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Genetic Neuro-Fuzzy Approach towards Routing in Industrial IoT

Olena Semenova, Natalia Kryvinska, Andriy Semenov, Volodymyr Martyniuk, and Olha Voitsekhovska

***Abstract*—The Internet of Things has rapidly grown in the past years as emerging technology. Moreover, 5G networks start to offer communication infrastructure for applications of the Industrial Internet of Things (IIoT). However, due to energy limitations of IIoT devices and heterogeneity of 5G networks, managing IIoT networks is a challenging task. One of the most critical issues in IIoT that requires consideration is traffic routing that has a significant impact on energy consumption, and thus, lifetime of the network. Artificial Intelligence (AI) has been widely employed to solve complex scientific and practical problems. Such AI techniques as neural networks, fuzzy systems, genetic algorithms are commonly employed in wireless networks to promote their optimization, prediction, and management. This study suggests using an Adaptive Neuro-fuzzy Inference System (ANFIS) in 5G networks of IIoT for improving the routing process. A flow-chat of routing protocol was suggested. For input and output values of the ANFIS linguistic variables, terms and membership functions were defined. A rules base was developed. To improve the rule base of the ANFIS, a genetic algorithm was proposed. The operation of ANFIS was simulated in Matlab software.**

***Keywords*—ANFIS; genetic algorithm; routing; Internet of Things**

I. INTRODUCTION

THE fourth industrial revolution is the latest technological advancement of humanity. This revolution has been made possible by the technological advances that are available to the population today. It is primarily based on the digitalization and automation of factories through the application of the Internet of Things (IoT); it is also coupled with cyber-physical systems. Industry 4.0 will enable the exploitation of technologies such the Internet of Things (IoT), Big Data and data analytics, augmented reality, cybersecurity, cloud computing, additive manufacturing, artificial intelligence, and 5G networks.

The Internet of Things (IoT) is a developing technology that enables physical objects to connect through 5G communication [1]. In recent years, IoT technology has been applied to various aspects of smart cities, including farming, e-healthcare, education, smart homes, and weather monitoring [2]. These applications involve collaborative communication between embedded IoT devices to systematize daily tasks. Industrial IoT networking encompasses a broad range of use cases, from extended enterprises to vertical markets and services, each with specific requirements that are typically well-defined by industrial architecture and specifications.

Communication technologies are a critical component of the Internet of Things (IoT). It enables interconnection of devices through various networks. 5G could be a significant development for the industrial internet of things (IIoT) due to its specifications for higher broadband throughput, ultra-reliable and low-latency communication, and massive scale of IoT communications. Enhancing industrial autonomy through 5G communication is one of the most significant prospects for IoT devices [3]. The potential of 5G technology is undoubtedly exciting. However, its deployment is fraught with difficulties and risks [4].

The IoT network differs from common wireless sensor networks (WSNs) in that its devices dynamically connect to the Internet and collaborate with other similar devices to perform various tasks. Similar to conventional WSNs, IoT devices periodically send the collected data to a base station (BS), which then transmits the data to the admin. In most cases, IoT devices consist of transceivers, batteries, microprocessors and sensors to perform essential functions. To attain all applications, the primary requirement is to collect and transmit data. Due to its limited communication capability, data transfer from any IoT device can only be done within a specific distance. To transmit data from the IoT device to the base station, cooperation from other intermediate devices is necessary [5].

The major challenges of the internet of things consider the problem of dynamic topology, scalability, mobility of nodes and limited bandwidth [6]. To provide effective wireless transmission of the sensor data from one source node to another, the sensor node utilizes infrared or radio frequency signals to communicate with other nodes. However, these two transmission techniques are associated with multiple route propagation, high error rates, delays, reflection, and fading. As IoT devices are battery-driven and extremely resource-restricted, energy is one of the most critical concerns for almost all IoT applications. On the Internet of Things, collected data are transmitted via nodes to the sink node in a multihop manner. Moreover, neighboring nodes can redundantly send the same data to the sink node, resulting in increased traffic and wasteful energy use. In order to conserve energy on the nodes, it is important to minimize unnecessary data transfer.

