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RESEARCH ARTICLE

Estimation Single Output with A Hybrid of ANFIS and MOPSO_HS

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ABSTRACT
Adaptive Neuro-Fuzzy Inference System (ANFIS) has gained popularity in recent years due to its predictive capabilities. Proper adjustment of ANFIS parameters is an optimization problem but integrating it with traditional optimization techniques has led to challenges such as local minima and slow convergence, resulting in obstacles to its prediction. Additionally, some researchers focusing on incorporating single-objective optimization often face issues with reliability and stability in parameter adjustment. This study, focused on multi-objective optimization, presents an algorithm that integrates ANFIS with MOPSO_HS. The proposed model, compared and applied to three real-world datasets, has demonstrated robustness in prediction problems. A comparative analysis is conducted between the proposed integrated model and well-known integrated algorithms with 20 runs. For further comparison, the Wilcoxon signed-rank test is used to determine whether there is a statistically significant difference in performance. The experimental results indicate the algorithm's accuracy, stability, and reliability in solving integration problems, highlighting its superiority over alternative approaches.

Keywords: Metaheuristic, Multi-Objective Optimization, ANFIS, Exchange Rate, Neuro Fuzzy, RMSE

1. Introduction

Numerous artificial intelligence (AI) techniques have been widely used in practical applications over the past few years. In the field of neuro-fuzzy techniques, the Adaptive Neuro-Fuzzy Inference System, also known as the Adaptive Network-Based Fuzzy Inference System (ANFIS) [1], has become more well-known. Fuzzy logic (FL) and artificial neural networks (ANN) are combined in ANFIS, which has applications in Data Science, Image processing, Finance Technology, traffic control studies, feature extraction, estimate, prediction, and more [2]. Fuzzy logic, introduced by Zadeh [3], defines membership between 0 and 1, while ANN models certain functions of human brain neurons. In ANFIS, the premise and consequence layers play pivotal roles in the network's training process. The setting of ANFIS parameters involves the use of optimization algorithms.

The original ANFIS, proposed by Jang [1], employed hybrid learning using the gradient descent (GD) algorithm for antecedent parameters and the Least Squares Error (LSE) algorithm for consequent parameters. These classical optimizations were applied to the set of ANFIS parameters. However, due to GD and LSE's tendency to get trapped in local minima, researchers turned to metaheuristic algorithms, which explore the global minimum effectively. In the metaheuristic optimization field, two types of algorithms exist: based on the derivative (gradient descent) and not based on the derivative (metaheuristic and heuristic) algorithms. While derivative-based algorithms work only on differentiable functions, ANFIS parameters can be transformed into non-differentiable functions. Hence, in this study, metaheuristic methods can solve ANFIS parameters as non-differential functions.

Fewer studies have investigated multi-objective algorithms for integration, even though some have combined ANFIS with single-objective metaheuristic optimization techniques. This paper focuses on using multi-objective algorithms to carry out tune ANFIS configurations. Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Genetic Algorithms (GA), Simulated Annealing (SA), and Hybrid Approaches that combine ANFIS with various algorithms are some of the strategies that have been investigated in this field.

The objective in this endeavor is to develop a prediction system for complicated data by emphasizing on multi-objective optimization and ANFIS. Several well-known multi-objective optimization algorithms include Non-dominated Sorting Genetic Algorithm (NSGA) [19], Non-dominated Sorting Genetic Algorithm II (NSGAII) [20], Strength–Pareto Evolutionary Algorithm 2 (SPEA2) [21], Multi-Objective Particle Swarm Optimization (MOPSO) [22], Multi-Objective Artificial Bee Colony (MOABC) [23] and Multi-Objective Grey Wolf Optimizer [24]. When combined with Adaptive Neuro-Fuzzy Inference Systems (ANFIS), these techniques greatly aid in solving practical problems and give results that are highly precise.

Hybrid ANFIS techniques have been increasingly applied to real-life scenarios in recent years, with definite advantages and disadvantages. This study aims to find out how adjusting operational factors, such as engine load and syngas composition, can improve the efficiency of a dual-fuel syngas/diesel engine while reducing pollution emissions. Using a hybrid technique of ANFIS and response surface methodology (RSM), the research simulates engine performance under different syngas compositions and compares the predicting capacities of ANFIS and RSM [25].

The other study used genetic algorithms (GA) to optimize multi-objective age-hardening process parameters while leveraging the improved performance of artificial neural networks (ANN) beyond experimental points. This demonstrated the effectiveness of ANNs [26]. The objective of other work is to precisely calculate the recompression coefficient (Cr) for over-consolidated soil using a hybrid ANFIS-PSO Machine Learning (ML) model. The model compares favorably to benchmark models of single ANFIS and Support Vector Machines (SVM) using PSO and ANFIS techniques [27].

The hybrid ANFIS-GA-PSO model, along with an extreme learning machine (ELM), is used in the research for predictive analysis. The results show that the ANFIS-GA model performs better than ELM in analyzing shear behavior. The comparison shows how well the hybrid model predicts shear strength and is analyzed using regression indices [28]. The objective of this research is to develop prediction models for a range of cut quality variables, including surface roughness, kerf taper, and material removal rate, during abrasive aqua jet cutting (AAJC) of natural fiber composite laminates. The models are created using an ANFIS and the Taguchi-genetic algorithm (TGA) [29].

In general, it has been shown in the studies that layers one and four of ANFIS have been looked at as a problem of setting parameters. So far, no study has been done on different measurements for each solution-providing parameter. In this study, with the efficiency of multi objective, it has been tried to use at least two different measurements or functions for layer one and four so that Anfis can show better accuracy. In line with the proposal, it has been tried to use the existing multi-objective algorithms. Finally, by combining the existing algorithms, efficiency, and improvement in this type of problem can be achieved.

The structure of this research paper is as follows: Section 2 provides a detailed overview of the ANFIS model. In contrast, Section 3 delves into multi-objective optimization and discusses the integration of PSO and HS algorithms for multi-objective optimization. Section 4 presents the experimental results and evaluations. Section 5 Application of Proposed Model is described, and Section 6 concludes the study, offering recommendations for further research.

2. ANFIS Tool

An artificial intelligence method called the adaptive network-based fuzzy inference system (ANFIS) blends fuzzy logic (FL) and artificial neural networks (ANN). There are five levels in the approach for each layer that provides the data set. Figure 1 is a representation of the ANFIS Framework.

