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Original Article

Design and Development of Fuzzy Based Complex Machine Learning Models: Two Soft Computing Based Approaches

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Abstract *- This paper discusses designing and developing a TSK type-0 fuzzy logic-based machine learning model using two metaheuristic approaches. The optimized model evolved from the available numerical data. Two recent soft computing-based search and optimization algorithms, namely three-parent genetic algorithm (3PGA) and parallel three-parent genetic algorithm (P3PGA), have been used in the proposed approaches to deal with higher complexities and nonlinearities efficiently. The proposed approaches work in three phases. In the first phase, the proposed approaches evolve the model structure of a fuzzy system. The second phase optimizes the parameters of the fuzzy system with the help of MSE (Mean Squared Error). In the third phase, the code generation of the optimized machine learning model was done for testing purposes. The proposed approaches are tested on a rapid battery charger dataset. These approaches are compared with manually evolved machine learning approaches like KNN, ANN, Multi Regression, and SVR. The proposed approaches successfully evolved, optimized, and implemented the model into a working program. It was observed that P3PGA based approach completely outperforms other machine learning-based approaches by a wider margin. Once evolved and tested, models, can be physically realized in hardware if needed.*

Keywords - *Fuzzy system, Model-identification, Machine Learning, 3PGA, P3PGA, NIC.*

1. Introduction

Machine learning is one of the most promising areas of artificial intelligence, offering tremendous opportunities for improved efficiency in almost every field. Owing to its excellent performance, machine learning (ML) has specifically found its way to industrial applications, business, trade, transportation, agriculture, medicine, health care, social sciences, entertainment, and social networks. Due to its ability to learn from data and support quick and correct decision-making, it has found widespread exploration in management. Considering the exponential growth and ever-increasing complexity of the systems being modeled, new fast and efficient ML algorithms have been expected from the research community. Fuzzy logic is the branch of machine learning which takes intelligent decisions using procedural knowledge. Professor Zadeh invented fuzzy logic technology. As shown in Fig.1, A fuzzy system consists of fuzzification, inference engine, knowledge base, and defuzzification modules.

The fuzzification module transforms the crisp inputs into fuzzy values. These fuzzy values are processed in the fuzzy domain by an inference engine based on the knowledge base. Last, the processed output is transformed from fuzzy domain to crisp values by the defuzzification module. Fuzzy model identification is the process of identifying the different parameters of a fuzzy system. Two approaches are available for fuzzy model identification: (1) the Knowledge-Based approach and (2) the Data-Driven approach. In the Knowledge-Based approach, the fuzzy system is designed with the help of a domain expert. The knowledge-based systems are usually designed manually. In the second approach complete fuzzy system is developed using the existing dataset. It is challenging in both approaches to identify the significant knowledge for the system and different optimum parameters of a fuzzy system. Another issue of the existing fuzzy system approaches was writing the code for a specific one because coding is time-consuming and complex. So, there is a need for intelligent approaches to develop the complete fuzzy system-based machine learning model from the existing dataset automatically and write the code for the developed machine learning model intelligently.

This paper focuses on the developed model's fuzzy-based machine learning model development and code generation for implementation purposes. Literature is rich with knowledge extraction and model identification algorithms [1-14]. Some additional algorithms can be explored for this kind of ML model development can be found in [15]. Fuzzy model identification is used in many ways to handle nonlinear problems [20-28]. In this paper, two new machine learning approaches are proposed, based upon a three-parent genetic algorithm (3PGA) [16] and paralleled three-parent genetic algorithm (P3PGA) [17]. 3PGA is an extension of G.A.s (Genetic Algorithm) [18], a soft computing-based search and optimization algorithm. P3PGA is an extension of 3PGA. Whereas 3PGA is a single-population algorithm, P3PGA is a multi-population algorithm. The two are relatively very recent algorithms.

The contribution of the proposed work is as follows: -

1. Automatically evolves different parameters of the fuzzy model using two nature-inspired computing approaches.
2. The proposed approaches are validated on the rapid battery charger dataset.
3. The code for a battery charger application is generated automatically using the evolved parameters of the fuzzy model.

This paper consists of five sections. Section 1 introduces the motivation behind this work, section 2 describes the ML model development concept, and Section 3 lists the 3PGA and P3PGA algorithms. Section 4 presents the ML model evolving, encoding, and optimization process. Section 5 presents simulations, results, and discussions, and section 6 concludes the paper.

