*International Journal of*
*Mathematical Modelling & Computations*
Vol. 12, No. 04, Fall 2022, 299- 312
DOI:10.30495/ijm2c.2023.1955549.1251

# Improving the Performance of Adaptive Neural Fuzzy Inference System (ANFIS) Using a New Meta-Heuristic Algorithm

M. Khadem[a], A. Toloie Eshlaghy[a,*] and K. Fathi Hafshejani[b]

[a]*Department of Industrial Management, Science and Research Branch, Islamic Azad University, Tehran, Iran,*
[b]*Department of Industrial Management, South Tehran Branch, Islamic Azad University, Tehran, Iran.*

**Abstract.** The adaptive fuzzy neural inference system (ANFIS) is an efficient estimation model not only among fuzzy neural systems but also among other types of machine learning techniques. Despite its acceptance among researchers, ANFIS cited limitations such as inefficiencies in large data and data problems, cost of computation, processing time and optimization, and error training. The ANFIS structural design is a complex optimization problem that can be improved using meta-heuristic algorithms. In this study, to optimize and reduce errors, a new meta-heuristic algorithm inspired by nomadic migration was designed and used to design an adaptive fuzzy neural system called the Qashqai nomadic meta-heuristic algorithm. The results of the hypothesis test showed that the Qashqai optimization algorithm is not defeated by the genetic algorithm and particle swarm and works well in terms of convergence to the optimal answer. In this hybrid algorithm, random data set are first generated and then trained by designing a basic fuzzy neural system. Subsequently, the parameters of the basic fuzzy system were adjusted according to the modeling error using the meta-heuristic optimization algorithm of Qashqai nomads. The fuzzy nervous system with the best values was obtained as the final result. The main achievements of the study are:

- Improving ANFIS accuracy using a novel meta-heuristic algorithm.
- Fix and remove some problems and Limitations in the ANFIS model, such as inefficiencies in large data, cost of computation, Answer accuracy, and reduce errors.
- Comparing the proposed ANFIS+QA with some recent related work such as ANFIS+QA and ANFIS+Pso.

Received: 25 March 2022, Revised: 02 December 2022, Accepted: 25 December 2022.

**Keywords**: Optimization, Adaptive neural fuzzy inference system (ANFIS), Meta-heuristic algorithm, Genetic algorithm (GA), Particle swarm algorithm (PSO), Qashqai algorithm (QA).

**Index to information contained in this paper**



## 1. Introduction

The optimization concept extends from engineering design to financial markets, stock exchanges, hotels, and tourism. An organization seeks to maximize profits, minimize costs, and maximize efficiency. With the rapid development of computers and the increasing volume of information and data, we have encountered concepts such as big data

*Corresponding author. Email: toloie@gmail.com

and large dimensions in recent decades. Among these, the science of machine learning has found a special place. In the science of machine learning, the subject of designing machines is dealt with, using the examples given to them and learning from their own experiences. In machine learning, instead of programming everything, the data is given to a general algorithm, and it is this algorithm that builds its logic based on the data given to it. These algorithms are classified into three categories: supervised learning, unsupervised learning, and reinforcement learning.

One of the applicable optimization models is artificial fuzzy neural system, which has various applications in solving significant scientific and practical problems Such as predicting financial markets, medicine, predicting Covid-19, robot navigation, network intrusion, and rainfall modeling [12,14,27,31,48,50,52,53,59].

Adaptive neuro-fuzzy inference system (ANFIS) is a soft computation approach that includes the powers of fuzzy inference mechanisms as well as artificial neural networks (ANN). ANFIS is driven by a strong generalization capacity with a quick and accurate learning process [15].

This paper aims to design an adaptive neural fuzzy inference system optimally.

Although widely used, ANFIS has a major weakness in computational complexity. The number of rules and their configurable parameters increases exponentially when the number of inputs is large. Furthermore, the standard ANFIS learning process involves gradient-based learning, which tends to collapse into local minima [15].

In order to solve these troubles, we use the Qashqai meta-heuristic algorithm to approach the optimal solution, adjust its parameters, and enhance the artificial neural network system performance. Meta-heuristic algorithms are algorithms inspired by natural, physical, and biological processes [24]. Meta-heuristic algorithms use the fitness function, exploration (diversification), and intensification to evaluate and search, and they can discover the answer due to collective intelligence.