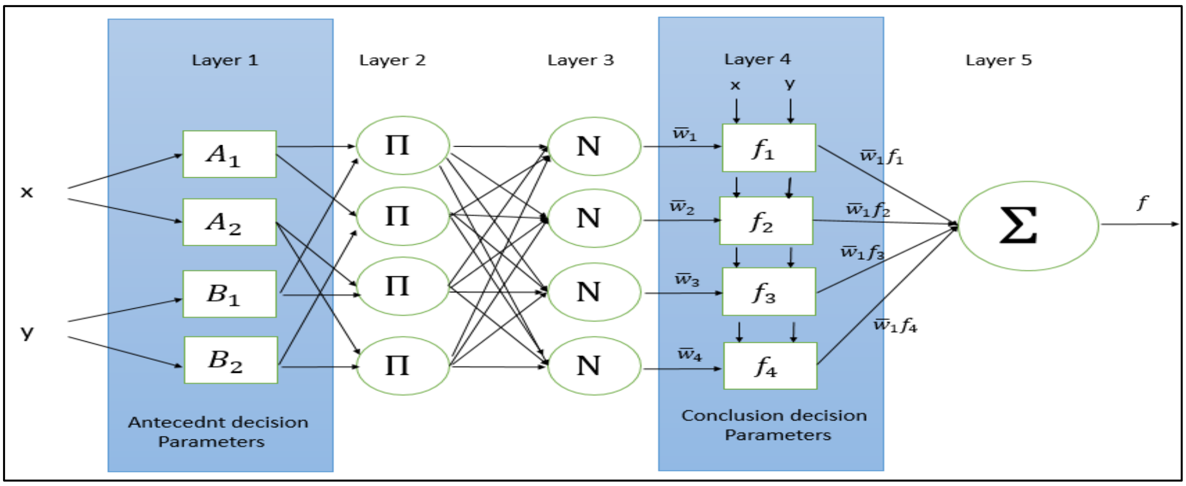


Fig 1. Example: an ANFIS Two-input Model

First Rule: İF x is A_1 and y B_1 then z is $f_1(x,y)$
Second Rule: İF x is A_2 and y B_2 then z is $f_1(x,y)$

x, y: Inputs for ANFIS
A, B: Fuzzy sets
z: $f_i(x,y)$ Outputs for Sugeno Fuzzy inference systems.

The first- and fourth-layer nodes represent parameters that have been optimized. The structure has been fixed at layers 2 and 3. The first layer has responsive nodes with the following characteristics:

$o_{1,i}$-$\mu_{A_x}(x)$ *for i=1,2* (1)
$o_{1,i}$-$\mu_{B_{i-2}}(x)$ *for i=3,4* (2)

$\mu(x)$, $\mu(y)$ are the membership functions, which can be defined as a bell shape. The formula is given as follows:

$$\mu(x) = \frac{1}{1+\left(\frac{x-c_i}{a_i}\right)^{2b_i}} \quad (3)$$

Or

$$\mu(x) = \exp\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\} \quad (4)$$

$a_i, b_i,\ c_i$ Parameters are called premise parameters. They will be changed in the training step. The output of them illustrates the power of a rule. Every fixed node in the second layer has been multiplied with the signal input from the previous layer.

$$o_{2,i} = w_i = \mu_{A_i}(x).\mu_{B_i}(y) \text{ for i=1,2} \quad (5)$$

Every node in the third layer normalizes the input data by taking into account all relevant criteria. The following formula is provided:

$$o_{3,i} = \overline{w_i} = \frac{w_i}{\sum w_i} = \frac{w_i}{w_1+w_2} \text{ for i=1,2} \quad (6)$$

Every node in the fourth layer is an adaptive layer, which has the following definition and description:

$$o_{4,i} = \overline{w_i}.f_i \text{ for i=1,2} \quad (7)$$

First Rule: if x is A_1 and y is B_1 thenf_1=p_1x+q_1y+r_1
Second Rule: if x is A_2 and y is B_2 thenf_2=p_2x+q_2y+r_2

p_i, q_i, and r_i Consequential parameters are parameters. The final layer assesses the output while it is running and computes the total output [17, 18].

$$o_{5,i} = f_{out} = \sum_i \overline{w_i}.\ f_i = \text{overall output} \quad (8)$$

3. Multi-Objective Optimization

In mathematical terms, a multi-objective optimization problem can be formulated as follows:

$$\begin{aligned}
&Min/Max\ f_m(x), && m=1,2,\ldots,M\\
&Subject\ to\ g_i(x) \geq 0, && j=1,2,\ldots,J\\
&h_k(x) = 0, && k=1,2,\ldots,K\\
&x_i^{(L)} \leq x_i \leq x_i^{(L)}, && i=1,2,\ldots,n
\end{aligned} \quad (9)$$

The optimal solution in the single-objective optimization problem is the first or last of the sorted solutions. The comparison of solutions is based on the sorting. Conversely, in the case of a multi-objective optimization issue, a solution's superiority can be determined by its domination over many values of the optimal solution.

3.1. Definition of Dominance

A solution is considered dominant if it does not perform worse than any of the objective values, and the solution on the opposing side performs better than the other in at least one of the objective values. Refer to Figure 2. A set of solutions is called a non-dominated solution set if it contains all of the solutions that are not dominated by any other feasible solution. This is how the term "Pareto front" is defined. (see Fig 2)

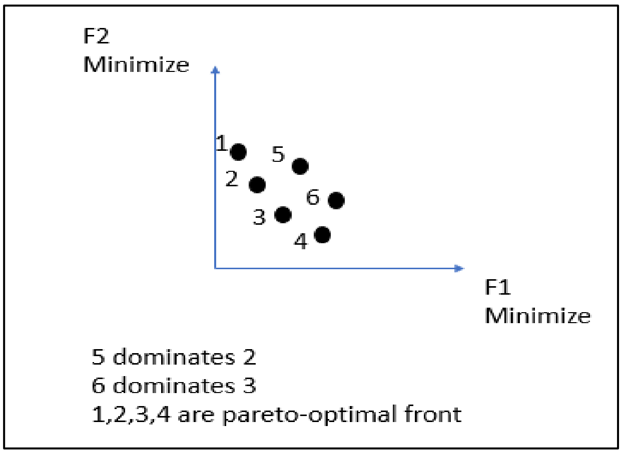


Fig 2. The Concept of Domination and Non-Pareto Front.

