Fitness Value) using the Objective function
3. Validation of solution based on the comparison of objective value
4. Selection of best set of solution with repeated iteration
5. Repeat the solution formation till reaching the convergence point of the algorithm or reaching the maximum number of iterations.

In the first step of the optimization process, the generic view of the problem has to be encoded into an optimal code format which is otherwise known as the 0,1 encoding of the input. In the output stage the reverse of encoding is applied to retrieve the original code as the output in the form of required solution to the problem. The binary encoding phase in the initial set search space is stated by [6] with the least complexity of encoding process.

The initial solution to the problem is generated by using the specific characteristics required to provide the solution to the problem with the well-defined parameters. These parameters are very specific to the problem with describing the depth of the reachability to solve the problem with the maximum probability. The generation of initial solution to the problem is explained by [11]. The representation of the encoded initial solution depicts one-by-one to differentiate the various levels of requirement satisfaction to solve the problem.

The satisfaction level of the solution [2] to the problem is identified by using the objective function which takes the initial solution set as the input to the evaluation system. The preparation of objective categorization is defined with respect to the requirement of the problem with the maximum level of consistency under the well defined constraints related to the problem methodology. A solution is differentiated from the group of solutions using the objective criteria with the following specifications

1. The production of expected output must match with the stated problem
2. The termination of the algorithm must be handled by using the convergence point in the end of local solution as well as in the global solution

Once the initial set of solutions is generated, a small subset of the solution is extracted by using the selection operator which determines the selection level satisfaction of the solution to the problem. And the selected subset of solutions is evolved to produce the new combination of solutions by applying the recombination process which is otherwise stated as CrossOver and Mutation. Here the merging operator is used to create the new solution set from the partial set which is merged with another combination of the partial set solutions. The recombination operation is repeated to create the new subset solution with the maximum objectiveness of the solution. Here the repeated solutions are removed by validating the redundancy of the solution set.

The selection operator applies the selection of best solution set based on the estimated value in terms of the objective value of the solution set. Here the comparison operation is performed to find the maximum objective solution and the remaining unwanted solution set is removed from the original solution set. This operation reduces the execution level of the computation by reducing the number of iterations is the main factor to decrease the running time complexity of the algorithm.

The categorization of solution is applied to select the required feasible solution to solve the problem is estimated by using the objective estimation suggested by the [16]. The closeness of the solution to the problem with the maximum probability is estimated in the form of numerical value using the objective function with the various factors that affecting the quality of the solution with respect to the problem. The boundary conditions of the objective evaluation are determined by the various boundary levels in min-max optimization. These points are evolved to differentiate the quality the solution to separate the other unwanted solutions.

The grouping or merging of the solution to create the qualified solution is stated by [18] with the defined number of iterations and Repeatedly merging operation is performed with the highest level of accuracy by validating the objective value computed from the objective function which takes the current local optimal solution as an input to the system. The probability of problem solving mechanism is computed from the number of optimal solution generated with respect to the number of solutions generated by the system. The termination of the solution formation is handled by using the convergence mechanism of an algorithm with the highly comparable value of the system. From the set of solution, a better solution is selected with the maximum objective value. This solution is considered as the formal solution which is used to solve the problem.

The choice of describing solution is calculated by applying an objective approximation called the objective function. This procedure is assessed between the problem and the generated solution as the input and it computes the component holding the relation of the solution to the problem. This is done by normalizing the several components that catches with the problem notation.

[13] indicated that the target value of the solution is calculated, the assortment is employed to choose the expected resolution to solve the problem. It is based on the closeness of the solution to the corresponding problem which is calculated as a numeric value in the form of representational value. In order to differentiate the expected solution, the conditions bounds are delimited with the boundary values. These boundary points distinguish the specified solution from the unwanted solution.

[1] stated that the moderated solutions are sorted collectively or combined in collaboration to produce a new set of solutions. These rendered solutions are combined repeatedly with delimited number of iterative executions or with the establishment of extremely characterized solution. Once the solution is generated, then the problem solving method finishes the execution with the rendered solution. If it fails to produce the solution with highly corresponding objective value, then it will terminate with the local optimal solution. From the set of solution, a better solution is selected with the maximum objective value as a global optimal solution. This solution is considered as the formal solution which is used to solve the problem.