The main question of this research is:

• How can we enhance the ANFIS model's performance, improve the answers' accuracy and reduce the error by using a novel meta-heuristic algorithm?

## 2. The adaptive neuro-fuzzy inference system (ANFIS)

The adaptive neural fuzzy inference system (ANFIS) is a type of artificial neural network based on the Takagi-Sugeno fuzzy inference system developed by Jang in 1993[17]. Because it integrates both neural networks and fuzzy logic principles, it is possible to take advantage of both in a single framework. Its inference system corresponds to a set of if-then ambiguous rules that can learn approximate nonlinear functions. ANFIS combines neural network and fuzzy inference systems so that both algorithms complement each other to minimize the limitations of a single algorithm. It is a useful modeling tool for a complex and nonlinear process in a single framework. The schematic module diagram of the ANFIS model is shown in Figure 1, which consists of five functions: fuzzy maker, database, rule base, inference motor, and defuzzification maker module [19].

In general, the structure of ANFIS consists of two main parts: introduction and conclusion. These sections interact with each other through fuzzy rules in the network structure. ANFIS is trained and updated using parameters.

ANFIS in solving various problems including spatial prediction of groundwater potential [6], intelligent prediction of ground vibrations [56], modeling of 3D printer parameters [55], brain tumor diagnosis [51], determining factors Infection rate covid19 [4], drought prediction [38], text summary [26], robot navigation [29], prediction of residential power consumption in smart grid [39], distribution networks [35], improving power system stability [28], induction motor error detection [33] has been used.

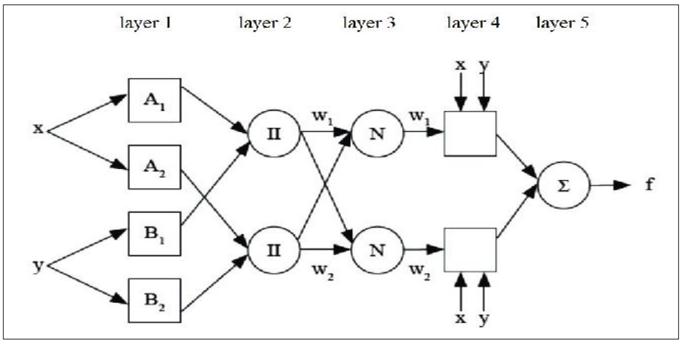



Figure 1. General structure of adaptive neuro-fuzzy inference system (ANFIS).

## 3. Optimization of neural-fuzzy inference system using meta-heuristic algorithms

Today, in solving optimization problems, the idea of using only a single model has been replaced by more powerful hybrid models. Meta-heuristic optimization algorithms are the most common methods for which the development of hybrid models has been proposed and used [20].

In recent years, meta-heuristic algorithms have been used to solve various complex problems such as job-shop scheduling problems [58], hub network design [7, 25, 42], supply chain [11], electric vehicle operation [18], and wireless sensor networks [30].

Table 1 summarizes the hybrid meta-heuristic neural network algorithms. Table 2 summarizes the use of meta-heuristic algorithms to optimize the neural-fuzzy inference system.

Table 1. Hybrid meta-heuristic neural network algorithms.

| | Title | Hybrid | Authors | Year | journal | Ref |
|---|---|---|---|---|---|---|
| 1 | A new hybrid optimization algorithm for multiple mobile robots navigation based on the CS-ANFIS approach | CS-ANFIS | PK Mohanty, DR Parhi | 2015 | Memetic Computing | [34] |
| 2 | Speed Control of Brushless DC motor using bat algorithm optimized Adaptive Neuro-Fuzzy Inference System | Bat -ANFIS | K Premkumar, Manikandan | 2015 | Applied Soft Computing | [43] |
| 3 | Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization, wavelet transform, and mutual … | Pso -ANFIS | GJ Osório, JCO Matias, JPS Catalão | 2015 | Renewable Energy | [40] |
| 4 | Modeling of compressive strength of Geopolymers by a hybrid ANFIS-ICA approach | ICA-ANFIS | A Nazari, JG Sanjayan | 2015 | Journal of Materials in Civil Engineering | [37] |
| 5 | Accelerated mine blast algorithm for ANFIS training for solving classification problems | mine blast algorithm-ANFIS | P Raja, B Pahat | 2016 | International Journal of Software Engineering | [46] |
| 6 | A framework of training ANFIS using chicken swarm optimization for solving classification problems | chicken swarm optimization-ANFIS | M Zarlis, ITR Yanto, D Hartama | 2016 | International Conference on Informatics and Computing (ICIC) | [60] |

