Introducing Bee-Eater Hunting Strategy Algorithm for IoT-Based Green House Monitoring and Analysis

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***Abstract*—By skyrocketing of Internet of Things (IoT) applications in the recent decade, research improvement on its algorithms for more optimized manner is soared, too. Green house monitoring is one of the most in demand usages of IoT, as it decreases monitoring maintain cost and error. Data returned by IoT system could be transferred to regression task in order to analysis the relation between inputs and targets alongside with its correlation coefficient. At the same time these data could be clustered into similar groups, in order to make data easily understood and manipulated. To employ these two tasks, a new bio-inspired algorithm is introduced. Proposed Bee-Eater Hunting (BEH) Algorithm, not only can compete with famous evolutionary algorithms such as Genetic Algorithm (GA) but also, returns more optimized cost in comparison with other algorithms. Live data returned by ThingSpeak platform, sends to proposed Bio-inspired BEH algorithm for fuzzy regression and cluster analysis task and compares with other algorithms. Results shows considerable improvement in both tasks.**

Keywords*— *Internet of Things, Greenhouse monitoring, Bee-Eater Hunting Algorithm, Fuzzy Regression, Clustering

I. Introduction

Each and every living creature and even device, needs its corresponding fuel and humans need agriculture to gain main part of its fuel which is food. Employing Internet of Things (IoT) [1] as an expert system [2] to monitor greenhouses has lots of advantages. Reducing maintaining cost, human resource, human error, human fatigue and increasing yield efficiency, is just part of using expert systems. Based on late technology development of Artificial Intelligence (A.I) [3] in industry, agriculture [4], medicine, and other interdisciplinary areas, future has potential to hold huge range of computer tasks which is doing by human resource nowadays. In the other hand, increasing population around the globe, soared the need of agricultural products in past half century. So, optimizing agriculture activities through greenhouse monitoring, to produce enough food supplies goes in the center of attention.

ThingSpeak [5] platform made IoT easy to handle by proving live data from different sensors for different activities, including green houses. By analyzing, data returned from sensors, it is possible to get feed backs and adjust the system for better performance. This analysis could be done by regression [6] and clustering [7] tasks.

As, Nature holds the best solutions for our problem, a novel bio-inspired [13] algorithm is introduced for conducting both mentioned tasks. Bee-Eater Hunting (BEH) strategy algorithm is proposed in this paper which hold robustness over a lot of other bio-inspire algorithms for regression and clustering tasks. The paper is consisted of five parts of introduction, prior researches, proposed method, validation and conclusion.

II. Prior Related Researches

As, a novel bio-inspired algorithm called Bee-Eater Hunting (BEH) strategy algorithm is propose, some other famous algorithms should be mentioned. One of the most famous bio-inspired or evolutionary algorithms [8] is Genetic Algorithm (GA) [9], which is consisted of crossover and mutation operators as its main body. Another benchmark optimization algorithm is Particle Swarm Optimization (PSO) algorithm [10] which is inspired from birds and fished swarm movement toward better solution. From new nature-inspired algorithm, Firefly algorithm [12] and Biogeography-Based Optimization (BBO) [11] algorithm is mentionable. FA is based on Movement of fireflies toward more shiny fireflies based on attraction factor and BBO is movement of creatures toward better habitat based on immigration and emigration factors. Proposed BEH algorithm would be compared with these four mentioned algorithms in the third section.

One of the best examples of using A.I in IoT in greenhouse monitoring is [14] which authors used Adaptive Neuro Fuzzy Inference System (ANFIS) [15] to make a system which boosts the crop production. Another IoT based greenhouse control system belongs to [16] which they made a system to monitor light intensity, temperature, humidity and soil moisture of the green house by A.I algorithms. Authors of [17] research, used NodeMCU esp 8266 sensor for humidity, soil immersion, temperature, fire proximity and strength of light in their greenhouse. A mentionable example of PSO algorithm in temperature prediction for Chinese solar green house is conducted in [18] and [19]. Also, a decent review of using bio-inspired algorithm in greenhouse monitoring and control is made in [20].