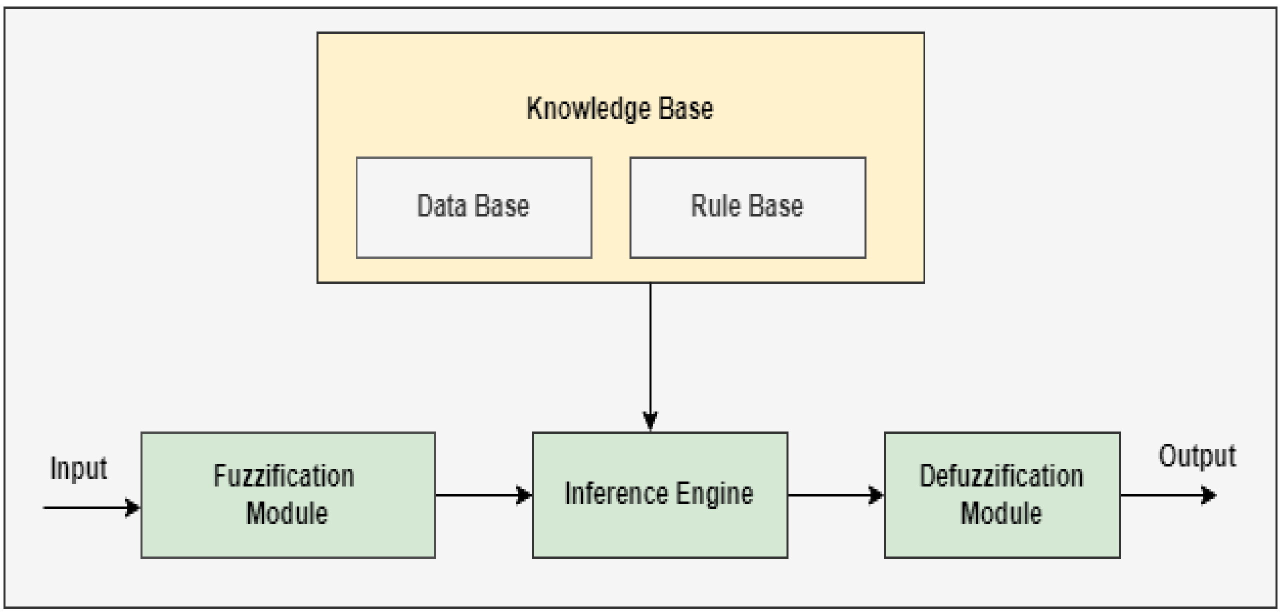


Fig. 1 Architecture of a Fuzzy system

2. Optimized Machine Learning Model Development Concept

According to the observations, a model uses existing experiences in Machine learning. Here, Experiences could be the existing data. This section proposes a novel machine learning approach using 3PGA and P3PGA soft computing algorithms. Fig.2 represents the block diagram of the proposed approach.

In the proposed approach, the model is trained using P3PGA or 3PGA algorithms, then automatically writes the code of the developed machine learning model. The soft computing approach aims to evolve a fuzzy model by identifying all optimum components of a fuzzy system. The evolved components are the fuzzification module, knowledge base, and inference engine. A population represents a set of candidate solutions in the soft computing approaches, and each candidate solution represents a complete fuzzy system with different parameters. P3PGA or 3PGA algorithms optimize candidate solutions with the help of loss function. The mean squared error (MSE) loss function is used in our proposed approach. The MSE can be implemented by using equation 1.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i + \hat{Y}_i) \tag{1}$$

Where Y_i is the actual output of i^{th} input observation, $\hat{Y}_i$ is the predicted output for i^{th} input observation, and n is the number of data points taken to train the machine learning model. The working of the proposed approach to evolve an optimized machine learning model is shown in algorithm 1.

Algorithm. 1. Proposed soft-computing-based approach to developing a fuzzy-based machine learning model

Step 1. Identify the model

Identify the most relevant input and output variables.

For each input and output variable, identify its universe of discourse.

Partition each input and output space into specified' kj' regions. These regions are called membership functions (M.F.s).

The number of M.F.s can be different for each of the variables.

Any approach to partition input and out spaces may be used. Here, a modified Fuzzy C-Means Clustering algorithm [19] is used to cluster the input and output data (for the initial setting of M.F.s).

Formulate the number of rules and antecedents of rules as follows:

Letting represent the number of membership functions (M.F.s) of jth input

(xj) where can be one of the = 2, 3, 4, …. The number of rules for the rule-base can be enumerated as follows:

$$Number\ of\ rules\ n = \prod_{j=1}^{m} k_j \qquad (2)$$

Here 'm' is the total number of inputs of the system. Combining one membership function from each of the inputs constitutes the antecedent of one rule.

Randomly assign consequent parameters to rule antecedents from within the universe of discourse of the corresponding output variable.

Step. 2. Encode the model for optimization on error measures such as mean squared error (MSE).

Step. 3. Optimize the model

A suitable algorithm may optimize the model parameters and rule-base based on performance measures such as MSE.

Depending upon the complexity of the model under development, any algorithm may not perform. If the system is highly complex and nonlinear classical algorithms become increasingly inefficient, some soft computing algorithms may be needed. Owing to their advantages, 3PGA and P3PGA unconstrained global optimization algorithms have been used.

Step. 4. Implement the model

Once the model is evolved and optimized, this part of the algorithm codes the model into a program; once the algorithm has been coded, it can predict the output for the known and unknown input data.

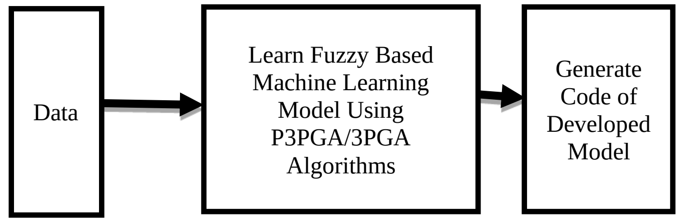


Fig. 2 Block Diagram of Proposed Machine Learning Approach

3. A Revisit to Algorithms Used for Optimizing Models

In our model generation and optimization approach, the following two algorithms are used for optimizing the evolved models:

3.1. 3PGA Algorithm [16]

1. Initialize the 3PGA parameters (individual size, population size, bounds, maximum number of generations)

   generation = 1.