Moreover, path breaks may occur due to node mobility, requiring the routing protocol to relearn the path to continue data transmission. Route interruptions caused by node mobility have a greater impact on routing protocol capability than on network

Olena Semenova, Andriy Semenov, Volodymyr Martyniuk and Olha Voitsekhovska are with Vinnytsia National Technical University, Ukraine (e-mails: semenova.o.o@vntu.edu.ua, semenov.a.o@vntu.edu.ua, vm4ukr@gmail.com, olgav1085@gmail.com).

Natalia Kryvinska is with Comenius University in Bratislava, Slovak Republic (e-mail: natalia.kryvinska@fm.uniba.sk).

capability. To overcome this, the routing protocol needs to include a better hand-over mechanism to minimize the frequency of route disruptions caused by mobility and to find an alternative method to continue the transmission of information [7]. Improving network lifespan and mobility assistance is a challenging task in the context of the Internet of Things. A special attention should be paid to secure routing [8, 9].

II. Literature Review

There is a high demand for approaches that would address the mentioned issues. One of the eligible approaches is applying Artificial Intelligence (AI) methods that is being regarded as a successful tool to analyze the collective behavior of service-oriented computing software and provide human-like knowledge, such as understanding, learning and recognition. Moreover, they are widely utilized to improve quality-of-service in service-oriented architectures. The fusion of AI and IoT has brought about a paradigm shift in the realm of engineering, thus introducing intelligent technologies that enhance monitoring and control significantly [10].

The Artificial Intelligence methods include fuzzy logic, artificial neural networks, genetic algorithms, simulated annealing and particle swarm optimization [11].

One of the most significant advantages of fuzzy logic is that it provides a practical approach for designing nonlinear control systems, which are challenging to design and stabilize using conventional methods.

Artificial neural networks (ANN) are information processing systems that draw inspiration from the human brain and nervous system. The goal of neural networks is to get traditional computers to function a little more like the human brain. Highly non-linear relationships between inputs and outputs are ideal for ANNs to function. ANNs are very good at addressing situations for which there are no predetermined rules or algorithms to follow. Inspired by human neurons, a neural network is a vast web of interconnected components.

The fundamental premise of a genetic algorithm (GA) is to emulate the process of natural selection in nature with the objective of identifying an optimal solution for a given application. A genetic algorithm is essentially a machine learning model that draws inspiration from the principles of evolution observed in nature. This approach can be employed to address complex search problems commonly encountered in engineering applications. For instance, a genetic algorithm can scan through a multitude of designs and components to identify the most effective combination that will result in a superior and cost-effective design.

In IoT these techniques have been applied to solve various problems. Thus, paper [12] considers a security assessment discipline on fuzzy sets for allocation of security resources. Paper [13] suggests a fuzzy approach for increasing the lifetime of devices, which are connected to the IoT environment. Study [14] discusses a fuzzy weight queuing to optimize network resources for IoT networks. Work [15] develops a fuzzy trust-based access control to be used in the IoT. Paper [16] presents a self-regulating learning technique to increase the accuracy of sensory data tracking in IoT systems. Study [17] discusses an ANN to classify the large amount of input data from sensors. Paper [18] proposes a framework of Internet of robotic things and an ANN to provide the universal connectivity among robots to maintain the necessary quality of service. Study [19] suggests a localization algorithm base on GA, which estimates position of nodes of the IoT and declines the effect of indoor interference. Work [20] proposes to implement a GA to obtain a multi-objective function for determining the optimal path in the IoT. In study [21] an algorithm for intrusion detection system of IoT applications is discussed. Optimization strategy of IoT sensors based on GA and ANN is investigated in [22]. Moreover, intelligent routing schemes for IoT networks are outlined in [23-25].

The purpose of this study is developing a hybrid approach to the routing problem which encompasses the three mentioned AI techniques that may overcome their drawbacks and enhance advantages.