III. Proposed Method

A. Bee-Eaters

Bee-eaters are type of birds from the family of Meropidae, containing twenty-seven species [21, 23, 24] living in Africa, Asia, few in southern Europe, Australia and New Guinea. They are easily recognizable by their colorful Plumage and their male and female are usually similar. As their name suggest, they feed from insects, especially bees and wasps. They attack their prey in the air by targeting and twisting their bodies and a final dive toward their prey. After hunt, they smash and rub their prey into hard surface to destroy any sign of life and stinger and discharging most of the venom. They live in groups and nest in sandy walls or the ground nearby each other. Their peak or bill is long, sharp and curved which is suitable for biting and crushing small preys like forceps [21, 22, 25]. Sometimes, they will fight over a big prey in the sky which could hurt them or provide them a big prize.

B. Bee-Eater Hunting (BEH) Algorithm

Having above paragraph in mind, BEH equation would be as (1). There is x population of bee-eaters in the first generation. There are two operators of peak power (ζ) and adjustment power (η) based on pitch, yaw and roll [29] rates of the bird. Also, there is mutation rate operator of (μ) which is their fight over a big prey. Fig 1, shows the bee-eater hunting strategy.

$$BEH = \sum_{i=1}^{n} \sum_{j=1}^{n} (xij\ [\zeta ij, \eta \text{ij}]) * (\mu) \qquad (1)$$

BEH Algorithm Pseudo Code

Generating population of Bee-Eaters x_i (i=1,2,…,n)
Define Peak Power ζ in x_i
Define Adjustment Power η in x_i
Define Fight Mutation Rate of μ = 0.2
While *maximum iterations are not satisfied*
  For *i=1 to n bee-eaters*
    For *j=1 to n bee-eaters*
      If *(ζ + η $_{ii}$ > ζ + η $_{ij}$) for xi (i=1,2,…,n)*
        Best bee-eater (x) = x (ζ + η $_{ii}$)
        Else
        Best bee-eater (x) = x (ζ + η $_{ij}$)
      End if
        Apply fight mutation of μ
        Evaluate new solutions by cost function and update
    End
  End
  Sort and rank bee-eaters
  Generating new generation
End of while

Proposed BEH algorithm is evaluated by four performance metrics or test functions of Ackley [26], Beale [26], Booth [26] and Rastrigin [26] which are single and multi-objective optimization [13] types to assess robustness, precision and convergence rate of the algorithm. Fig 2 illustrates these functions in three-dimensional form. Also, the algorithm is compared with other bio-inspired algorithms of GA [9], PSO [10], FA [12] and BBO [11] with same parameters of 200 iterations, 10 populations size, variables lower and upper bounds of [-10, 10] with 10 variables and mutation rate of 0.2. Fig.3 presents, the performance of BEH algorithm on test functions. Also, Fig.4 shows the performance comparison of different algorithms on Ackley and Rastrigin functions. Table I shows cost functions values after 100 iterations for all algorithms. Clearly, BEH and PSO are competing with each other over test functions. BEH has better performance on Ackley and Rastrigin functions and PSO has better performance on Beale and Booth functions. Also, GA, FA and BBO are in the third, fourth and fifth places based on their performances.

$$Ackley = -20\mathrm{e}^{\left(-0.02\sqrt{D^{-1}\sum_{i=1}^{D} x_i^2}\right)} - \mathrm{e}^{\left(D^{-1}\sum_{i=1}^{D}\cos(2\pi x_i)\right)} + 20 + \mathrm{e} \qquad (2)$$

$$Beale = (1.5 - x_1 - x_1x_2)^2 + (2.25 - x_1 - x_1x_2^2)^2 + (2.625 - x_1 - x_1x_2^3)^2 \qquad (3)$$

$$Booth = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2 \qquad (4)$$

$$Rastrigin = -20\exp\left(-0.5\sqrt{-0.2(\mathrm{x}^2 + \mathrm{y}^2)}\right) - \exp\left(0.5(\cos(2\pi \mathrm{y}))\right) \qquad (5)$$