3.2. Multi-Objective Particle Swarm Optimization (MOPSO)

Swarm intelligence is used by MOPSO, in which a collection of particles works together to search the solution space. According to their previous best positions and the best positions discovered by their neighbors, each particle represents a potential solution to the optimization issue, and their positions are updated all over iterations. MOPSO aims to provide a set of solutions that gives decision-makers a variety of trade-offs to choose from when dealing with conflicting objectives by combining Pareto dominance with diversity-preserving processes. A sequential algorithm's general form is provided below.

1- Initialization: The population of particles should be initialized with random velocities (v_i) and coordinates (x_i). Decide on your own best positions.P_{best_i} of every particle to its starting location.
2- Objective Evaluation: Evaluate each particle's objective values:$F = \{f_1, f_2, \dots, f_k\}$
3- Pareto Dominance: Pareto dominance is used to compare particles. We have discussed before.
4- Update Individual Best and Archive:
5- Position and Velocity Updates:
Utilizing the following formulas, adjust each particle's position and velocity:V_i(t+1)=w·V_i(t)+ $c_1 \cdot r_1 \cdot (P_{best_i} - x_i$(t))+ $c_2 . r_2 \cdot (P_g - x_i$ (t)) and x_i(t+1)= x_i(t)+ V_i (t+1)
6- Mechanisms of Convergence and Diversity:
Use techniques to promote the dispersion of solutions along the Pareto front, such as crowding distance calculation, in order to achieve a balance between convergence and diversity.
7- Termination Standards:
Search for conditions that indicate when the process should end, like completing a certain number of iterations or approximating the Pareto front to a reasonable degree.
8- Goal:
The collection of non-dominated solutions that indicate the Pareto front in the external archive is the final outcome.

Wherever,
w is the weight of inertia.
The coefficients of acceleration are c_1 and c_2
There are two random variables, $r_1$and r_2 , in [0,1]
The position with the best global ranking among the non-dominated solutions in the external archive is P_g.

3.3 Multi-Objective Particle Swarm Optimization and Harmony Search (MOPSO_HS)

The proposed algorithm combines multi-objective particle swarm optimization (MOPSO) and harmony search (HS), offering flexibility and stability while seeking the global minimum. It seamlessly adapts to the ANFIS model and operates as follows: The main body of algorithms is the probability operators and mutation operators, which are complementary to each other. The Poisson cumulative distribution, the Gaussian distribution, and the mutation operator all work together to keep the balance between exploration and exploitation in our algorithm. They let the suggested algorithm look for new solutions in a way that is based on probability, get scape of around local optima, and add variety solution, which guarantees a thorough and successful search for the global minimum.

Poisson Cumulative Distribution: The Poisson cumulative distribution represents the probability that several events will take place within a specific window of time or space. About the proposed algorithm: The number of separate occurrences (represented by the variable x) is given. When calculating the Poisson cumulative distribution function, the parameter pm is employed. In point of view of Application for proposed Algorithm: Using the Poisson cumulative distribution function, randomization is added while still following a structured methodology. It enables the algorithm to balance exploitation and exploration in the search space by allowing it to investigate novel solutions probabilistically. The algorithm can take into account different probabilities when developing new solutions because of the cumulative structure of the distribution.

Gaussian Distribution: A continuous probability distribution that is symmetric about its mean and resembles a bell curve is the Gaussian distribution, commonly referred to as the normal distribution. R stands for a random variable that was utilized to choose a particular dimension.

The fret width (FW) is a parameter that affects how widely spaced out the Gaussian distribution is. Application in Algorithm: In order to add randomness to the algorithm's progress through the search space, the Gaussian distribution is used. The program searches a larger search space by producing arbitrary numbers using a Gaussian distribution and exploring the region surrounding the current solutions. This exploration technique helps the algorithm achieve global optimization by assisting in escaping local optima.

Evolutionary algorithms need to include the mutation operator. By adjusting some of the search space parameters used for determining the solutions, it provides genetic diversity to the existing population. By altering the existing solutions, the mutation operator assists in introducing novel solutions and promotes the algorithm to proceed toward uncharted areas of the search space.

MOPSO_HS Algorithm

1. **BEGIN**
2. **Initialize** swarm Positions, Velocities and evaluate fitness value
3. FW=0.02*(VarMax-VarMin);   /*Fret Width (Bandwidth)*/
4. MaxIt=100; /*Max generation*/
5. It /*generation number
6. **WHILE** (**Check** Terminate or Maximum Number of Generation is reached)
7. **BEGIN**
    a. **Select** Leader by RouletteWheelSelection method.
    b. **Update** Positions and Velocities.
    c. **Rand** (par);
    d. **If** par>0.7 Then Apply Mutation by Formula pm=(1-(it-1)/(MaxIt-1))^(1/2)
    e. **Else If** ((par<=0.7) && (par>0.3)) Then /*Gaussian*/
        i. R=Random [1..5]
        ii. Delta=FW*randn();
        iii. NewSol.Position (R)=OldSol.Position(R)+ Delta
    f. **Else**   /*Poisson cumulative distribution*/
        i. R=Random [1..5]
        ii. x = 0:4;
        iii. pm=(1-(it-1)/(MaxIt-1))^(1/2);
        iv. y = poisscdf(x,pm);
        v. Delta=FW*y;
        vi. NewSol.Position(R)=OldSol.Position(R)+ Delta
    g. **Update** Repository by truncating its member.
    h. **Update** Grid
    i. **Check** if the Repository is Full Remove the bad solution
8. **END**
9. **END**

Fig 3. MOPSO_HS Algorithm for Global Optimization

As viewed in Figure 3, which includes three sections. Roulette Wheel Selection, a fundamental genetic algorithmic technique, is used to choose a leader at the beginning of this repetitive algorithmic process. It then modifies particle placements and velocities according to selected leaders and other variables, allowing efficient search space exploration. To decide whether a mutation should be applied, a random value par between 0 and 1 is generated. If par is greater than 0.7, a decreasing factor is used to carry out the mutation, providing a balanced exploration-exploitation strategy (Figure 3-d). When 0.3<=par<=0.7,

the specified dimension's particle positions are perturbed using a Gaussian distribution (Figure 3-e).
Alternatively, the Poisson cumulative distribution is used for position perturbation if par<=0.3 (Figure 3-f). By updating the repository and grid structures, truncating inappropriate solutions, and controlling solution variety, the algorithm preserves solution quality. It dynamically adjusts to the repository's capacity while ensuring the retention of top-notch solutions. The execution of the algorithm brings this complex process to a successful conclusion, delivering a flexible and efficient optimization framework.