III. Proposed Routing Method

In our case, fuzzy logic theory may be utilized to calculate the best route for the most efficient and energy-saving transportation of data in 5G wireless networks of IIoT.

By combining fuzzy logic with artificial neural network technology, we can create a more efficient and accurate machine learning model. For this purpose, we have applied Adaptive Neuro-fuzzy Inference System (ANFIS).

The ANFIS learning algorithm is a mechanism for fuzzy modelling operations to have sufficient knowledge about a data set required to compute the membership function for tracking input-output data, which works similarly to that of artificial neural networks. ANFIS uses a backpropagation gradient descent method to train and adapt the membership function parameters of the fuzzy inference system to simulate a given training data set. The backpropagation learning algorithm aims to minimize the error surface by moving the solution's vector space along the steepest vector towards a global minimum value. However, it can get trapped in a local minimum and fail to reach the global minimum. In addition, techniques based on gradient descent are heavily dependent on the structure of the ANFIS network. To overcome these challenges, GAs are introduced as global optimum search algorithms that are highly effective and independent of the ANFIS structure [26].

The transfer of data packets in an IoT network among the nodes necessitates the expenditure of energy. In many cases, the energy consumed exceeds the actual energy demand, potentially due to various factors that contribute to energy wastage. The optimization of the network lifetime is of high importance in the context of wireless networks. The duration for which the network operates until the first node ceases to operate can be defined as the network lifetime. The proposed in this study approach may improve energy usage, increase throughput, and enhance network lifetime.

In order to optimize the transmission of data, the best path is determined by considering the one-hop neighbors of the sink node. The proposed routing protocol utilizes node parameters to make intelligent and decisions about the accurate node selection.

According to the proposed technique, the optimal routes are selected by a sink node based on the suggested fuzzy system (fig.1). This can be achieved by delivering information about neighbor nodes to the fuzzy logic system. Then, the system converts the data into fuzzy values, which is known as fuzzification. Next, in the aggregation process, the output is computed by the inference engine considering a rule base. The final stage of the system is defuzzification. Here, the system converts the fuzzy output to crisp values, which represent the route status and indicate the status of the eligible routes. Therefore, the sink node should select routes with maximal status.

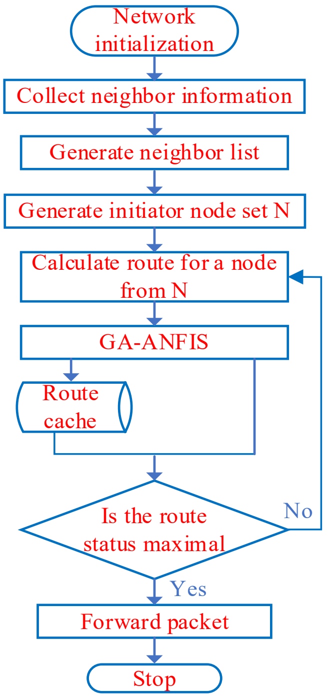

Fig. 1. Flow-chart of routing protocol

IV. GENETIC NEURO-FUZZY CONTROLLER

A. ANFIS Structure

Overall, a fuzzy inference system comprises of four basic functional units of fuzzification, rule base, decision-making and defuzzification.

Fuzzification unit converts the crisp inputs into linguistic variables. Rule base is a set of fuzzy if-then rules. Decision-making unit performs inference on the fuzzy if-then rules. Defuzzification unit transforms the fuzzy results from the inference system into crisp outputs.

In our case, the rule base unit has been completed with a genetic algorithm unit, while the decision-making unit has been replaced with a neural network unit, thus creating an adaptive neuro-fuzzy inference system (ANFIS). Figure 2 shows the structure of the proposed genetic neuro-fuzzy controller.