3. Learning for automation using GA-GSA

The classification, pattern matching and the identifying optimal placement position of sensor are the complex phases in the crop disease detection. But these three stages posses the same characteristics in terms of identifying the optimal solution. And the problem is characterized as NP problem due to the ability of generating the more number of possible solutions. The solution to the NP-problem is achieved by using an optimization algorithm named as Genetic Algorithm (GA) with the less number of iterations when compared to the other optimization methodology in real time computation. In the NP-problem with the real time applied to the maximum level of objective categorization is easily solved by using GA. In the process of GA, the initial solution set is encoded with respect to the problem as encoding set combination as a main requirement to solve the problem. If it is failed to create an encoded solution, then GA unable to process the problem with the initial solution set.

The initial solution set is invoked to the computation of the objective value to select the best combination of solution to solve the problem with the maximum probability. The generated solutions are combined together in the form of crossover & mutation and the process of recombination is repeated with the defined number of iterations to converge the algorithm with the best solution set to solve the problem. The converged solution is considered as the best combination of solution to the input problem handled by the GA.

The solution generated by the GA is contained the collection of gene which is used to solve the input problem that is named as a chromosome. The chromosome is represented in binary format with the well-defined model of computation. The set of generating chromosome collected together is relatively known as population. It contains the subset of the solution to solve the problem in terms of 0,1. The mechanism of combining the generated solution together is called as reproduction and population generation.

The reproduced chromosomes are generated by applying the operations of crossover, mutation, and recombination. The iterative process of selection, objective evaluation in terms of fitness value, and new chromosome generation is known as iteration in the GA operation.In the operation of genetic operators, the initial sets of solution are formed based on the problem statement and these are marked as chromosomes, which has the solution in the form of the binary variable (0 and 1). The input level required by the problem is encoded as the number of bits in the solution chromosome and it is fixed for the entire set of solution to avoid the variant complexity of the algorithm. The factors behind the problem is represented by the each bit in the solution and the generated solution is unique one ie., there is no identical solution to the problem.

After the formation of the initial solution set, the evaluation of the solution set is handled by using the objective computation in the form fitness evaluation. This computation takes the bit representation as input to the processing system and to characterize the chromosome. The representation of the chromosome with the exact characteristics is handled in the objective function to validate the quality of the solution to solve problem. Each and Every bit the chromosome is taken as an input validates the feasibility of the solution.

From the generated initial chromosomes, after completing the computation of the fitness value using the fitness function, the subset combination of the solution is differentiated from the original solution set. This solution set is called as the selected solution set to process with the maximum probability to solve the input problem handled by the GA which is highly feasible to solve the problem in the binary format. This solution set selection is list out all the available solution with the objective value to solve the problem domain.

The formation of new subset chromosome is executed from the set of selected feasible solution by applying the crossover operation.

The crossover operation takes the two unique chromosomes as an input and the bits in the selected chromosomes are exchanged with the order of the operation to make use of the feasible solution set to the problem domain. In order to apply the mutation operation the bits in the usable solution set is reversed. Based on the mutation probability, the mutation execution system reverses the ‘0’ bit into ‘1’ and vice-versa, in the generated chromosome. The mutated chromosome is again ordered to make the feasible solution to the problem. This is done by matching the solution with the problem characteristics. If it fails to match the characteristics, then the formed solution is ignored. Otherwise, the solution is selected as new chromosome.

The fitness evaluation is again applied for the newly generated chromosome to classify the various chromosomes from one another. If the newly generated chromosome has the greatest value in terms of fitness value compare to the old one, then it is selected for the next sequence of GA operation. Once the chromosome selection operation gets completed, then the crossover, mutation, fitness evaluation, and selection operations are repeated. This iterative process is repeated with the specific number of iterations to form the robust solution which is more effective to solve the problem.

In case of final iteration of validating the maximum iteration or in the convergence point of the algorithm, the population contains the largest set of solution to solve the problem. With these generated sets of solutions, the best one is selected with the maximum fitness value with the required solution under the defined criteria to solve the problem. The selected solution is the final best solution as global optimal which has a maximum level of quality in terms of fitness value. The final solution is in the form of binary representation and the selected solution is decoded into normal form to obtain the actual readable form of solution.