| | | | | | | |
|---|---|---|---|---|---|---|
| 7 | Training ANFIS using catfish-particle swarm optimization for classification | catfish-pso -ANFIS | N Hassan, R Ghazali, K Hussain | 2016 | International Conference on Soft Computing and Data Mining | [13] |
| 8 | Assessing the suitability of hybridizing the Cuckoo optimization algorithm with ANN and ANFIS techniques to predict daily evaporation | Cuckoo -ANFIS | J Piri, K Mohammadi, S Shamshirband | 2016 | Environmental Earth Sciences | [41] |
| 9 | Optimization of ANFIS using artificial bee colony algorithm for classification of Malaysian SMEs | ABC-ANFIS | MNM Salleh, K Hussain, R Naseem | 2016 | International Conference on Soft Computing and Data Mining | [49] |
| 10 | Training ANFIS by using the artificial bee colony algorithm | ABC-ANFIS | D KARABOĞA, E Kaya | 2017 | Turkish Journal of Electrical | [21] |
| 11 | A novel hybrid ICA-ANFIS model for prediction of manufacturing processes performance | ICA- ANFIS | H Baseri, M Belali-Owsia | 2017 | Proceedings of the Institution of Mechanical Engineers | [3] |
| 12 | Shear wave travel time estimation from petrophysical logs using ANFIS-PSO algorithm: A case study from Ab-Teymour Oilfield | ANFIS-PSO | M Anemangely, A amezanzadeh | 2017 | Journal of Natural Gas Science and Engineering | [2] |
| 13 | H2-selective mixed matrix membranes modeling using ANFIS, PSO-ANFIS, GA-ANFIS | ANFIS- PSO, GA | M Rezakazemi, A Dashti, M Asghari | 2017 | International Journal of Hydrogen Energy | [47] |
| 14 | Application of constitutive description and integrated ANFIS–ICA analysis to predict hot deformation behavior of Sn-۵Sb lead-free solder alloy | ANFIS–ICA | H Vafaeenezhad, SH Seyedein, MR Aboutalebi | 2017 | Journal of Alloys and Compounds | [54] |
| 15 | Feasibility of pso-anfis-pso and ga-anfis-ga models in the prediction of peak ground acceleration | pso-anfis-pso , ga-anfis-ga | A Kaveh, SM Hamze-Ziabari | 2018 | International Journal of Optimization in Civil Engineering | [22] |
| 16 | Application of ANFIS-GA algorithm for forecasting oil flocculated asphaltene weight percentage in different operation conditions | ANFIS-GA | E Keybondorian, B Soltani Soulgani | 2018 | Petroleum Science and Technology | [23] |
| 17 | Training ANFIS using The Whale Optimization Algorithm | ANFIS -Whale | M Canayaz, R Özdağ | 2018 | International Conference on Advanced Technologies | [5] |
| 18 | An Improved ANFIS with Aid of ALO Technique for THD Minimization of Multilevel Inverters | ANFIS- ALO | R Francis, D Meganathan | 2018 | Journal of Circuits, Systems, and Computers | [10] |
| 19 | Novel hybrids of adaptive neuro-fuzzy inference system (ANFIS) with several metaheuristic algorithms for spatial susceptibility assessment of seismic-induced landslide | PSO, GA, ACO, DE-ANFIS | H Moayedi, M Mehrabi | 2019 | Geomatics, Natural Hazards, and Risk | [32] |
| 20 | Genetic and firefly metaheuristic algorithms | ANFIS- GA and firefly | A Jaafari, SVR Termeh | 2019 | Journal of Environmental | [16] |