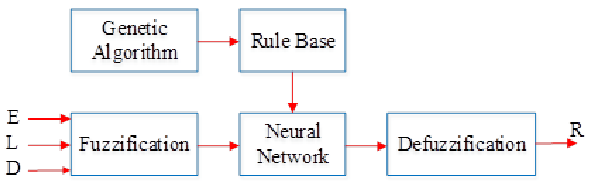

Fig. 2. Block diagram layout of the genetic neuro-fuzzy controller

The proposed neuro-fuzzy system has three input variables, each with three levels. As inputs, such essential parameters like residual energy, traffic load, and distance were chosen.

Residual energy of a node is an important metric, which impacts on the IoT network performance and lifetime duration. The total residual energy is the sum of harvested energy and remaining energy of the sensor node. So, for defining the linguistic variable of energy, we use such terms: low, average, high.

Since in the IoT networks data are sent in a multihop way via nodes to the sink node. This means, that some neighboring nodes redundantly transmit the same data, which increases traffic load in the network. Traffic load is a crucial parameter which corresponds to a quantity of data that passes the network during a particular time period and must be carefully balanced to ensure the efficient functioning of the entire wireless network. For defining the linguistic variable of load, we use such terms: light, normal, heavy.

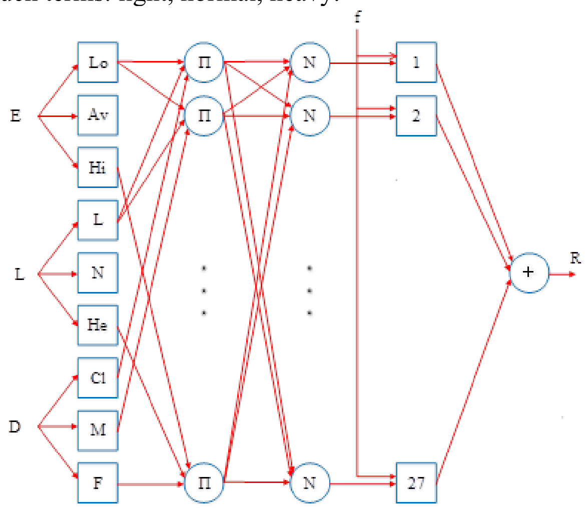

Fig. 3. Architecture of the neuro-fuzzy controller

Data transfer from an IoT device can be performed only up to a specific distance value due to its low communication capability. The distance between the IoT device to the base station or a neighbor node is determined based on the Euclidean distance. For defining the linguistic variable of distance, we use such terms: closer, medium, far.

The output of the ANFIS is the route status, which has 11 levels: 0, 0.1, 0.2 … 0.9, 1, where 1 is the highest status.

Fig. 3 illustrates an architecture of the neuro-fuzzy controller.

The proposed routing neuro-fuzzy inference system will be developed through the Matlab software. The simulated in Matlab fuzzy inference system is presented in Fig.4.

The routing ANFIS is a Sugeno-type controller and has rules of the form:

$$\begin{aligned} &if\ x\ is\ A_i, y\ is\ B_i\ and\ z\ is\ C_i \\ &then\ f = p_i x + q_i y + r_i\ z + t_i \end{aligned} \tag{1}$$

In general, the inference system is created using five different layers: fuzzy layer, product layer, normalized layer, de-fuzzy layer, and the total layer, each consisting of different nodes (fig.5).

Layer 1: Each node is defined by a membership function. Input variables are transformed into fuzzy variables by means of membership functions, which map a point in the input space to a membership value in the range [0,1].