The algorithm is integrated with ANFIS, and then the obtained general model is applied to the data set. The dataset is categorized into 7 systems, where each system includes inputs and targets that are fed to ANFIS. The data set related to the exchange rates in Turkish Lira and Dolar from 2007 to 2020. As you can see in Figure 4, the general system contains two components: ANFIS and the real system, which are fed to ANFIS. For setting the parameters of ANFIS, all parameters in each iteration map to a vector, individual, or particle in multi-objective optimization.

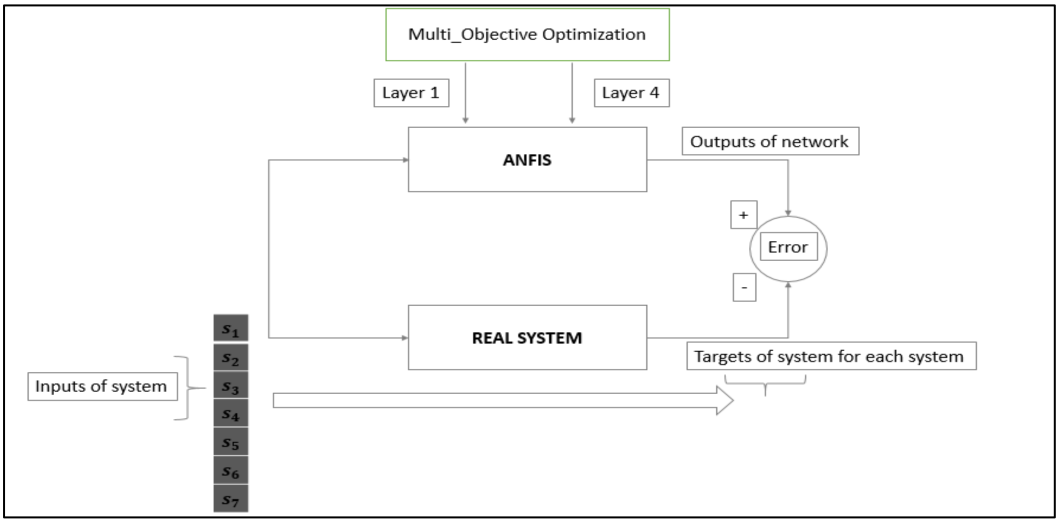


Fig 4. ANFIS and Dataset with Definition of 7 Systems

For integrating the proposed algorithm with ANFIS. Layers 1 and 4 of ANFIS are converted to one vector, which is the proposed algorithm that tries to find the best parameters for ANFIS. As you view Figure 5, parts (a) and (c) of a vector are antecedent decision parameters and conclusion decision parameters, respectively. Seven other systems also have different parameters.

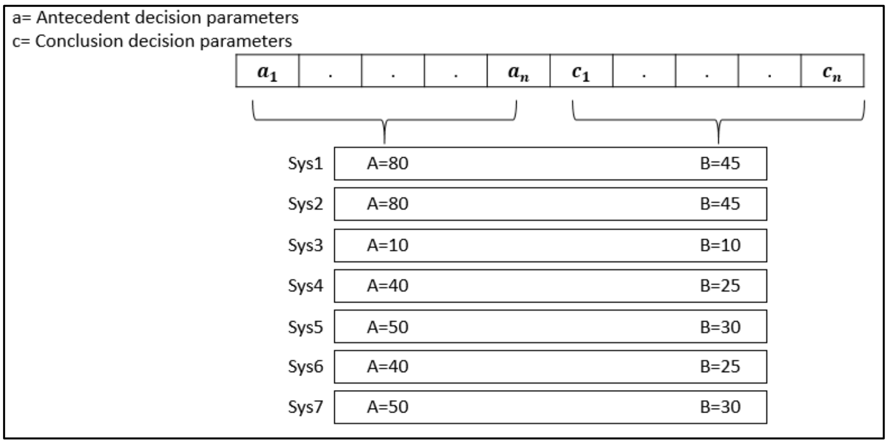


Fig 5. The Decision Variables or Vectors

Tables 1 and 2 are the definitions and descriptions of the components of systems. As you view seven systems generated by two inputs called buy and sell, the systems are generated based on the last few days for easy feed to the ANFIS. By taking this action, it will be clear and easy to extract a pattern from the complex dataset. The data set instance 151 has two inputs and is generated with a supposed target from one of the inputs.

Table 1. Definition of a Finance Problem Utilized in the Application

Name	Definition	Systems
$\boldsymbol{f_1}$	Calculating the exchange rate between USD and YTL	$\boldsymbol{S_1..S_7}$
x	Buy	x(t), time-based on the day
y	Sell	y(t), time-based on the day

Table 2. Applications Using Data Systems

Systems	Inputs of system	Target of system
$\boldsymbol{S_1}$	x(t-1),x(t-2),x(t-3),x(t-4),x(t-5),x(t-6),x(t-7)	x(t+1)
$\boldsymbol{S_2}$	y(t-1),y(t-2),y(t-3),y(t-4),y(t-5),y(t-6),y(t-7)	y(t+1)
$\boldsymbol{S_3}$	x(t)	y(t)
$\boldsymbol{S_4}$	x(t-1),x(t-2),x(t-4), x(t-6)	x(t+1)
$\boldsymbol{S_5}$	x(t-1), x(t-3),x(t-5), x(t-7)	x(t+1)
$\boldsymbol{S_6}$	y(t-1),y(t-2),y(t-4), y(t-6)	y(t+1)
$\boldsymbol{S_7}$	y(t-1),y(t-3),y(t-5), y(t-7)	y(t+1)

3.4. Fitness Function

The calculation of Mean Squared Error (MSE) involves averaging the squared deviations between the values $\hat{Y}_i$ that were predicted and those Y_i that were observed. The MSE formula is:

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(Y_i-\hat{Y}_i\right)^2 \tag{10}$$