| | | | | | | |
|---|---|---|---|---|---|---|
| | for an optimized neuro-fuzzy prediction modeling of wildfire probability | | | | Management | |
| 21 | Feasibility of ANFIS-PSO and ANFIS-GA models in predicting thermophysical properties of Al2O3-MWCNT/oil hybrid nanofluid | ANFIS- PSO, GA | IM Alarifi, HM Nguyen | 2019 | Materials | [1] |
| 22 | Performance Evaluation of a Hybrid ANFIS Model and Meta-Heuristic Algorithms in Optimal Operation of Dam Reservoir | Hybrid ANFIS Meta-Heuristic | MH Rabiei, MT Aalami | 2019 | Water and Soil Science | [44] |
| 23 | Performance evaluation of gang saw using hybrid ANFIS-DE and hybrid ANFIS-PSO algorithms | ANFIS-DE, PSO | AR Dormishi, M Ataei, R Khaloo Kakaie | 2019 | Journal of Mining and Environment | [8] |
| 24 | Optimized ANFIS model using hybrid metaheuristic algorithms for Parkinson's disease prediction in IoT environment | ANFIS-hybrid metaheuristic | IM El-Hasnony, SI Barakat, RR Mostafa | 2020 | IEEE Access | [9] |
| 25 | Pattern-based Short-Term Load Forecasting using Optimized ANFIS with Cuckoo Search Algorithm | ANFIS-CS | M Mustapha, S Salisu, AA Ibrahim | 2020 | Intl Congress on Human-Computer Interaction | [36] |
| 26 | Customer Churn Modeling via the Grey Wolf Optimizer and Ensemble Neural Networks | ANFIS-Grey Wolf | Rahmaty, M., Daneshvar, A., Salahi, F., Ebrahimi, M., & Chobar, A. P. | 2022 | Discrete Dynamics in Nature and Society | [45] |

Table 2. Summary of the use of meta-heuristic algorithms to optimize the artificial neural-fuzzy inference system (ANFIS).

| | Algorithm | References |
|---|---|---|
| **Optimization of artificial neural-fuzzy inference system (ANFIS) using meta-heuristic algorithms** | Genetic algorithm (GA) | [1],[16],[22],[23],[32] |
| | Particle swarm algorithm (PSO) | [1],[2],[8],[13],[22],[32],[40],[47] |
| | Imperialist competitive algorithm (ICA) | [3],[37],[54] |
| | Cuckoo search (CS) | [34],[36],[41] |
| | Artificial bee colony algorithm (ABC) | [21],[49] |
| | Differential evolution algorithm (DE) | [6],[8] |
| | Other meta-heuristic algorithms | [46],[60],[13],[5],[10] |

ANFIS structure design is a complex optimization problem that can be improved using meta-heuristic algorithms. Meta-heuristic algorithms are algorithms that are inspired by natural, physical, and biological processes. The method proposed in this paper first designs an initial ANFIS structure and then uses a new meta-heuristic algorithm called the Qashqai nomad's meta-heuristic algorithm to optimize it.

## 4. Qashqai nomad’s meta-heuristic algorithm (QA)

A meta-heuristic algorithm is a higher-level innovative method that can be used, especially with little information and little change, to search for and find optimal solutions to various optimization problems. The use of meta-heuristic algorithms significantly increases the ability to find high-quality solutions to solve complex optimization problems. A common feature of these algorithms is the use of local optimal exit mechanisms [1].

The Qashqai nomads' meta-heuristic algorithm is a population-based meta-heuristic algorithm introduced in this article. Collective intelligence How nomads migrate the components and subtleties of life and nomads that result from group experience, perseverance, and cooperation of tribal members and the achievement of desirable solutions that are intuitively and systematically passed from generation to generation, the idea of designing an algorithm It has been a Qashqai initiative. The algorithm's name has been chosen in honor of the Qashqai tribe from the famous tribes of southwest Iran Qashqai algorithm.

## 5. Method of designing the meta-heuristic algorithm of Qashqai nomads

### 5.1 *Create an initial population*

Suppose the tribe has $n$ members, each with a starting point for migration (from summer to winter and vice versa). The starting point for the migration of each member of the tribe is random in the possible space of the problem.