For j=1,2,3

$$O_{1j} = \mu_{Aj}(x), \tag{2}$$

for j=4,5,6

$$O_{1j} = \mu_{Bj-3}(x), \tag{3}$$

for j=7,8,9

$$O_{1j} = \mu_{Cj-6}(x). \tag{4}$$

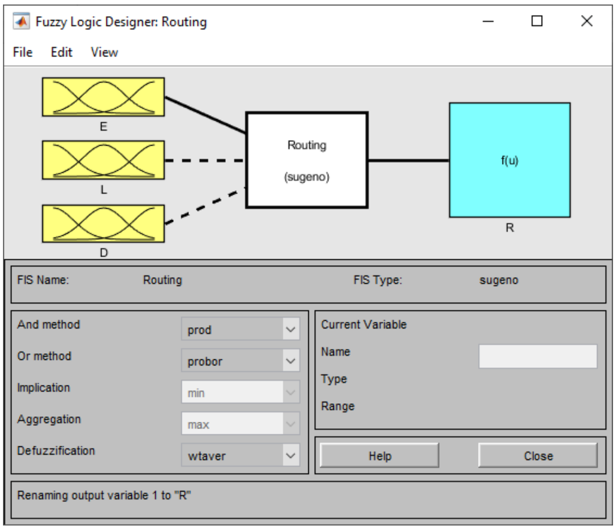

Fig. 4. Fuzzy inference system in Matlab

Membership functions may have various forms. In this study we apply triangular and trapezoidal ones.

$$\mu(e) = \begin{cases} 0 \;\; if \; e \le q_1, \\ \dfrac{e - q_1}{q_2 - q_1} \;\; if \; q_1 < e \le q_2, \\ \dfrac{q_3 - e}{q_3 - q_2} \;\; if \; q_2 < e \le q_3, \\ 0 \;\; if \; q_3 < e. \end{cases} \tag{5}$$

$$\mu(e) = \begin{cases} 0 \;\; if \; e \le p_1 \;\; e > q_2, \\ \dfrac{e - p_1}{p_2 - p_1} \;\; if \; p_1 < e \le p_2, \\ 1 \;\; if \; p_2 < e \le q_1, \\ \dfrac{q_2 - e}{q_2 - q_1} \;\; if \; q_1 < e \le q_2. \end{cases} \tag{6}$$

Membership functions for the output variable are singletons:

$$T(e) = \begin{cases} 0 \;\; if \;\; e \ne r, \\ 1 \; if \;\; e = r. \end{cases} \tag{7}$$

Layer 2: The firing strength of a rule is defined by the following equation:

$$O_{2i} = w_i = \mu_{Ai}(x) \cdot \mu_{Bi}(y) \cdot \mu_{Ci}(z). \tag{8}$$

Layer 3: The firing strength of each rule is normalized by dividing the firing strength of the ith rule to the total firing strength of all rules.

$$O_{3i} = n_i = w_i / w_1 + w_2 + \cdots + w_{27}. \tag{9}$$

Layer 4: The neuron output is calculated as the product of normalized firing strength and individual rule output:

$$O_{4i} = n_i \cdot f_i. \tag{10}$$

Layer 5: The outputs of the previous layer are added to each other.

$$O_5 = \sum_i n_i \cdot f_i. \tag{11}$$

First of all, we need to establish membership functions for the input and output variables.

Specifying the energy linguistic variable is shown in Fig.6.