The square root of the MSE is the RMSE. Because the error metric has the same units as the dependent variable, it is frequently employed to improve its readability.
The RMSE formula is:

$$\text{RMSE}=\sqrt{MSE} \tag{11}$$

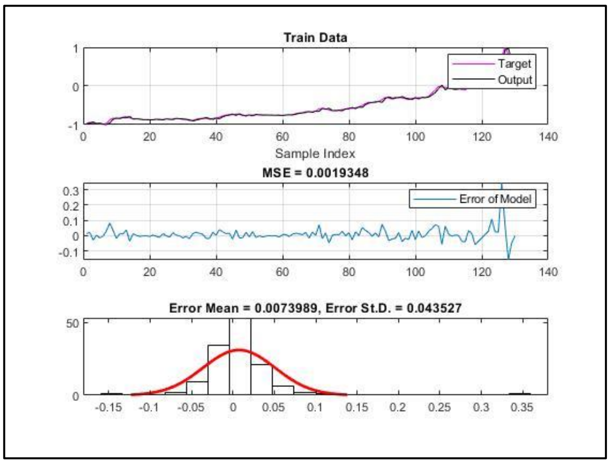
In this case, it can be said that the formulas are of the same type, and both of them are different interpretations of information. Here, the algorithms should provide the minimum value of each as a solution to a problem. The question is, if we consider these two together, the act of dominating does not make sense. By combining a small amount of imaginary noise, the problem can be transformed into a demonization. Finally, after successive execution of multi-objective algorithms, the Pareto front solution of the desired case can be obtained.

4. Result and Experiments

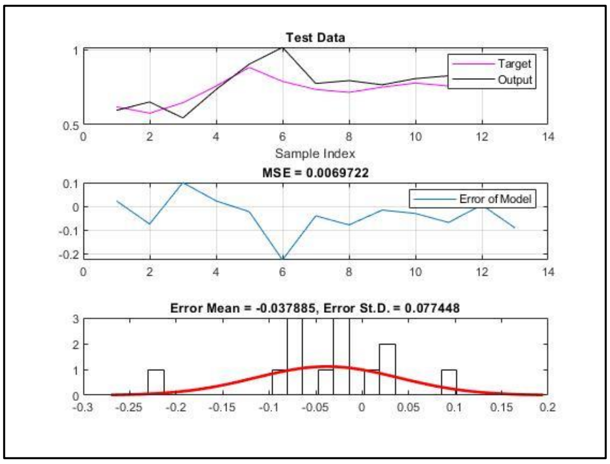
All the parameters of algorithms are tuned according to Table 3, and the other specified parameters are standard. For the input of ANFIS, Using the SUGENO technique, take five cluster inputs based on the Gaussian. Figure 6 shows one example of sys1, which is estimated using some integrated methods with ANFIS. The two basic steps of ANFIS are the train and test steps, with 138 and 13 instances of the dataset, respectively. As you observe each figure, you can find the training dataset, test dataset, mean squared error (MSE) of the target and output of the network for each instance, standard deviation, and error mean based on the bin for proper presentation. As a result, as shown in Table 4, the comparison of performance with 20 runs for the integrated ANFIS with MOPSO, NSGA2, SPEE2, MOGWO and MOPSO_HS. It is demonstrated that MOPSO_HS algorithms with specific features and complex systems outperform the others in sys 3,4,6, which is a significant feed that is odd or even intervals operate well. MOPSO in sys 1,2,7 indicates the best performance and have diversity in solving problem and it is not able to work in sequence interval. NSGA2 also only proposed the best result in sys 5. We try to prove the algorithm that provides the best results according to the given sequence based on Table 2.

Table 3. Parameters of the Metaheuristic Algorithms

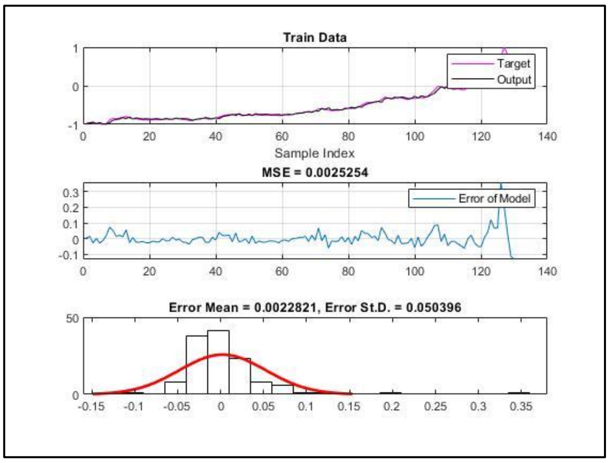
parameters	MOPSO	NSGA2	MOPSO_HS
Population size	25	25	25
iteration	100	100	100
Upper and Lower Bound	[0.1..1]	[0.1..1]	[0.1..1]



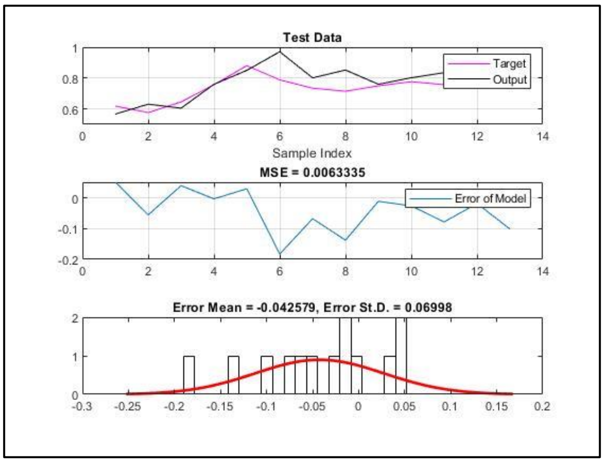
a) Train phase of the MOPSO algorithm for sys1



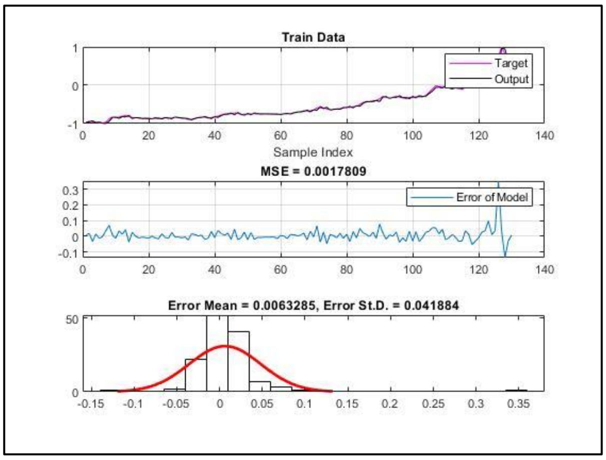
b) Test phase of the MOPSO algorithm for sys1