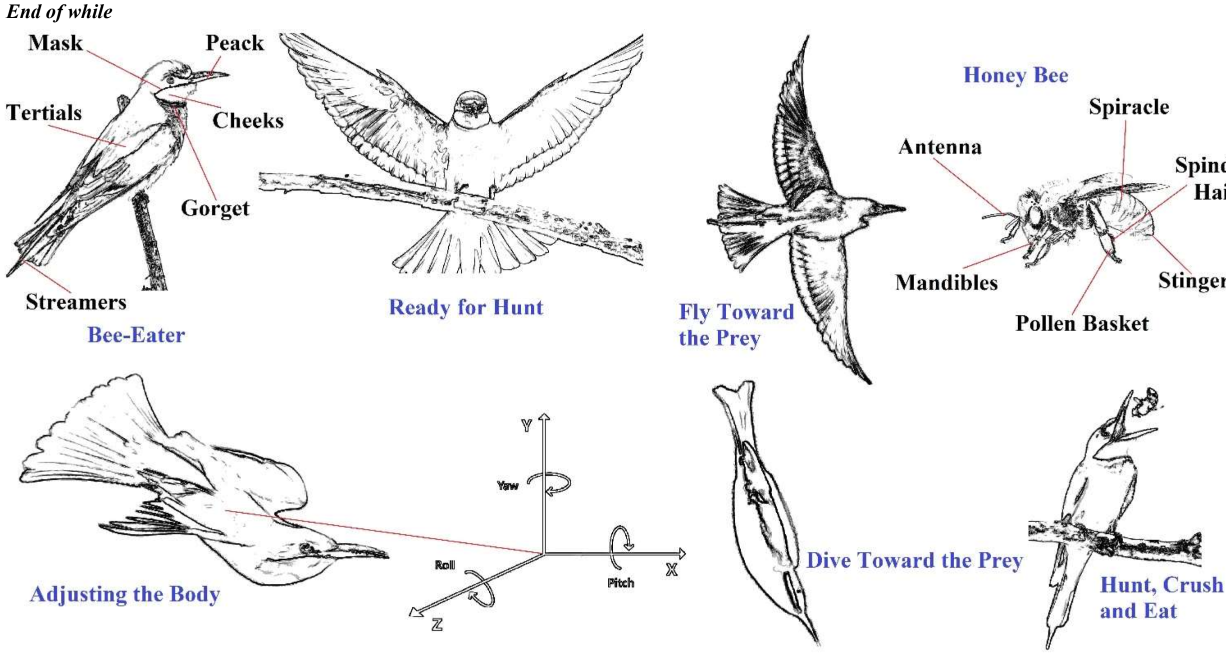

Fig. 1. Bee-Eater Hunting Strategy

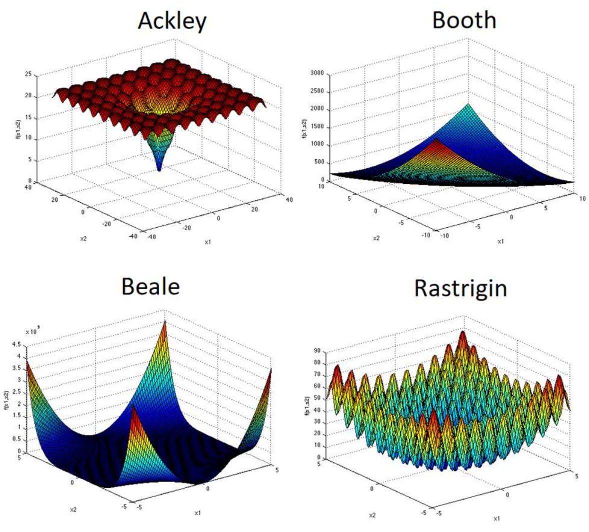

Fig. 2. Performance metric test functions (Ackley (multimodal), Booth (multimodal), Beale(unimodal) and Rastrigin(multimodal))