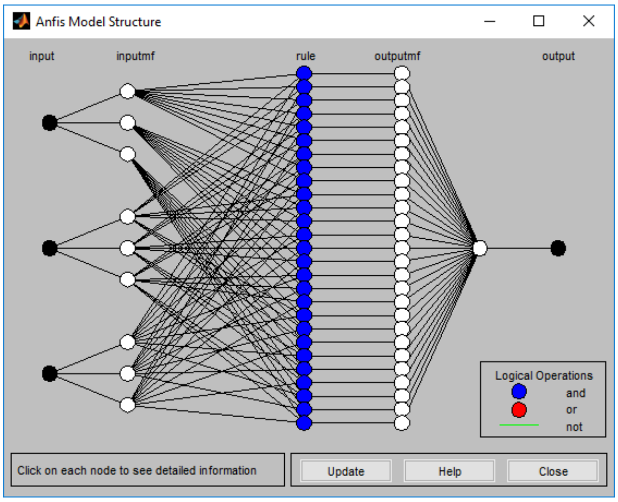

Fig. 5. ANFIS structure

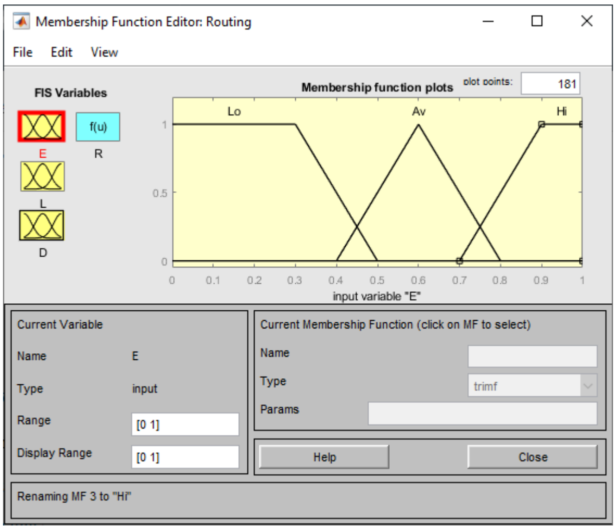

Fig. 6. Specifying of the E input variable

Specifying the load linguistic variable is shown in Fig.7.

Specifying the distance linguistic variable is shown in Fig.8.

Next, we need to establish the fuzzy rule bases for the neuro-fuzzy inference system. Specifying of the fuzzy rule base is shown in Fig.9.

To check the operability of the neuro-fuzzy system, the simulation was run to obtain the output value.