2. Randomly generate a 2-parent initial population of candidate solutions.
3. Depending upon decision variables, each individual is represented by a set of genes
4. Effect Mitochondrial Change to transform the current 2-P population into a new, 3-Parent (3-P) population
5. Add current 2-Population with new 3-Population. Now population size is' 2N.'
6. Evaluate the fitness of each fuzzy model and calculate MSE (fitness function) for each model over the entire set of training examples. Select best' N' candidate solutions.
7. Using general Mechanics of G.A.s, generate a new 2-P population as given below:
   a) Select fit individuals for Crossover.
   b) With a high Px, perform the crossover process.
   c) With a low Pm, carry out mutation operation.
   d) Evaluate the fitness of each individual.
   e) Reinsert
   f) Check if any bounds are violated; correct if required.
8. If an acceptable solution is found, go to Step 11.
9. Generation = generation + 1.
10. If generation < max generation, then go to Step 4
11. Save the results
12. Stop

3.2. Parallel 3PGA (P3PGA) based approach [17]

begin

Initialize the P3PGA parameters (number of populations N, population size N.C., and individual size N.G., bounds, number of generations)

Randomly generate N populations, each consisting of N.C. candidates, with each candidate consisting of N.G. genes;

for generation = 1 : Max_generations

for i = 1 : N

Effect Mitochondrial Change to ith population to Generate a new 3-P population.

Merge current ith 2-P population with newly generated 3-P population. Evaluate fitness, sort population, and choose the best 'N.C.' individuals. Save the best solution.

Using general Mechanics of G.A.s, generate new ith 2-P population as given below:

a)

(i) Apply some fitness criteria to select fit individuals for Crossover

(ii) With a high crossover probability, perform the crossover process.

(iii) With a low mutation probability, carry out mutation operation.

b) Evaluate fitness.

c) Reinsert (Replace weak individual with more vigorous offspring keeping pop size fixed at N).

d) Check if any bounds are violated; correct if required.

e) For ith population save local best candidates ℓbest(i);

end

Considering all the best local N candidates, the globally best (gbest) candidate has been selected;

for j = 1: N do //* move population towards global best

for i = 1:NC

With a specified probability, every after a fixed number of generations, modify ith gene of each individual as given below:

Individual(i) (Individual(i) + (gbest(i)))/2

end

end

end

end

4. Model Evolving, Encoding, and Optimization

This section illustrates the application of concept and optimization algorithms, as stated in sections 2 and 3, to evolve, encode, and optimize an ML model. The following partial data set from the 2AA Nickel Cadmium battery data set as the training data set has been considered. Using this training data set in Table 1, the fuzzy logic-based machine learning model is evolved, optimized, and implemented. From the training data set, it is observed that it is a two-input single-output model.

Let us further partition Temperature into 3 membership functions, namely Temperature "Low," Temperature "Medium," and Temperature "High"; the second input Temperature gradient (TempGard) is partitioned into two membership functions, namely "Low" and High." There are 5 output membership functions identified from the training dataset.

The two input variables and their membership functions constituted the antecedents of rules, as shown in Fig 1(e). The overall model can be represented by Fig.3(a) to Fig.3(e) as given below:

Table 1. Training dataset

Temperature	TempGrad	Charging Current
0	0	4
37	0.2	4
37	1.0	4
38	1.0	3
40	0.2	3
40	1.0	2
41	0.5	2
42	1	1
43	0.5	1
43	1	1
44	0	0.1
44	0.4	0.1
45	0.5	0.1
50	0.1	0.1
50	1.0	0.1

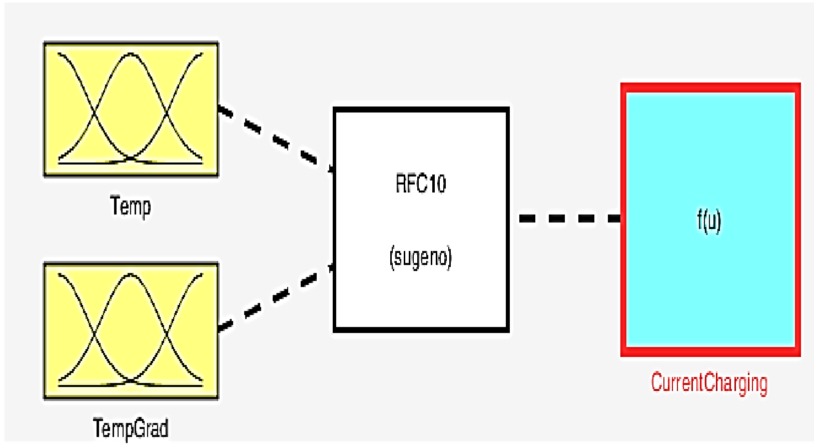


Fig. 3(a)

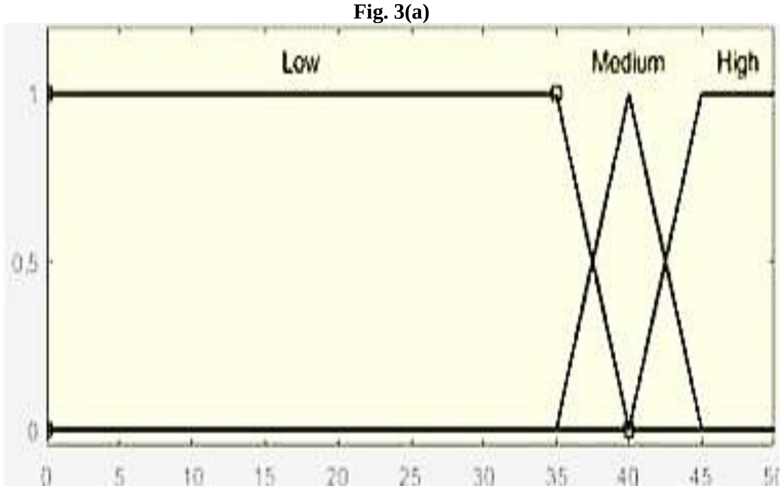


Fig. 3(b)