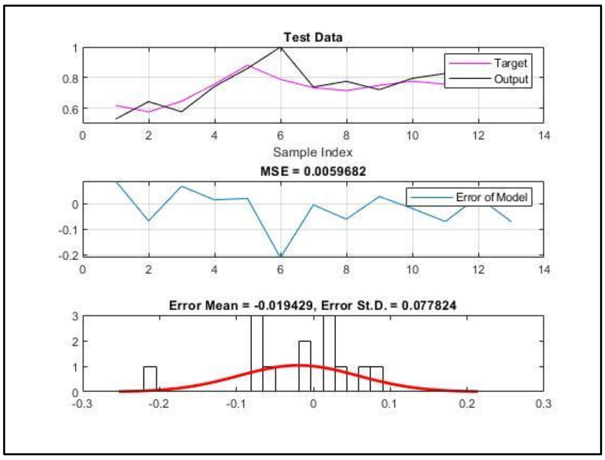
c) Train phase of the NSGA2 algorithm for sys1



d) Test phase of the NSGA2 algorithm for sys1



e) Train phase of the MOPSO_HS algorithm for sys1



f) Test phase of the MOPSO_HS algorithm for sys1

Figure 6. The Integrated Algorithms in Train and Test steps

One of the performance comparisons for each system using algorithms based on the training and testing steps' root-mean-square deviation (RMSE) appears in Table 5. We just give an example of the estimated Sys 3 using algorithms to demonstrate the performance of the models. As you view Table 6, the comparison between the target and the output of ANFIS_MOPSO_HS exhibits strong performance. To further prove the estimation model, we used one real dataset for traffic in the LTE network in 2018, which included 8735 training sets and 167 testing sets (Kaggle community). The traffic of data collected from the 4G cell for mobile phones adjacent to the cell is examined and predicted. Traffic is the total data capacity of all users within an hour that are served by an antenna cell [22]. Example: Cell 01000 is serving 60 users; each user uses an average of 10 Mb in 1 hour. Traffic in cell 01000. So, the traffic of this cell in hours x = 60 * 10 = 600 Mb. The data set includes 57 cells, and it is gathered in approximately 1 year x 24 hours x 57 cells. In Table 7. As you can see, as in the previous case, three systems have been used for modeling. The results of our algorithm are obtained with less error than other algorithms.

Table 4. Evaluation of Multi-objective Metaheuristic Algorithms' Performances in ANFIS Comparison

Algorithms	Statistic Value	Sys1	Sys2	Sys3	Sys4	Sys5	Sys6	Sys7
MOPSO	Average	4.06E-02	4.18E-02	1.80E-03	4.89E-02	4.51E-02	4.85E-02	4.38E-02
	Minimum	3.09E-02	3.27E-02	1.76E-03	4.37E-02	3.35E-02	4.22E-02	3.17E-02
	Maximum	5.05E-02	5.05E-02	1.88E-03	5.16E-02	4.97E-02	5.24E-02	5.04E-02
	Variance	2.69E-05	1.65E-05	9.16E-10	6.42E-06	1.65E-05	1.15E-05	2.74E-05
NSGA2	Average	4.29E-02	4.35E-02	1.82E-03	4.95E-02	4.34E-02	5.01E-02	4.46E-02
	Minimum	3.30E-02	3.31E-02	1.76E-03	4.32E-02	3.30E-02	4.27E-02	3.25E-02
	Maximum	4.70E-02	5.10E-02	1.99E-03	5.22E-02	4.89E-02	5.46E-02	5.12E-02
	Variance	8.41E-06	1.25E-05	3.98E-09	6.93E-06	3.18E-05	9.99E-06	3.08E-05
SPEA2	Average	4.28E-02	4.20E-02	1.93E-03	4.80E-02	4.40E-02	4.95E-02	4.32E-02
	Minimum	3.45E-02	3.39E-02	1.68E-03	3.76E-02	3.48E-02	3.69E-02	3.45E-02
	Maximum	4.48E-02	7.41E-02	3.62E-03	6.19E-02	6.41E-02	7.75E-02	5.33E-02
	Variance	4.66E-05	1.51E-05	7.13E-08	3.80E-05	3.35E-05	1.52E-05	6.20E-05
MOPSO_HS	Average	4.49E-02	4.45E-02	1.91E-03	4.76E-02	4.38E-02	4.90E-02	4.20E-02
	Minimum	3.11E-02	3.36E-02	1.65E-03	3.59E-02	3.43E-02	3.61E-02	3.39E-02
	Maximum	5.47E-02	5.39E-02	2.64E-03	5.79E-02	5.28E-02	6.05E-02	5.31E-02
	Variance	4.55E-05	1.82E-05	6.63E-08	3.70E-05	3.34E-05	2.56E-05	4.10E-05
MOGWO	Average	3.25E-01	3.60E-02	1.73E-02	3.70E-01	3.50E-04	3.85E-02	3.32E-01
	Minimum	2.20E-02	3.59E-02	1.68E-02	3.63E-02	3.47E-02	3.39E-02	3.30E-02
	Maximum	5.47E-02	4.81E-02	4.72E-02	7.25E-02	5.36E-02	8.45E-02	5.63E-02
	Variance	3.45E-02	2.61E-03	8.14E-03	4.70E-01	1.76E-02	6.22E-01	3.30E-02

* The most statistically significant outcomes are shown in bold.

Table 5. One of the Comparisons of Performance in Each System Based on RMSE

Problem	MOPSO		NSGA2		ANFIS_SPEA2		MOPSO_HS		MOGWO	
System	TR	TS	TR	TR	TR	TS	TR	TS	TR	TS
S_1	0.04	0.104	0.041	0.093	0.04	0.0102	0.093	0.206	0.05	0.098
S_2	0.042	0.102	0.04	0.086	0.051	0.077	0.086	0.219	0.081	0.075
S_3	0.002	0.003	0.002	0.056	0.002	0.052	0.056	0.24	0.030	0.046
S_4	0.052	0.075	0.051	0.072	0.057	0.072	0.072	0.107	0.046	0.064
S_5	0.046	0.101	0.045	0.078	0.046	0.089	0.078	0.118	0.075	0.095
S_6	0.052	0.086	0.052	0.078	0.021	0.091	0.078	0.118	0.039	0.076
S_7	0.044	0.089	0.045	0.07	0.048	0.077	0.07	0.121	0.65	0.47

* The most statistically significant outcomes are shown in bold.