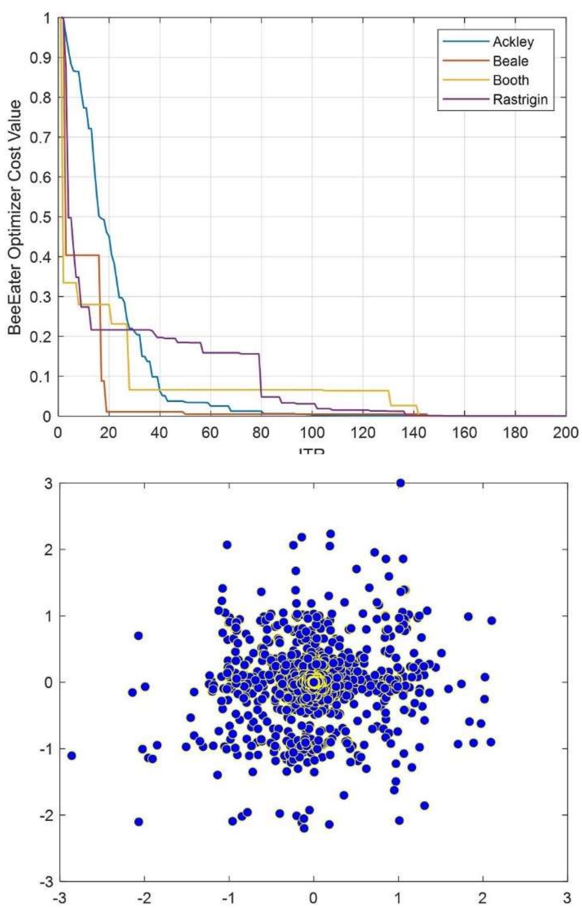

Fig. 3. Top: BEH algorithm performance on five metric test functions over 200 iterations and Bottom: Bee-Eaters scattering on Ackley function going toward best solutions.

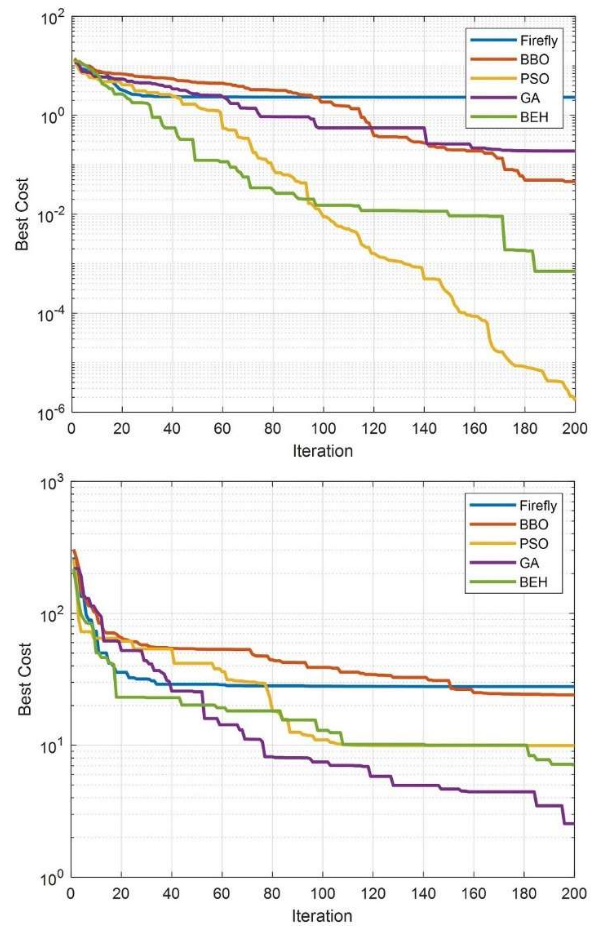

Fig. 4. Top: Comparison performance of different algorithms on Ackley function and Bottom: Comparison performance of different algorithms on Rastrigin function over 200 iterations.