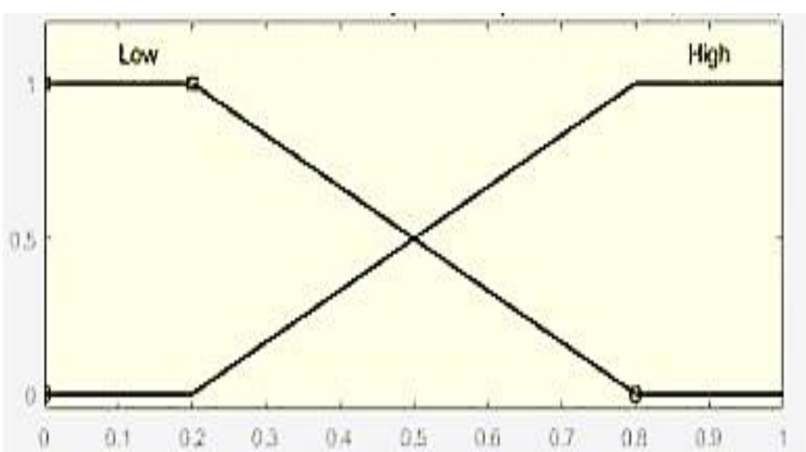


Fig. 3(c)

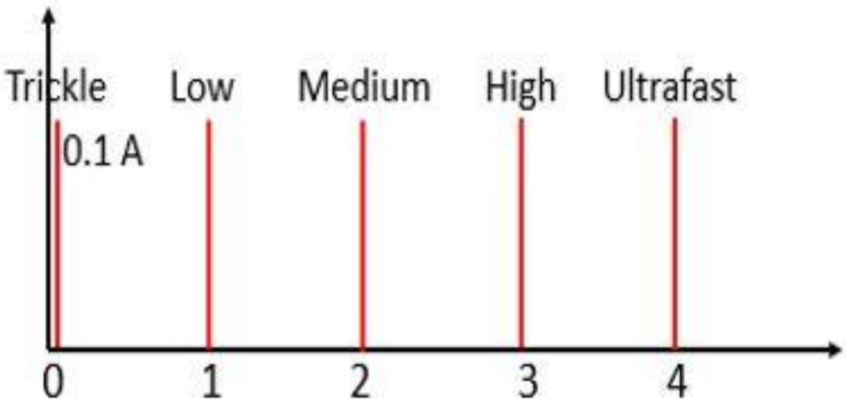


Fig. 3(d)

Knowledge Base:

If temp is LOW and TG is LOW then Charging current is ???
If temp is LOW and TG is HIGH then Charging current is ???
If temp is MED and TG is LOW then Charging current is ???
If temp is MED and TG is HIGH then Charging current is ???
If temp is HI and TG is LOW then Charging current is ???
If temp is HI and TG is HIGH then Charging current is ???

Fig. 3(e)

4.1. Encoding the Model for Optimization

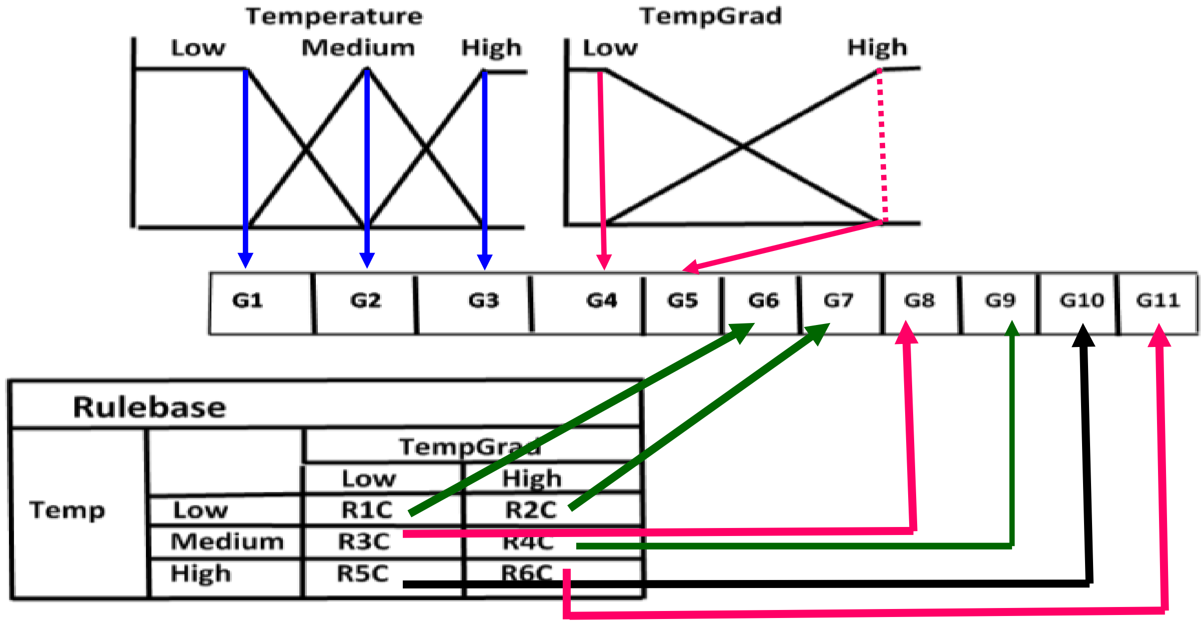
Once the model is evolved, there is a need to optimize the model. To optimize the model, the model is encoded, as shown in Fig.4. Fig.5 represents one of the models (individual). The decision variables are called genes to keep compatibility with optimization algorithms. The given inputs in the training data set are applied and compute the output of this evolved model. The computed output is compared with the desired (Target) output as specified in the training example. The error between the computed output and the target output is evaluated.

Similarly, the error for every input-output dataset (training example) has been computed, and the mean squared error (MSE) for the entire training dataset has been computed. The MSE for the training data set can be computed using equation 1. An optimized model is a model whose MSE is minimal for the given training dataset.