### 5.2 *Elite selection (Elitism)*

Tribes usually have their tribal territory and are governed by the leadership of Ilkhan or Il Bey. Tribal elders have a rich collection of experiences on the best and least dangerous routes in their memory, and they refer to their long-term memory more when crossing migration routes. Younger members of the tribe, on the other hand, have less experience and short-term memory, and therefore rely less on their memory and more on their previous position. On the other hand, the white-bearded people of the tribe are less likely to use their previous position as a criterion for their next move. The algorithm for updating new locations inspires this.

$$x_i^{t+1} = C_1 * \frac{fitness(pop(i)) - m_1}{m_2 - m_1} * {x_i}^t + C_2 * \frac{m_2 - fitness(pop(i))}{m_2 - m_1} * rand[varmin, varmax] \tag{1}$$

Other members of the population have been updated according to Equation (2). $m_1$ is the best solution in each iteration and $m_2$ is the worst solution.

$$x_i^{t+1} = C_1 * \frac{m_2 - fitness\big(pop(i)\big)}{m_2 - m_1} * {x_i}^t + C_2 * \frac{fitness\big(pop(i)\big) - m_1}{m_2 - m_1} * rand\big[varmin, varmax\big] \tag{2}$$

Table 3 shows the parameters of the Qashqai algorithm (QA).

### 5.3 *Migration route*

The set of best points traveled (best answers) forms the general path of the migration.

Table 3. parameters of the Qashqai algorithm (QA).

| Parameter | Description |
|---|---|
| ***Varmax*** | Maximum number of tribe members |
| $x_i^t$ | The position of the $i$th member in the iteration of $t$ |
| $x_i^{t+1}$ | The position of the $i$th member in the iteration of $t+1$ |
| ***Pop(i)*** | The $i$th member of the tribe population |
| $fitness(pop(i))$ | The fitness function of a member of the $i$ population of the tribe |
| ***Varmin*** | Minimum number of tribe members |
| ***C1, C2*** | Algorithm parameters |
| $m_1$ | The best solution to each iteration |
| $m_2$ | The worst solution (answer) of each iteration |

## 5.4 *Strategies to prevent the optimal answer from getting worse*

In this algorithm, a strategy was adopted to prevent the optimal solution from deteriorating. In this way, if the optimal answer of the algorithm in one iteration is worse than the previous iteration of the algorithm, the worst current iterative answer is replaced by the optimal point of the previous iteration.

## 5.5 *Diversification and intensification strategy*

The strategy of diversification and intensification in this algorithm is such that the more attention to the previous situation, the more intensification we will have, and the less attention to the previous situation, the more diversification we will see.

## 5.6 *Algorithm stop conditions*

Different conditions can be considered for stopping the algorithm, such as certain execution times, a certain number of iterations, and no improvement of the answer.

Table 4. Qashqai Optimization Algorithm (QA) pseudo-code.

**Result: Find The best solution**

**Objective min or max $f(x), X = (x_1, x_2, \dots, x_d)^T$**
**Generate initial population, of $n$ members of tribes (or nomads)**
**Find the best solution $g_*$ in the population in each iteration**
**While (t<MaxIteration) or (stop criterion) do**
**For $i = 1{:}n$ (all n members of each tribe)**
$m_1 \leftarrow$ **The best solution(it)**
$m_2 \leftarrow$ **Worst solution(it)**
**Update Position**
**if pop(i) is the best solution of each Iteration**
**then**

$$x_i^{t+1} = C_1 * \frac{\text{fitness}(pop(i)) - m_1}{m_2 - m_1} * x_i{}^t + C_2 * \frac{m_2 - fitness(pop(i))}{m_2 - m_1} * rand[varmin, varmax]$$

**else**

$$x_i^{t+1} = C_1 * \frac{m_2 - fitness(pop(i))}{m_2 - m_1} * x_i{}^t + C_2 * \frac{\text{fitness}(pop(i)) - m_1}{m_2 - m_1} * rand[varmin, varmax]$$

**end if**
**Evaluate new solutions**
**If new solutions are better, update them in the population**
**end for**
**Find the current best solution $g_*$**
**end while**

### 5.7 *Qashqai algorithm (QA) pseudo-code*

Table 4 shows the Qashqai algorithm (QA) pseudo-code.

### 5.8 *Qashqai optimization algorithm (QOA) parameter tuning*

Because input parameters influence the output of meta-heuristic algorithms, to adjust the parameters, the Taguchi method and Minitab software have been used. For example, according to Table 5, in five levels for the parameters of MaxIt, Npop, C1, and C2, the parameter adjustment of the Qashqai meta-heuristic algorithm has been made.