Table 6. Compute the Sys 3 Using Multi-Objective Metaheuristic Algorithms and ANFIS

TARGET	ANFIS_MOPSO	ANFIS_NSGA2	ANFIS_SPEA2	ANFIS_MOPSO_HS	ANFIS_ MOGWO
0.247601	0.2476008	0.247601	0.247745	0.247600768	0.247901
0.328215	0.328215	0.328215	0.328316	0.328214971	0.328314
0.37428	0.3742802	0.37428	0.334587	0.37428023	0.34536
0.754319	0.7543186	0.754319	0.744901	0.754318618	0.75012
1	1	1	1	1	1
0.804223	0.8042226	0.804223	0.806040	0.804222649	0.807200
0.616123	0.6161228	0.616123	0.616421	0.616122841	0.624600
0.589251	0.5892514	0.589251	0.516401	0.58925144	0.560520
0.616123	0.6161228	0.616123	0.616147	0.616122841	0.616201
0.573896	0.5738964	0.573896	0.512606	0.573896353	0.540120
0.642994	0.6429942	0.642994	0.642910	0.642994242	0.650230
0.754319	0.7543186	0.754319	0.769512	0.754318618	0.753201
0.877159	0.8771593	0.877159	0.778418	0.877159309	0.870230
0.785029	0.7850288	0.785029	0.718202	0.785028791	0.790212
0.731286	0.731286	0.731286	0.748601	0.731285988	0.740230
0.712092	0.7120921	0.712092	0.748730	0.712092131	0.720210
0.746641	0.7466411	0.746641	0.746649	0.746641075	0.746452
0.773512	0.7735125	0.773512	0.775124	0.773512476	0.773210
0.754319	0.7543186	0.754319	0.754318	0.754318618	0.754160
0.796545	0.7965451	0.796545	0.796541	0.796545106	0.796402

Table 7. Performance of Algorithms on the Traffic of LTE Network Problem

The traffic of the LTE network				
Algorithms	Statistic Value	Sys1	Sys4	Sys5
MOPSO	Average	0.0078	0.0075	0.0082
	Minimum	0.0071	0.0071	0.0080
	Maximum	0.0079	0.0085	0.0087
	Variance	2.64E-03	2.64E-03	2.64E-03
NSGA2	Average	0.0081	0.0080	0.0082
	Minimum	0.0079	0.0079	0.0078
	Maximum	0.0082	0.0088	0.0086
	Variance	2.32E-03	2.94E-02	2.71E-03
SPEA2	Average	0.0080	0.0082	0.0090
	Minimum	0.0062	0.0069	0.0070
	Maximum	0.0085	0.0086	0.0089
	Variance	2.71E-02	2.69E-02	2.31E-02
MOPSO_HS	Average	0.0050	0.0057	0.0054
	Minimum	0.0049	0.0050	0.0048
	Maximum	0.0057	0.0059	0.0060
	Variance	3.71E-02	6.69E-02	5.61E-03
MOGWO	Average	0.0060	0.0067	0.0076
	Minimum	0.0042	0.0055	0.0068
	Maximum	0.0078	0.0088	0.0091
	Variance	6.23E-02	1.79E-02	2.52E-02

*The most statistically significant outcomes are shown in bold.

Two real benchmark datasets were also used. The first is the lowest daily temperature recorded in Melbourne, Australia, between 1981 and 1990. There are 3650 instances and it is based on degrees Celsius. The Australian Bureau of Meteorology is the data's original source. The second is a monthly total of sunspot observations spanning little more than 230 years, from 1749 to 1983. There are 2,820 instances, and the units are a count. The dataset's original source is given credit to Andrews & Herzberg (1985). The aforementioned datasets are split in half and supplied to the model for testing and training. (Refer to Table 8)

Table 8. Comparison of the Minimum daily temperatures and Sunspots datasets

Minimum daily temperatures						Sunspots			
Algorithms	Statistic Value	S1	S4	S5	Algorithms	Statistic Value	S1	S4	S5
MOPSO	Average	0.1902	0.1916	0.1915	MOPSO	Average	0.1186	0.1202	0.1190
	Minimum	0.1901	0.1917	0.1913		Minimum	0.1185	0.1201	0.1188
	Maximum	0.1904	0.1918	0.1916		Maximum	0.1188	0.1204	0.1194
	Variance	4.50e-10	5.0e-12	4.50e-10		Variance	2.0e-11	4.5e-11	1.8e-10
NSGA2	Average	0.1903	0.1917	0.1914	NSGA2	Average	0.1186	0.1202	0.1191
	Minimum	0.1901	0.1917	0.1913		Minimum	0.1185	0.1201	0.1188
	Maximum	0.1904	0.1918	0.1915		Maximum	0.1188	0.1202	0.1194
	Variance	4.5e-11	5.0e-12	2.e-12		Variance	4.5e-11	5.e-13	1.8e-10
SPEA2	Average	0.1910	0.1917	0.1911	SPEA2	Average	0.1200	0.1208	0.1208
	Minimum	0.1908	0.1917	0.1909		Minimum	0.1194	0.1207	0.1199
	Maximum	0.1912	0.1918	0.1914		Maximum	0.1206	0.1209	0.1217
	Variance	8.0e-11	5.0e-11	1.2e-10		Variance	7.2e-10	2.0e-11	1.62e-08
MOPSO_HS	Average	0.1191	0.1914	0.1905	MOPSO_HS	Average	0.1188	0.1193	0.1188
	Minimum	0.1877	0.1913	0.1905		Minimum	0.1186	0.1188	0.1188
	Maximum	0.1896	0.1916	0.1906		Maximum	0.1190	0.1199	0.1189
	Variance	1.805e-7	4.5e-11	5.e-13		Variance	8.e-12	6.05e-09	5.e-13
MOGWO	Average	0.1289	0.1990	0.1990	MOGWO	Average	0.1195	0.1223	0.1202
	Minimum	0.1280	0.1980	0.1992		Minimum	0.1194	0.1200	0.1199
	Maximum	0.1915	0.1990	0.1999		Maximum	0.1216	0.1235	0.1220
	Variance	7.2e-11	1.1e-10	4.2e-5		Variance	1.2e-05	1.0e-06	2.63e-04

* The most statistically significant outcomes are shown in bold.

4.2. Wilcoxon Signed Rank Test for Comparison

Three algorithms—NSGA2, SPEA2, and MOGWO—with min metric are compared to the algorithm MOPSO_HS in seven different systems (Sys1 through Sys7). The Wilcoxon signed-rank test, which is the foundation of every comparison, indicates whether there is a statistically significant difference in performance. In Table 9. Indicates the result of the Wilcoxon Signed Rank Test for each Sys.