4.2. Optimizing the model

For the given training dataset, the mean squared error (MSE) for the entire training dataset has been computed. There is the need to search for the optimal set of structure parameters and the consequent value for each rule to minimize Mean Squared Error (MSE). The proposed algorithms simultaneously search/tune parameters of membership functions and appropriate values for rule consequents to minimize the objective function, i.e., MSE. This system identification problem can now be restated in terms of a minimization problem as follows:

Here,
'N' is the number of training examples in the training dataset.
$X_{n_{min}}$ and $X_{n_{max}}$ are the minimum and maximum values of the nth variable. G_{n_m} is mth gene associated with the nth variable. These values must stay in that order for the fuzzy system to work correctly.



Temp			TempGrad		Rule Consequents					
G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11
30	38	46	0.3	0.8	2.1	4.0	1.6	2.8	3.8	2.5

Fig. 5 Parameters of an encoded Model (individual)

5. Simulation, Results, and Discussion

As discussed in section 4, the rapid fuzzy charger problem is taken to test and validate our proposed approaches. We have implemented the two proposed approaches in MATLAB and tested the approaches on a core i7@ 2.4 GHz processor-based Laptop with 8GB RAM. Fig.7 and Fig.8 show optimization performances of one of the trials of 3PGA and P3PGA approaches. There are 51 trials conducted for each of the approaches. These proposed approaches have also been compared with manually evolved machine learning models like KNN, ANN, SVR, and multi-regression. The result of the comparative study is given in Table 2 and Fig 6. The results show that the two proposed approaches perform better than manually evolved machine learning approaches like KNN, ANN, Multi Regression, and SVR. KNN has 0.078756 MSE, and AN has an MSE of 0.024181. Moreover, the MSE of Multi Regression and SVR is 0.075119 and 0.2649181, respectively. The two proposed approaches give a better performance with 0.0096188 and 0.0094059 MSE.

The trial results of two proposed 3PGA and P3PGA-based approaches are placed in Table 3 and Fig. 9. Fig.10 presents the structure of the evolved model, and Fig.11 presents the rule base (knowledge) extracted from the given training dataset. From Table 3 and Fig. 9, it has been observed that though the worst- and best-case performances of the 3PGA approach are little better than P3PGA, the mean MSE and standard deviation performance of P3PGA are far superior to 3PGA. This difference is due to the multi-population feature of the P3PGA approach. Table 3 shows that P3PGA uses fewer (400) maximum generations compared to the 3PGA approach (2000); hence, the worst-case and best-case performances of 3PGA are better. However, with the maximum number of generations increased a bit, the P3PGA approach can also outperform the worst-case and best-case performances of the 3PGA approach.

Rule antecedents of the rule base used in Fig.11 are as defined in Fig.3(e). The model evolving and optimization approach evolved consequences for the rule base. Once the optimized structure was evolved, the third part of model implementation (coding) was carried out using the last module of the model design and development software.

Table 2. Comparative result analysis

Dataset	Machine Learning Approach	Mean Square Error (MSE)
Rapid Battery Charger	KNN	0.078756
	ANN	0.024181
	Multi Regression	0.075119
	SVR	0.2649181
	3PGA based approach	0.0096188
	P3PGA based approach	0.0094059

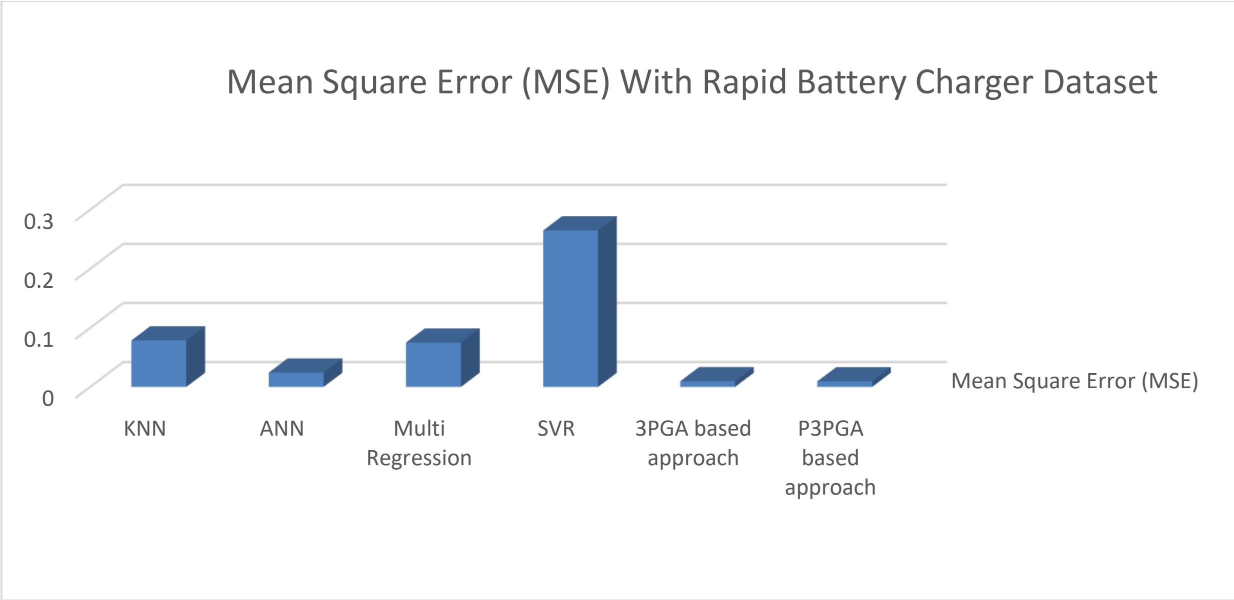
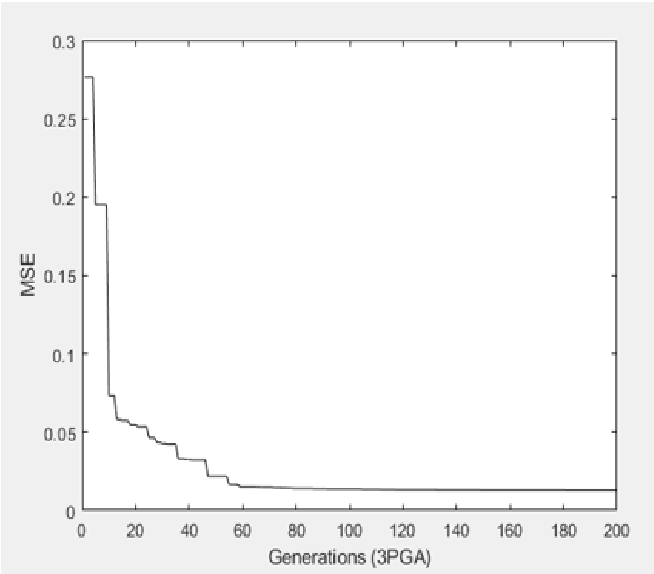