Table 5. Tuning the parameters of the Qashqai optimization algorithm (QOA).

| Row | Parameter | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 |
|---|---|---|---|---|---|---|
| 1 | MaxIt | 50 | 100 | 150 | 200 | 250 |
| 2 | Npop | 50 | 100 | 150 | 200 | 250 |
| 3 | C1 | 0.1 | 0.5 | 1 | 2 | 3 |
| 4 | C2 | 0.1 | 0.5 | 1 | 2 | 3 |

Figures 2 and 3 show the analysis of the results of the parameter setting Taguchi method using Minitab software, according to which MaxIt = 200 or 250, Npop = 250, C1 = 0.5 and C2 = 3 have the best performance.

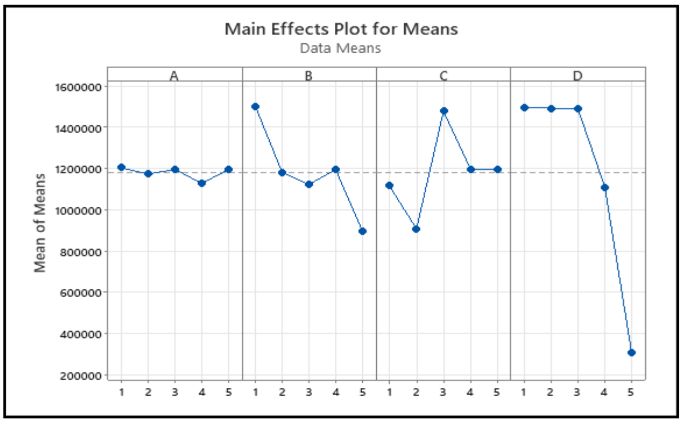



Figure 2. Average diagram of means for each level of Qashqai optimization algorithm parameters.

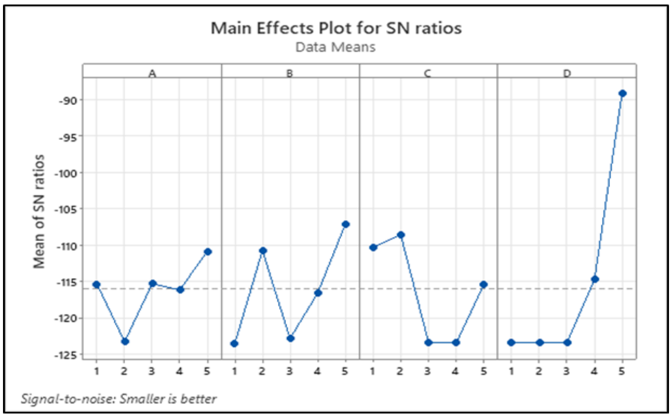



Figure 3. Graph of the average S/N for each level of Qashqai optimization algorithm parameters.

## 6. Presenting a hybrid algorithm for optimizing the artificial neural-fuzzy inference system (ANFIS) using the Qashqai algorithm (QA)

Figure 4 shows the method steps presented in this paper.

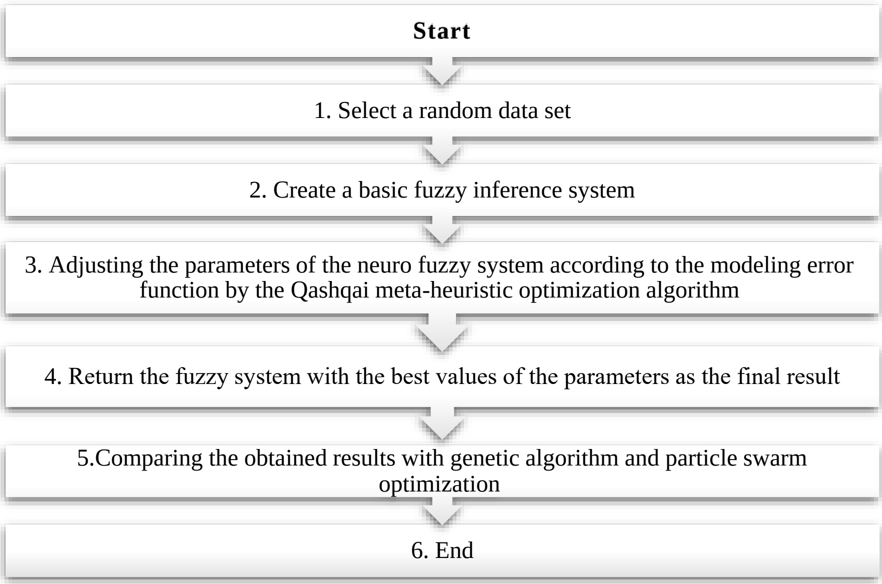



Figure 4. Steps of designing and implementing the proposed ANFIS-QA algorithm.