Based on the law of gravity and mass interaction, the optimization algorithm named, the Gravitational search algorithm is developed. This algorithm is based on the Newtonian gravity: “Every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them”. In the search space, the selection of best chromosomes to create a new solution using the crossover and mutation operation is considered as the problem which is solved using the GSA [4,8,9]. The GSA is applied with the GA in the fitness function as the GSA equation is considered as the primary equation of the objective function.

$$G(t) = G_0 e^{-\alpha t/T} \quad (1)$$

$G_0 - Initial\ fitness\ value$

$\alpha - Number\ of\ initial\ search\ samples$

Equation (1) represents the Gravitational input required to compute the Gravitational force between the two related genes validated in terms of mass. Based on the number of sample solution in the initial solution set is configured as the α and a markup value in terms of fitness value is represented in the form of initial fitness value. In GSA, four types of parameters are used to create the solution in terms of position, active & passive gravitational mass and relativity of quantum. Here the position represents the absolute difference of the solution to connect with the expected solution. The navigation of the gene in the solution space is determined from the location of the gene at various iterations.

The algorithm is navigated by adjusting the gravitational and inertial masses, whereas each mass presents a solution. Masses are attracted by the heaviest mass. Hence, the heaviest mass presents an optimum solution in the search space. Every population based algorithm has two capabilities: exploration and exploitation. This algorithm uses an exploration capability at the beginning to avoid the local optimization problem and after that exploitation.

$$F = G * \frac{M_1 * M_2}{d^2} \qquad (2)$$

$$M_1 = Mass\ of\ the\ first\ gene$$

$$M_2 = Mass\ of\ the\ second\ gene$$

$$G = Gravitational\ value\ using\ (1)$$

$$d = Genes\ Relativity$$

In a 2D search space movement of the gene is during the iterations i, j are represented from the location coordinates of the gene (x^i, y^i) and (x^j, y^j). Then the location coordinates of the two genes in two different iterations are represented as (x_1^i, y_1^i) (x_1^j, y_1^j) and (x_2^i, y_2^i) & (x_2^j, y_2^j). Then the relativity of genes in terms of distance is computed using (3), (4) & (5).

$$\vec{d} = \vec{d_1} * \vec{d_2} \qquad (3)$$

$$\vec{d_1} = \sqrt{(x_1^i - x_1^j)^2 + (y_1^i - y_1^j)^2} \qquad (4)$$

$$\vec{d_2} = \sqrt{(x_2^i - x_2^j)^2 + (y_2^i - y_2^j)^2} \qquad (5)$$

Movement angle of the two genes is computed as the inverse function of angle tan operation with the current location and movement location using the equation (6) & (7).

$$\theta = tan^{-1}\left(\frac{|(y_1^i - y_1^j)|}{|(x_1^i - x_1^j)|}\right) \qquad (6)$$

$$\varphi = tan^{-1}\left(\frac{|(y_2^i - y_2^j)|}{|(x_2^i - x_2^j)|}\right) \qquad (7)$$

The distribution of navigation of the two genes in both coordinates is modelled using the inverse sine and cosine function with the movement direction vector in the individual coordinates using (8) & (9).

$$n_x = \vec{d} * \sin^{-1}\theta * \sin^{-1}\varphi \qquad (8)$$

$$n_y = \vec{d} * \cos^{-1}\theta * \cos^{-1}\varphi \qquad (9)$$

If the navigation angle in continuously changing with the specific linearity in the search space is integrated and depicted using the equation (10) & (11).

$$n_x = \int_{\varphi 1}^{\varphi 2}\int_{\theta 1}^{\theta 2}(\vec{d} * \sin^{-1}\theta * \sin^{-1}\varphi)\, d\theta d\varphi \qquad (10)$$

$$n_y = \int_{\varphi 1}^{\varphi 2}\int_{\theta 1}^{\theta 2}(\vec{d} * \cos^{-1}\theta * \cos^{-1}\varphi)\, d\theta d\varphi \qquad (11)$$