Fig. 6 Comparative result analysis of machine learning approaches



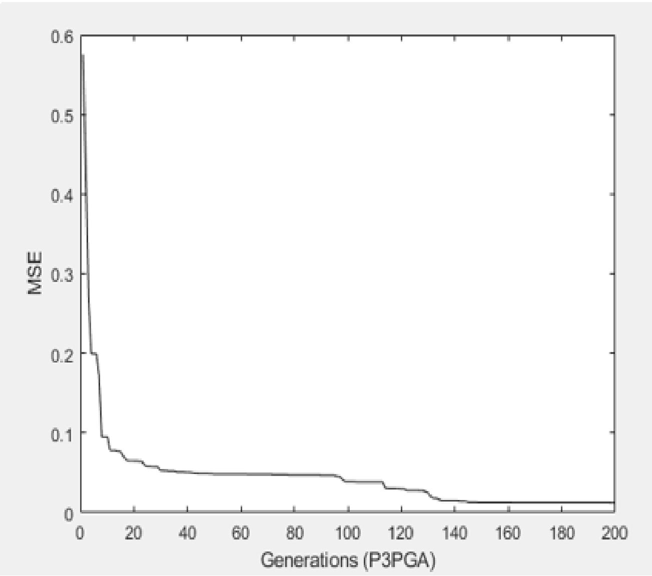


Fig. 7 MSE Vs. Generation 3PGA

Fig. 8 MSE Vs. Generation P3PGA

Table 3. Comparative Performance

	3PGA Population Size = 50; Max Generations = 2000 No. of Populations =1	**P3PGA** Population Size = 30; Max Generations = 400, No. of Populations = 5
Worst Case MSE	0.0101813884737069	0.0101845307158427
Mean MSE	0.00961889492127063	0.00940593868818421
Best Case MSE	0.0093240344541117	0.0093417645828582
Standard Deviation	0.00039555914640339	0.000197979056066777