## 7. Computational results

Table 6 compares the results of the Qashqai algorithm (QA) implementation using eleven well-known optimization functions with GA, PSO, and DE algorithms.

Table 6. Comparison the results of Qashqai algorithm implementation using eleven well-known optimization functions with GA, PSO, and DE algorithms.

| Function name | Computational Time (Average) | | | |
|---|---|---|---|---|
| | QOA | GA | PSO | DE |
| Sphere | 2.87E-01 | 1.86E+00 | 2.34E-07 | 1.67E-04 |
| Rastrigin | 2.74E-01 | 1.83E+00 | 4.41E+00 | 9.18E-01 |
| Rosenbrock | 2.76E-01 | 1.68E+00 | 2.00E+00 | 2.23E+00 |
| Griewank | 2.77E-01 | 1.70E+00 | 2.27E-02 | 1.28E-01 |
| Ackley | 2.80E-01 | 1.72E+00 | 5.71E-02 | 2.44E-01 |
| EggHolder | 2.70E-01 | 2.50E+00 | 5.56E+00 | 8.13E-01 |
| Michalewicz | 2.33E-01 | 1.78E+00 | 1.80E+00 | 1.80E+00 |
| Six-Hump Camel | 2.89E-01 | 1.62E+00 | 4.69E-08 | 1.15E-05 |
| Levy | 3.37E-01 | 1.57E+00 | 1.88E-01 | 5.81E-07 |
| Rotated Hyper-Ellipsoid | 2.86E-01 | 1.60E+00 | 2.68E-06 | 2.24E-04 |
| Shubert | 2.48E-01 | 1.58E+00 | -1.87E+02 | -1.84E+02 |

Then genetic algorithm (GA) and particle swarm algorithm (PSO) were implemented on the neural-fuzzy inference system to evaluate the proposed algorithm.

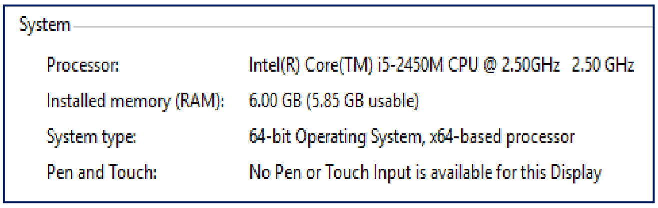
Qashqai algorithm was implemented on a neural-fuzzy inference system and performed 30 times in a row. The results were compared with the well-known meta-heuristic genetics and particle swarming algorithms according to the assumptions in Table 7.

Table 7. Test of hypotheses.

| | |
|---|---|
| $\boldsymbol{H_0}$ : The genetic algorithm overcomes the Qashqai algorithm to optimize the neural-fuzzy inference system. | $\boldsymbol{H_0: \mu > \mu_0}$ |
| $\boldsymbol{H_1}$: The genetic algorithm does not overcome the Qashqai algorithm to optimize the neural-fuzzy inference system. | $\boldsymbol{H_1: \mu \leq \mu_0}$ |
| $\boldsymbol{H_0}$ : The particle swarm algorithm(PSO) overcomes the Qashqai algorithm to optimize the neural-fuzzy inference system. | $\boldsymbol{H_0: \mu > \mu_0}$ |
| $\boldsymbol{H_1}$: The particle swarm algorithm (PSO) does not overcome the Qashqai algorithm to optimize the neural-fuzzy inference system. | $\boldsymbol{H_1: \mu \leq \mu_0}$ |

Because the comparisons of the two samples are independent, the Mann-Whitney statistical test was utilized. A computer with the specifications in Table 8 was used to perform the calculations.

Table 8. Specifications of the computer used to analyze the results.


System

| | |
|---|---|
| Processor: | Intel(R) Core(TM) i5-2450M CPU @ 2.50GHz 2.50 GHz |
| Installed memory (RAM): | 6.00 GB (5.85 GB usable) |
| System type: | 64-bit Operating System, x64-based processor |
| Pen and Touch: | No Pen or Touch Input is available for this Display |

Table 9 shows the average results of 30 times the implementation of the genetic algorithm (GA) and Qashqai algorithm (QA) on the problem of optimizing the neural-fuzzy inference system .MaxIT=500 and Npop=100 assumed.