The integration of navigation in the search space is computed and distributed using 'uv' integration. After the expansion of the navigation angle of the two genes is related with the final navigation distribution of genes is computed by applying the equation (12) & (13).

$$\begin{aligned} n_x = \vec{d} * \Big(&\left(\theta_2 * \sin^{-1}\theta_2 + \sqrt{(1-\theta_2)}\right) \\ &- \left(\theta_1 * \sin^{-1}\theta_1 + \sqrt{(1-\theta_1)}\right) \\ &* \left(\varphi_2 * \sin^{-1}\varphi_2 + \sqrt{(1-\varphi_2)}\right) \\ &- \left(\varphi_1 * \sin^{-1}\varphi_1 \right.\\ &\left. + \sqrt{(1-\varphi_1)}\right)\Big) \qquad (12) \end{aligned}$$

$$\begin{aligned} n_y = \vec{d} * \Big(&\left(\theta_2 * cos^{-1}\theta_2 + \sqrt{(1-\theta_2)}\right) \\ &- \left(\theta_1 * cos^{-1}\theta_1 + \sqrt{(1-\theta_1)}\right) \\ &* \left(\varphi_2 * cos^{-1}\varphi_2 + \sqrt{(1-\varphi_2)}\right) \\ &- \left(\varphi_1 * cos^{-1}\varphi_1 \right.\\ &\left. + \sqrt{(1-\varphi_1)}\right)\Big) \qquad (13) \end{aligned}$$

The final navigation of the genes in both coordinates is computed and given as an input to the Force computation as M_1& M_2 in equation (2) provides the force of the currently mutated genes in the current iteration. This value is considered as the fitness value of the genetic algorithm which continuously iterated to select the best combination of output with the various search models in the optimization process. The multi-heuristic is created with mass and the navigation of the generated solution in the search space.

The identified solution is given as an input to the information processing system to generate the knowledge perception and adaptation process. The solution generated over the NP solution phase is linearly given as optimal placement position identified to place the CCD sensor in the agriculture field to apply the automated detection process for the crop disease detection.

In the next phase, after identifying the Region Of Interest (ROI), the portion to be classified is characterized again applying the GSA solution generated by employing the possible GA vectors. During the image classification process, the pattern formation and the pattern recognition are evolved with the combined scheme of the GA-GSA.

4. Performance evaluation

The performance evaluation of the system is conducted to validate the quality of the proposed solution. The performance metrics such as number of iterations, running time are considered for the evaluation. The development of the Genetic algorithm and proposed GA-combined-GSA is coded in Matlab environment and input data set is generated from the Image taken for the validation. The optimal placement position and the pattern matching input points are identified by using the GA-GSA operation which considered two types of input as pixel points in the image and the random placement position in the agricultural region. The evaluation is conducted for 3 input samples and the comparison is displayed in the Fig.1-Fig.4.