TABLE I. COST FUNCTION VALUES AFTER 100 ITERATIONS

	Ackley	**Beale**	**Booth**	**Rastrigin**
GA	0.124 ± 0.031	0.023 ± 0.002	0.063 ± 0.029	0.021 ± 0.008
PSO	0.058 ± 0.014	0.024 ± 0.019	0.044 ± 0.001	0.032 ± 0.004
FA	0.091 ± 0.027	0.051 ± 0.044	0.092 ± 0.062	0.088 ± 0.032
BBO	0.103 ± 0.059	0.074 ± 0.035	0.067 ± 0.007	0.118 ± 0.046
BEH	0.048 ± 0.021	0.032 ± 0.001	0.051 ± 0.019	0.015 ± 0.006

IV. EVALUATIONS AND RESULTS

A. *ThingSpeak and IoT Data*

In ThingSpeak [5], you can have your own cloud or use other public IoT devices for online monitoring. We used ThingSpeak platform [5], in order to get required Realtime data from the green house. Here, we are using public ThingSpeak channel of "IeC Clock 1" under channel ID of 141950 which is located in Porto Alegre, Brazil. This IoT channel is consisted of eight features which we are using five active features of light, temperature, humidity, movement and sound. Data belongs to 100 days for eight field which here field number one is under experiment.

B. *Fuzzy BEH Regression and BEH Clustering*

Clustering [7] is to grouping similar objects into clusters by distance factor in various dimensions or features and has widely used in pattern recognition field. Here acquired data from the greenhouse is clustered with BEH clustering and compared with PSO clustering [27] and K-means clustering [7] techniques. Basic parameters are 100 iterations, 25 population size into four clusters. Fig.5 presents clustering results for first two features of light and temperature.

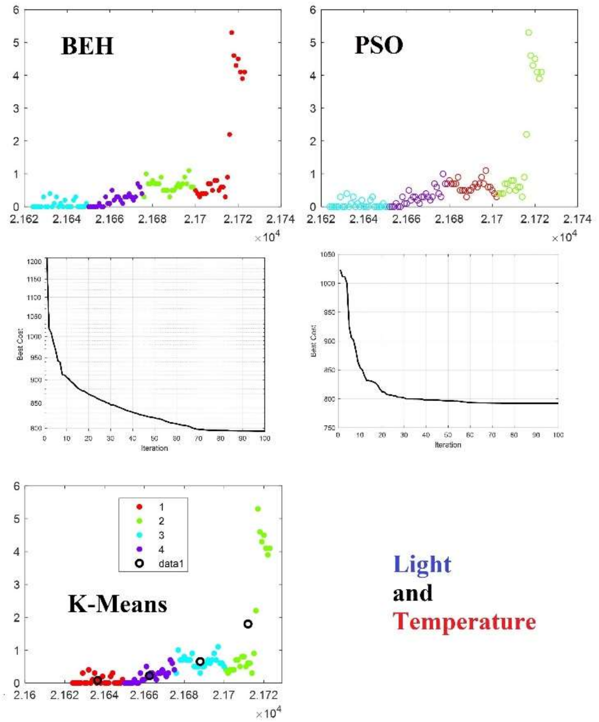

Fig. 5. Clustering comparison for BEH, PSO and K-means clustering algorithms on light and temperature features.