Table 9. Comparison of the average results of 30 times Qashqai algorithm (QA) and genetic algorithm (GA) on optimization of the artificial neural-fuzzy inference system (ANFIS).

| Average fitness function | | P-Value | Significance Level of Test | Test result Assumption |
|---|---|---|---|---|
| QA | GA | | | |
| 1.82 E-02 | 1.96E-02 | 0 | α=0.05 | Rejected $\boldsymbol{H_0}$ |

Table 10 shows the average results of 30 implementations of the Qashqai algorithm (QA) and particle swarm algorithm (PSO) on the optimization of the Artificial neural-fuzzy inference (ANFIS) model.

Table 10. Comparison of the average results of 30 times Qashqai algorithm (QA) and particle swarm algorithm (PSO) on optimization of the artificial neural-fuzzy inference system (ANFIS).

| Average fitness function | | P-Value | Significance Level of Test | Test result Assumption |
|---|---|---|---|---|
| QA | PSO | | | |
| 1.82 E-02 | 1.81 E-02 | 0 | α=0.05 | Rejected $\boldsymbol{H_0}$ |

Thus, according to the results of Tables 9 and 10 and the results of testing the hypotheses, it can be concluded that Genetic (GA) and particle swarm optimization (PSO) algorithms in the field of optimization of the artificial neural-fuzzy inference system (ANFIS) in terms of convergence do not overcome the optimal solution of the Qashqai algorithm. Figure 5 shows how to learn data using the Qashqai meta-heuristic algorithm (QA).

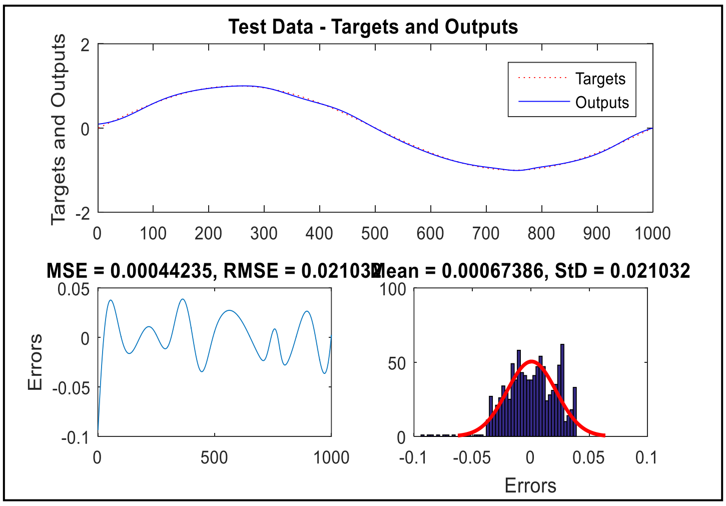



Figure 5. Results of training data using Qashqai optimization algorithm (QA).

## 8. Conclusion

This paper presents a new meta-heuristic algorithm for optimizing the neural-fuzzy inference system called the Qashqai algorithm. The Qashqai algorithm is designed inspired by the way nomads migrate. In this hybrid algorithm, the fitness function was designed based on the neural-fuzzy inference system and based on minimizing the data error using the results of the neural-fuzzy inference system. Then the Qashqai meta-heuristic algorithm was implemented in this system. The results were compared with well-known genetic algorithm (GA) and particle swarm (PSO) algorithms. The hypothesis test results showed that the Qashqai optimization algorithm (QA) for solving the neural-fuzzy inference system is not defeated by the genetic algorithm and particle swarm and works well in terms of convergence to the optimal solution.

## 9. Recommendations for future research

- For future research, it is suggested that the proposed hybrid algorithm be used to solve various practical problems in disease diagnosis, robot navigation, distribution network power consumption forecasting, and power system stability improvement.
- The methodology presented in this article is compared with other meta-heuristic algorithms and combined with other machine learning methods.
- New combined methods for adjusting the parameters of meta-heuristic algorithms and improving the performance of artificial neural-fuzzy inference system might be presented to reach better answers.

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