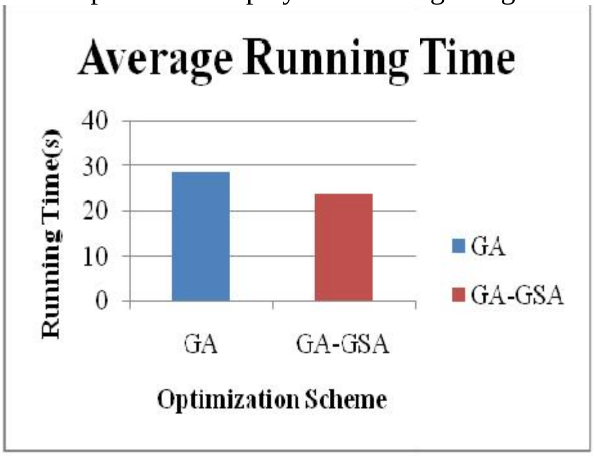

Fig.1 Average Running Time evaluation of GA and GA-GSA

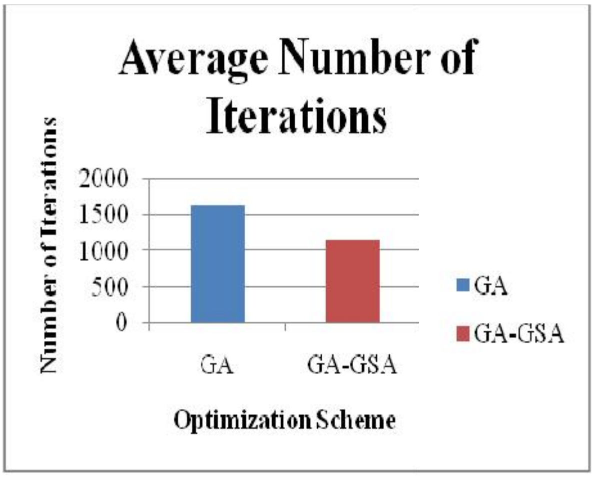

Fig.2 Average No.of iterations evaluation of GA and GA-GSA

Fig.1 shows that the performance evaluation of GA and proposed GA-GSA in terms of Average Running Time. The figure clearly outcomes the proposed solution achieves the minimum level of running time compared to the GA process.The performance evaluation of GA and proposed GA-GSA in terms of Average No. of iteration is depicted in Fig.2. From the figure it can easily outcomes the proposed solution achievable low level in a number of iterations while compare to the Genetic algorithm by reaching the convergence point at the earliest.

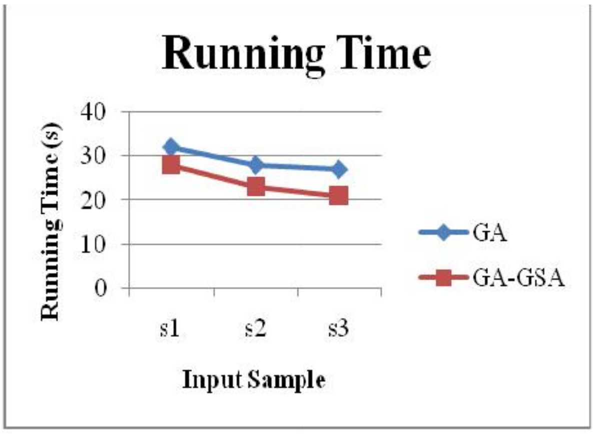

Fig.3 Running Time evaluation for various samples using GA and GA-GSA

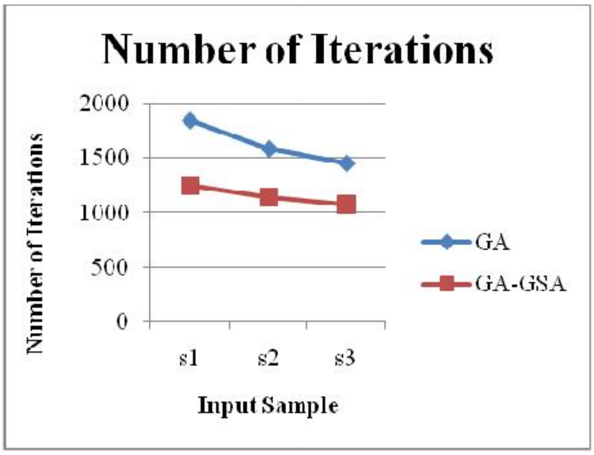

Fig.4 No.of iterations evaluation for various samples using GA vs GA-GSA

Fig.3 and Fig.4 represents the running time analysis and the Iterations of the GA and proposed GA-GSA algorithm for various samples.

5. Conclusion

The optimization algorithm is mainly used to reduce the computational complexity in the agriculture automation using the CCD sensor for crop disease detection. This required solving the problem of identifying the optimal placement position of sensor in the agriculture region. The evolution model of optimization is required to perform the pattern formation and classification in the image region. The optimization is achieved by using the heuristic process which selects the best combination of solution. In this paper, the gravitational search algorithm is modeled with the multi-heuristic which is combined with the fitness evaluation using the Genetic operator to reduce the complexity of the algorithm while identifying the solution for Non-Polynomial problems. Here the multi-heuristic is achieved by considering the navigation of the gene in the search space in different iterations. The results shown that the proposed GA-GSA obtained the significance performance compare to the existing GA in the search process in terms of Number of iterations and Running time complexity. In future, the GSA can be developed from binary Genetic algorithm to make use of the optimization algorithm in large scale applications. The classification process can be enhanced by using the learning, perception and adaptation process.