For Sys1, NSGA2 and SPEA2 (p-values of 0.688 and 0.109, respectively) did not show a significant difference when compared to MOPSO_HS. However, with a p-value of 0.031, MOGWO showed a statistically significant difference, indicating better performance in this situation. With p-values of 0.031 and 0.001, respectively, NSGA2 and MOGWO demonstrated statistically significant differences when compared to MOPSO_HS in Sys2. SPEA2, on the other hand, showed no discernible variation (p = 0.312). Sys3 showed a similar trend, with MOGWO demonstrating significance (p = 0.219), indicating its higher performance, whereas NSGA2 and SPEA2 failed to show significant differences (p-values of 0.109 and 0.031). Sys4 through Sys7 are analyzed, with different results for each system. Interestingly, Sys5 showed substantial differences for each of the three algorithms, suggesting that it performs differently from MOPSO_HS.

Table 9. The result of the Wilcoxon Signed Rank Test for each Sys

Algorithm	Test Statistic	p-value	Significant
Sys 1			
NSGA2	-0.5	0.688	No
SPEA2	-2.0	0.109	No
MOGWO	-3.0	0.031	Yes
Sys 2			
NSGA2	-3.0	0.031	Yes
SPEA2	-1.0	0.312	No
MOGWO	-6.0	0.001	Yes
Sys 3			
NSGA2	-2.0	0.109	No
SPEA2	-3.0	0.031	Yes
MOGWO	-1.5	0.219	No
Sys 4			
NSGA2	-0.5	0.688	No
SPEA2	-1.5	0.219	No
MOGWO	-2.5	0.078	No
Sys 5			
NSGA2	-4.0	0.004	Yes
SPEA2	-3.5	0.031	Yes
MOGWO	-4.5	0.004	Yes
Sys 6			
NSGA2	-2.0	0.109	No
SPEA2	-0.5	0.688	No
MOGWO	-3.0	0.031	Yes
Sys 7			
NSGA2	-2.5	0.078	No
SPEA2	-1.0	0.312	No
MOGWO	-5.0	0.004	Yes

When integrating these algorithms with ANFIS, their own set of disadvantages should be taken into consideration. NSGA-II algorithm maintains a variety of approaches and applies elitism to achieve several goals, but it might need numerous evaluations. SPEA2 algorithm comprises diversity preservation and elitism but requires parameter adjusting and can be computationally expensive. MOPSO_HS algorithm requires parameter tuning but combines the exploration of PSO with the local search of Harmony Search. It can be used for a variety of situations. MOGWO algorithm employs a population-based methodology inspired by the grey wolf; while effective, it necessitates careful parameter selection and may encounter certain issues.

5. Application of Proposed Model

The suggested model provides a wide variety of potential applications in various companies and industries since it combines innovative multi-objective optimization methods with an ANFIS model. The model can be used for business processes for market analysis, business process optimization, and financial forecasting. For example, it can predict stock prices better, improve the efficiency of supply chain operations, and improve marketing strategies by analyzing client behavior. The model's combination of an ANFIS model with multi-objective optimization algorithms may lead to more precise forecasts in the stock market. Using past stock data and market trends, the algorithm may be able to spot linkages and patterns that traditional analysis methods might have missed. This can help investors and financial analysts make better decisions about buying, selling, or holding onto stocks, which will ultimately enhance portfolio management and boost return on investment.

Moreover, the model can be used to assess and enhance several aspects of the supply chain, such as inventory control, production scheduling, and distribution, in terms of supply chain optimization. The approach considers several criteria, such as cost minimization, lead time reduction, and customer satisfaction maximization, to develop optimal solutions that strike a balance between conflicting objectives. This might result in a supply chain that is more adaptable and efficient, which would save costs, raise satisfaction with clients, and increase the company's overall competitiveness.

Additionally, the proposed methodology has the potential to revolutionize the product development process by offering insights into market demands and forecasting product performance. Through analyzing consumer behavior and market trends, the technique helps businesses find opportunities for new products. It fills gaps in the market, leading to more targeted and successful product launches. In order to ensure that the finished products meet customer needs and expectations, the model can also be used to improve product designs for greater usefulness and cost-effectiveness.

Systems and structures can be designed using the model to have the least amount of environmental impact and energy usage. Through the optimization of building design, insulation, lighting, and HVAC (heating, ventilation, and air conditioning) systems, the model has the potential to significantly reduce energy expenditures and carbon emissions. Additionally, the model can help with the development of intelligent energy management systems, which monitor energy consumption and adjust based on occupancy and usage trends. When everything is said and done, companies and the environment will benefit greatly from the implementation of the proposed model for energy efficiency and product development. Reduced expenses, improved competitiveness, and a lesser carbon impact are some of these advantages.

Overall, the suggested model offers a strong strategy for tackling difficult problems in a range of industries and provides a route forward for more effective, competitive, and environmentally friendly business operations. When put into practice, it could lead to beneficial changes in how businesses run and innovate, as well as open up new opportunities.

6. Conclusion and Future Work

The study introduces innovative multi-objective optimization algorithms integrated with an ANFIS model, demonstrating their superiority over other integrated estimation methods. The dataset, sourced from the Central Bank of the Republic of Turkey and spanning TL and dollar exchange rates from 2007 to 2020, served as the basis for the analysis. Notably, predictions in sys 3, 4, and 6 exhibited the best performance. To further validate the algorithm's efficacy, standard datasets including LTE network traffic, minimum daily temperatures, and sunspot dataset temperatures were examined. The investigation revealed that the proposed algorithm (ANFIS_MOPSO_HS) surpassed ANFIS_MOPSO, ANFIS_NSGA2, MOGWO, and ANFIS_SPEA2 in terms of stability and reliability when applied to real data. This indicates its potential applicability across various real-world systems. In conclusion, the study affirms the applicability of the proposed model in different real-world contexts. In order to further enhance the multi-objective optimization algorithms connected to the ANFIS model, the paper's future studies will concentrate on evaluating new features and increasing parameters. We intend to expand the model's use to non-financial domains such energy forecasting and other financial sectors include stock market forecasting. As well as we intend to improve algorithmic performance to handle larger datasets and integrate real-time data streams. To further guarantee the robustness and generalizability of the model, we plan to perform out validation tests utilizing a variety of datasets. In order to enhance prediction, the model also aims to investigate how well the model integrates with cutting-edge technologies, including edge computing, blockchain, and the Internet of Things.

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