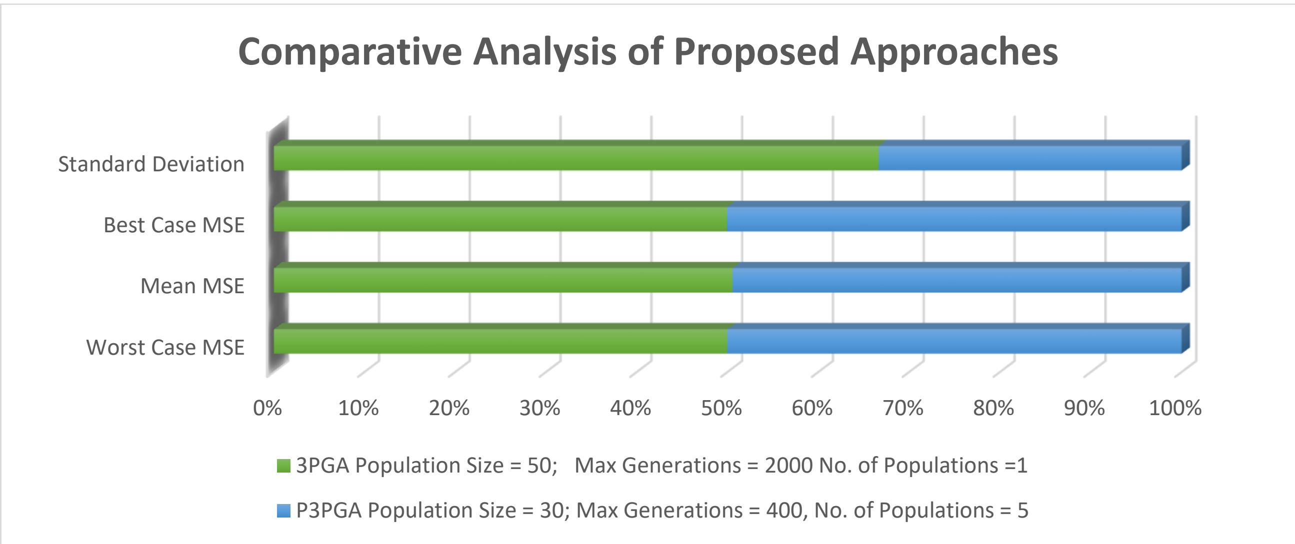


Fig. 9 Comparative Analysis of proposed approaches

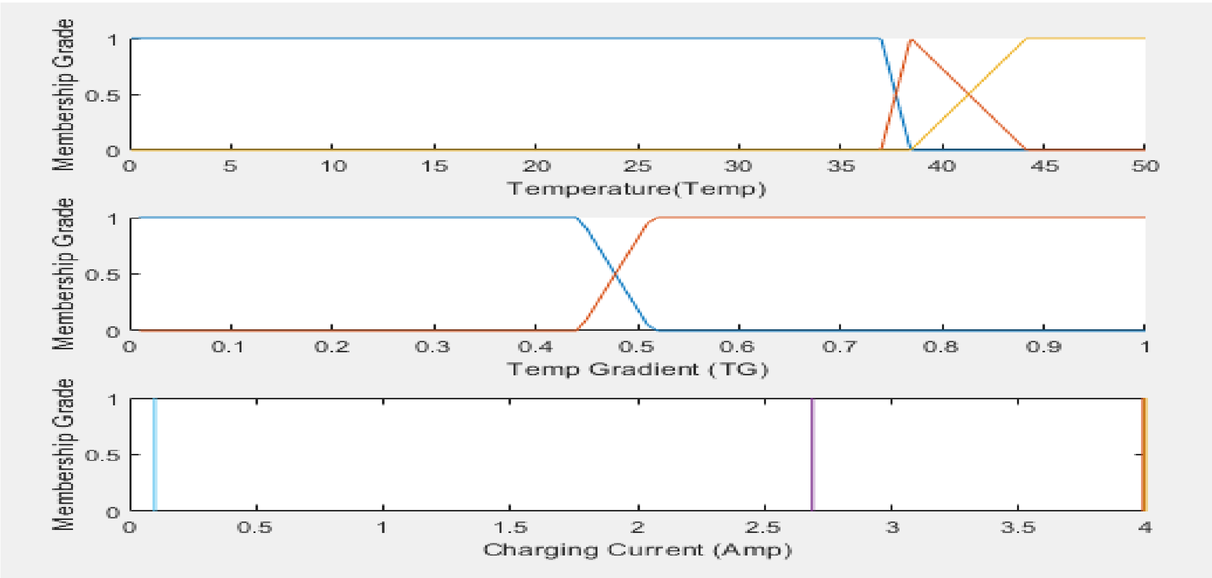


Fig. 10 Evolved Optimized Structure of a Model

```
If Temp is Low and TG is Low then Charging Current is Ultrafast
If Temp is Low and TG is High then Charging Current is Ultrafast
If Temp is Medium and TG is Low then Charging Current is Ultrafast
If Temp is Medium and TG is High then Charging Current is High
If Temp is High and TG is Low then Charging Current is Trickle
If Temp is High and TG is High then Charging Current is Trickle
```

Fig. 11 Rule base extracted from the training data set

6. Conclusion

This paper has proposed two new soft computing-based approaches to designing and developing TSK Type-0 fuzzy logic-based machine learning models from the training data. The two approaches to developing optimized models are 3PGA and P3PGA global unconstrained optimization algorithms. The proposed approaches extract optimized model structure and rule base from the training data and code the implementation model. The problem of evolving the model from training data was transformed into an optimization problem where the computed output of the model was compared with the desired output. Error for each training example was computed. The training error for each training example was used to compute the MSE for the entire training dataset. For the training dataset, 51 trials were conducted for both approaches and found that MSE for the P3PGA approach was 0.00941 against 0.00962 for the 3PGA-based approach. It has been observed that though the worst-case MSE and the best-case MSE of the 3PGA approach were better than the P3PGA-based approach, the P3PGA-based approach outperforms the 3PGA-based approach as the mean MSE of all the trials is concerned. The novel proposed approaches have also been compared with manually evolved machine learning models. The comparative results exhibit the better results of proposed approaches among manually evolved ones.

Further, the lower standard deviation also suggests the superiority of the P3PGA approach over the 3PGA approach. It has been concluded that for complex and highly nonlinear models, P3PGA produces better machine learning models than those evolved with 3PGA based approach. Once the optimized model was evolved, it was implemented (coded into a working program) by the last module of the design and development software.

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"Author 1, Author 2, and Author 3 contributed equally to this work.

Reference

[1] Li-Xin Wang and Jerry M. Mendel, "Generating Fuzzy rules from examples," *IEEE transactions on Systems, Man and Cybernetics*, Vol. 22, No.6, pp 1414-1427,1992.

[2] Jerry M. Mendel, George C Mouzouris, "Designing fuzzy logic systems," *IEEE transactions on Circuits and Systems II, Analog and Digital Signal Processing*, Vol. 44, No.11, pp 1414-1427, 1997

[3] Andreas Bastians, "Identifying fuzzy models utilizing genetic programming," *Fuzzy Sets and Systems*, 113, (2000) pp 333-350

[4] M. Setnes, R Babuska and H B Verbruggen, "Rule-based modeling: precision and transparency," *IEEE transactions on Systems, Man and Cybernetics*, Vol. 28, No.1, pp 165-169, 1998.

[5] Shiego Abe, Ming Shong Lan, "Fuzzy rule extraction directly from numerical data for function approximation," *IEEE transactions on Systems, Man and Cybernetics*, Vol. 25, No.1, pp 119-129,1995.

[6] Sugeno, M. and Kang, G.T., "Structure identification of fuzzy model," *Fuzzy Sets and Systems*, pp. 15-33, 1988.

[7] Takagi, T. and Sugeno, M. , "Fuzzy identification of systems and its applications to modeling and control" *IEEE Transactions on Systems, Man and Cybernetics*, 116-132,1985.