References

1. Asghar.A, Hosseinabadi.R, Ghaleh.M.R, Hashemi.S.E, and Branch.B: *Application of Modified Gravitational Search Algorithm to Solve the Problem of Teaching Hidden Markov Model*, International Journal of Computer Science Issues, vol. 10, no. 3, 2013, p.1–8.
2. Beigvand, Soheil Derafshi, Hamdi Abdi, and Massimo La Scala: *Combined heat and power economic dispatch problem using gravitational search algorithm.* Electric Power Systems Research. 133, 2016, p.160-172.
3. Cha, Sung-Hyuk, Tappert, Charles C: *A Genetic Algorithm for Constructing Compact Binary Decision Trees.*Journal of Pattern Recognition Research.4 (1) 2009, p.1-13.
4. Doraghinejad.M, Nezamabadi-pour.H, and Mahani.A: *Channel Assignment in Multi-Radio Wireless Mesh Networks Using an Improved Gravitational Search Algorithm*, Journal of Network and Computer Applications, 2013, p.1–9.
5. Kabassi, Katerina, and Maria Virvou: *Combining decision-making theories with a cognitive theory for intelligent help: A comparison*.IEEE Transactions on Human-Machine Systems 45, no. 2. 2015, p.176-186.
6. Kwang Mong Sim, Sun, WH: *Ant colony optimization for routing and load-balancing: survey new directions.* IEEE Transactions on Systems, Man, Cybernetics-Part A: Systems and Humans, vol. 33, no. 5, 2003,p.560-572.
7. Langley, Pat:*The changing science of machine learning*. Machine Learning. 82 (3) 2011, p.275–279
8. Li.C, Li.H, and Kou.P: *Piecewise function based gravitational search algorithm and its application on parameter identification of AVR system.* Neurocomputing, vol. 124, 2013, p.139–148.
9. Li.C, Zhou.J, Fu.B, Kou.P, and Xiao.J:*T - S Fuzzy Model Identification With a Gravitational Search-Based Hyperplane Clustering Algorithm.* IEEE Transactions On Fuzzy Systems, vol. 20, no. 2, 2012, p.305–317.
10. Mirjalili, Seyedali, and Amir H. Gandomi:*Gravitational Search Algorithm With Chaos*. Handbook of Neural Computation. 2017,p.1-16.
11. Mustafa Al-Ghazal, M, El-Sayed, Kelash H:*Routing optimization using Genetic Algorithm In Ad Hoc Networks*, International Symposium on Signal Processing and Information Technology, 2007,p.506-511.
12. Nezamabadi-Pour, Hossein, and Fatemeh Barani:*Gravitational Search Algorithm: Concepts, Variants, and Operators*. Handbook of Research on Modern Optimization Algorithms and Applications in Engineering and Economics. IGI Global, 2016, p.700-750.
13. Rashedi.E, Nezamabadi-pour.H, and Saryazdi.S:*GSA: A Gravitational Search Algorithm.* Information Sciences, vol. 179, no. 13, 2009, p.2232–2248.
14. Sheth, Amit: *Internet of things to smart iot through semantic, cognitive, and perceptual computing.*IEEE Intelligent Systems 31, no. 2 2016,p.108-112.
15. Tillmann.A.M:*On the Computational Intractability of Exact and Approximate Dictionary Learning.* IEEE Signal Processing Letters 22(1), 2015, p.45–49.
16. Wu Xiao-Yan, Yang, L:*Routing Optimizing Algorithm Of Mobile Ad-Hoc Network Based on Genetic Algorithm.* American Journal of Engineering and Technology Research. 2011, p.835-841.
17. Yildiz, Ali Rıza: *Optimization of thin-wall structures using hybrid gravitational search and Nelder-Mead algorithm*. Materials Testing 58.1 2016,p.75-78.
18. Zhang Jun, Zhan, Zhi-hui, Lin Ying, Chen Ni, Gong Yue-jiao: *Evolutionary Computation Meets Machine Learning: A Survey*. Computational Intelligence Magazine. IEEE.6 (4),2011, p.68–75.