In order to understand the relation and correlation coefficient between inputs and targets of the greenhouse data, nonlinear-regression [6] task is employed for our IoT data. Inputs are our features and targets are entry-id sampling, normalized into range of -1 and 1. Now, this regression could be aided with other clustering techniques as input data, which one of them is Fuzzy C-means clustering (FCM) [28]. Fuzzy C-means clustering is fuzzy model of K-means or Lloyd's clustering algorithm [7]. By clustering the data in the initial step, data will be organized in an optimized manner for training step. Clearly, more clusters, means more accuracy but brings more computational time too. The goal here is to adjusting base fuzzy parameters according to modeling error by BEH and returning best fuzzy parameters values as the final result. Firstly, data (inputs and targets) passing through fuzzy system divides into train and test parts by 70% and 30%, respectively. Second step is to define linguistic variables, constructing membership functions, sets and rules and finally converting crisp feature (inputs and target) matrix to fuzzy model (fuzzification) which end up to initial fuzzy model ready for training by BEH algorithm. Fuzzy part uses "Sugeno" inference system as it performs better than "Mamdani". Each input represents one feature so there are five inputs (each three membership functions) and three rules ("and" operator) followed by an output which contains targets in this step. This fuzzy model sends to BEH as input for adjusting basic fuzzy parameters by nature inspired behavior of BEH algorithm under value as it mentioned above. The change goes over membership functions and changes gaussian curve as range and variance to fittest form by BEH. Now, fuzzy input model is transformed to a better fuzzy model after taking effect by BEH algorithm on its membership functions and parameters. By evaluating fuzzy BEH model using fuzzy inference engine, final trained data (train and test) is available. In order to calculate error fuzzy data should return to its original crisp mode which this action is called defuzzification. Clearly, inputs are train and test inputs; and evaluated version of them are train and test outputs. The difference between train, test outputs and train, test targets, provide system error which here are MSE, RMSE, Mean Error and STD Error. Fig.6 illustrates, gaussian membership functions of fourth feature (movement), before and after main bio-inspired regression. Clearly, after BEH algorithm, gaussian membership functions are in more rational shape. Fig.7, presents, fuzzy and fuzzy BEH training result on 70 samples of the training stage. Also, Fig.8, represents regression result for fuzzy and fuzzy BEH algorithms. Table II, shows comparison results for fuzzy and fuzzy BEH regression.

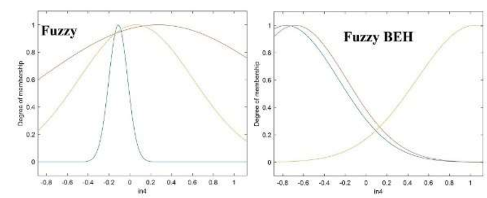

Fig. 6. Movement feature membership functions in both fuzzy and Fuzzy BEH models.

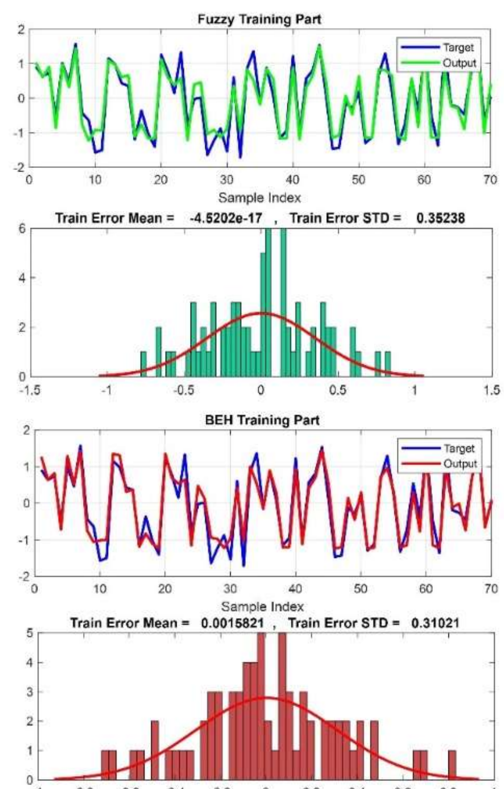

Fig. 7. Top: Fuzzy training result and Bottom: Fuzzy BEH training alongside with corresponding bin histogram.