[8] Homaifar, A. and Mc. Cormick, E., "Simultaneous design of membership functions and rule sets for fuzzy controllers using genetic algorithms," *IEEE Transactions on Fuzzy* Systems, vol.3, no.2, 129-139,1995.

[9] Chia-Feng Juang, "Combination of Online clustering and Q-value based G.A. for reinforcement fuzzy system design," *IEEE transactions on Fuzzy Systems*, Vol. 13, No.3, pp 289-302,2005.

[10] Parvinder K., Shakti Kumar, Amarpartap Singh, "Nature Inspired Approaches for Identification of Optimized Fuzzy Model: A Comparative Study," *Journal of Multiple Valued Logic & Soft Computing*, Vol. 25, pp 555-587, 2015.

[11] Shakti Kumar, K.K. Aggarwal, Arun Khosla, "Fuzzy Modelling with Emphasis on Analog Hardware Implementation - Part I: Design" *WSEAS TRANSACTIONS on SYSTEMS*, vol.3, no.3, pp.1066-1074, 2004.

[12] Arun Khosla, Shakti Kumar and K.K. Aggarwal, "IDENTIFICATION OF STRATEGY PARAMETERS FOR PARTICLE SWARM OPTIMIZER THROUGH TAGUCHI METHOD", *Journal of Zhejiang University Science A; An International Applied Physics and Engineering Journal*, Vol. 7, No. 12, 2006.

[13] Shakti Kumar, S.S Walia, A. Kalanidhi, "Fuzzy model identification: a new parallel BB-BC optimization based approach", *International Journal of Electronics and Communication Engineering* (IJECE) ISSN (P) 2278-9901, pp. 167-178.

[14] Amar Singh, Shakti Kumar, Olaf Simanski, Ajay Singh, "Evolving a Fuzzy Logic Based Electronic Insulin Delivery Model: Three Soft Computing Based Approaches," *IEEE Journal of Biomedical and Health Informatics* (Communicated).

[15] Fister, I., Yang, X., Brest, J., & Fister, D, " A Brief Review of Nature-Inspired Algorithms for Optimization, " *ELEKTROTEHNISKI VESTNIK* , vol. 80, no.3, pp. 116–122, 2013.

[16] Amar Singh, Ajay Singh, Sukhbir Singh Walia, Shakti Kumar, "Three-Parent GA: A Global Optimization Algorithm and its Applications to Routing in WMNs," *Journal of Multiple Valued Logic & Soft Computing*, Vol. 32, pp. 407–423, 2019.

[17] Amar Singh, Shakti Kumar, Ajay Singh & Sukhbir S. Walia, P3PGA: Multipopulation 3 Parent Genetic Algorithm and its Application to Routing in WMNs, Implementations and Applications of Machine Learning Editor(s) Prof. Saad Subair and Dr. Christopher Thron, *Springer International Publishing* AG, pp. 1-28.

[18] Holland J.H., Adaptation in Natural and Artificial Systems, Ph.D. thesis, 1975, University of Michigan Press, Ann Arbor, MI , 1975.

[19] Shakti Kumar, Arun Khosla & KK Aggarwal, "Fuzzy Modeling with Emphasis on Analog Hardware Implementation: Part I," *WSEAS Transactions on Systems*, Vol. 3, no.3, pp. 1066-1074, 2004.

[20] Anh, Ho Pham Huy, and Cao Van Kien, "Hybrid fuzzy sliding mode control for uncertain PAM robot arm plant enhanced with evolutionary technique," *International Journal of Computational Intelligence Systems*, vol. 14, no. 1, pp. 594-604, 2021.

[21] Ge, Dongjiao, and Xiao-Jun Zeng, "Functional Fuzzy System: A Nonlinear Regression Model and Its Learning Algorithm for Function-on-Function Regression," *IEEE Transactions on Fuzzy Systems*, 2021.

[22] Kalibatienė, Diana, and Jolanta Miliauskaitė, "A Hybrid Systematic Review Approach on Complexity Issues in Data-Driven Fuzzy Inference Systems Development," Informatica, vol. 32, no. 1 , pp.85-118, 2021.

[23] Huang, Fei, Alexandre Sava, Kondo H. Adjallah, and Zhouhang Wang, "Fuzzy model identification based on mixture distribution analysis for bearings remaining useful life estimation using small training data set," *Mechanical Systems and Signal Processing*, vol.148, pp.107173, 2021.

[24] Wang, Xiao-li, Wei-xin Xie, and Liang-qun Li, "Interacting T.S. fuzzy particle filter algorithm for transfer probability matrix of adaptive online estimation model," *Digital Signal Processing*, vol.110, pp.102944, 2021.

[25] Hussain, Walayat, Jose M. Merigó, Muhammad Raheel Raza, and Honghao Gao, "A New QoS Prediction Model using Hybrid IOWA-ANFIS with Fuzzy C-Means, Subtractive Clustering and Grid Partitioning," Information Sciences, 2021.

[26] Kaur, Ramandeep, Amar Singh, and Shakti Kumar, "Medical Diagnosis: Implementation of Different Machine Learning Based Approaches," In 2021 9th International Conference on Reliability, *Infocom Technologies and Optimization* (Trends and Future Directions)(ICRITO), IEEE, pp. 1-5, 2021.

[27] Kaur, R., Singh, A. and Singla, J, "Integration of NIC algorithms and ANN: A review of different approaches," *In 2021 2nd International* Conference on Computation, *Automation and Knowledge Management* (ICCAKM), . IEEE, pp. 185-190, 2021.

[28] Kaur RA, Singh A, "Fuzzy logic: an overview of different application areas," *Advances and Applications in Mathematical Sciences*. Vol.18, no.8, pp.677-89, 2019.