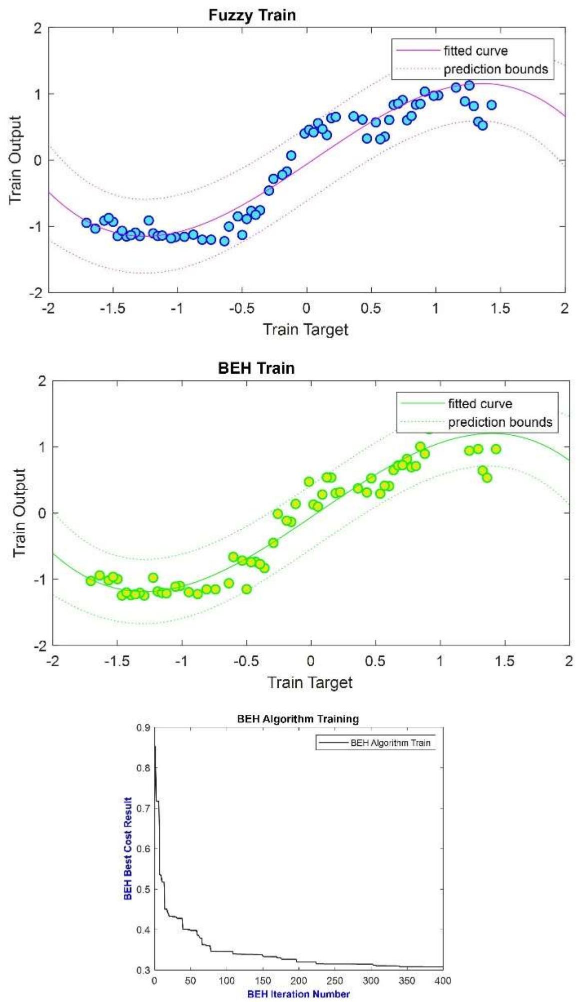

Fig. 8. Top: Left: Fuzzy regression and Bottom: Fuzzy BEH regression.

TABLE II. FUZZY AND FUZZY BEH REGRESSION COMPARISON (TRAIN AND TEST)

	MSE	RMSE	Correlation Coefficient
Fuzzy	Train = 0.021 Test = 0.023	Train = 0.148 Test = 0.152	Train = 0.8924 Test = 0.8455
Fuzzy BEH	Train = 0.016 Test = 0.021	Train = 0.125 Test = 0.145	Train = 0.9166 Test = 0.8623

Based acquired results from Figs. 5, performance of BEH clustering, PSO, clustering and K-means is almost identical. Figs. 7, 8 and Table II, present slightly better performance of BEH regression over Fuzzy regression for MSE RMSE, Error Mean, Error STD and Correlation Coefficient values

V. CONCLUSION, SUGGESTION AND FUTURE WORKS

Experiment results in this paper shows that, it is possible to get more efficient results by employing bio-inspired algorithm for analyzing IoT data by clustering and regression tasks. Fuzzy bio-inspired analysis could generate more flexible outcome and improve correlation coefficient between inputs and targets in regression task. Propose BEH algorithm could handle both clustering and regression optimization tasks for IoT data and showed more robustness versus other algorithms for the same tasks. Also, proposed BEH algorithm returned very decent performance results for performance test function comparing with other bio-inspired algorithms. It is suggested to employ proposed fuzzy BEH regression algorithm on other IoT based data with more than five features and testing BEH algorithm to check its performance with other single and multi-objective test functions or artificial landscapes. Furthermore, Using BEH algorithm on feature selection, Minimum Spanning Tree (MST) and Hub Location Allocation (HLA) is of future works

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