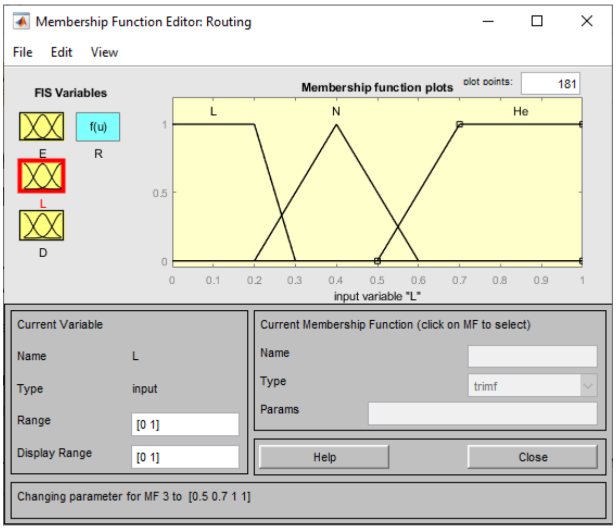

Fig. 7. Specifying of the L input variable

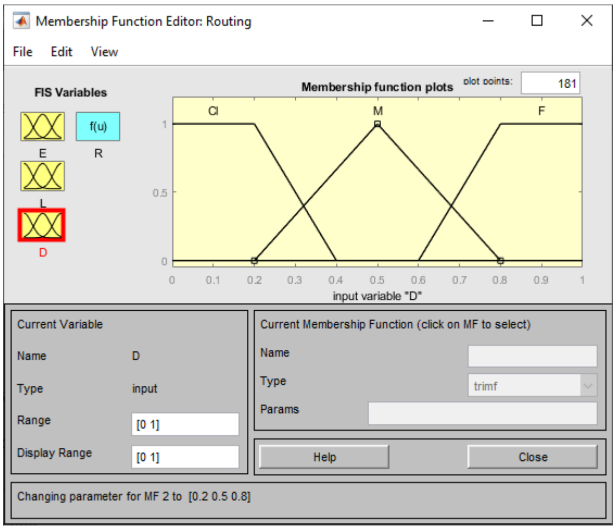

Fig. 8. Specifying of the D input variable

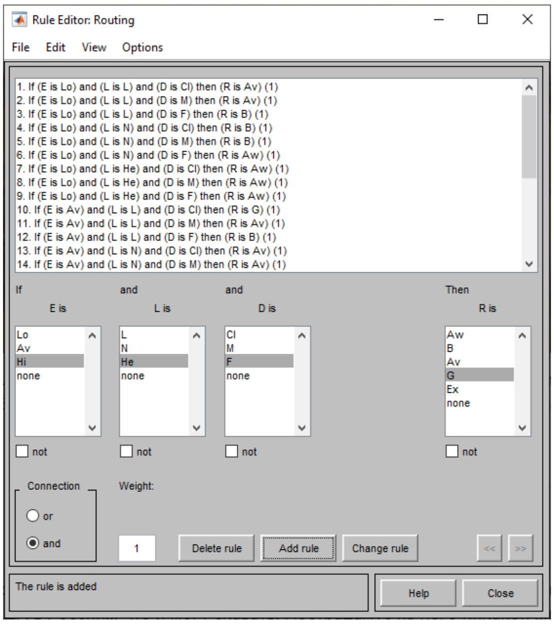

Fig. 9. Rule base

When the energy E=0.2, the load L=0.5, and the distance D=0.7, the route status is R=0.28 (fig. 10).

When the energy E=0.8, the load L=0.3, and the distance D=0.8, the route status is R =0. 8 (fig.11).

Data, which were applied for the training, are presented in Fig. 12.

Fig. 13 shows the error after training process. In the simulation a backpropagation learning algorithm was applied. Error tolerance was 0. The epoch value of 100 was chosen. The training promotes adaptation of the membership functions for inputs which after training are of trapezoidal type.

The applied backpropagation learning algorithm [27] can be represented in the following steps:

1. Initialization of weights with random values.
2. Input is sent to the network and the desired output is selected.
3. Estimate the output by randomly selected weights.
4. Calculate the errors:

for the hidden layer:

$$e_j = q_j(1-q_j)\sum_k \hat{e}_k w_{ik} \tag{12}$$

for the output layer:

$$\hat{e}_j = (z_j - r_j) r_j (1 - y r_j) \tag{13}$$

where z is the desired output, q and r are the transfer functions, k is the overall nodes after node j.

5. Adjustment of the weights

$$\begin{aligned} w_{ik}(n+1) &= w_{ik}(n) + b\hat{e}_k q_j + \\ &+ a(w_{ik}(n) - w_{ik}(n-1)) w_{ij}(n+1). \end{aligned} \tag{14}$$

Here b and a represent the learning rate and momentum, respectively.

6. Return to Step 2.

Fig. 10. Simulation results

B. Genetic Algorithm

The rule base of the proposed neuro-fuzzy inference system can be updated using a genetic algorithm.

A genetic algorithm is a global search methodology used in engineering to optimize solutions for complex problems. It applies such processes as inheritance, mutation, selection, and crossover. In this study, we propose to improve the efficiency of the ANFIS by combining it with a genetic algorithm GA, which imply tuning and optimizing the membership functions in the Sugeno-type fuzzy inference system.

Fig. 11. Simulation results

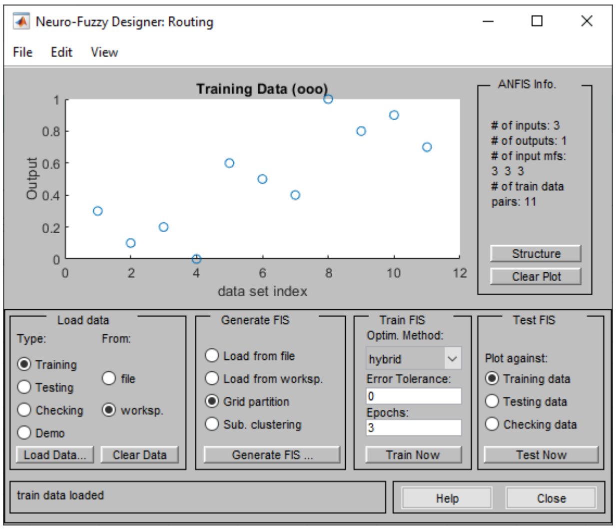

Fig. 12. ANFIS training data

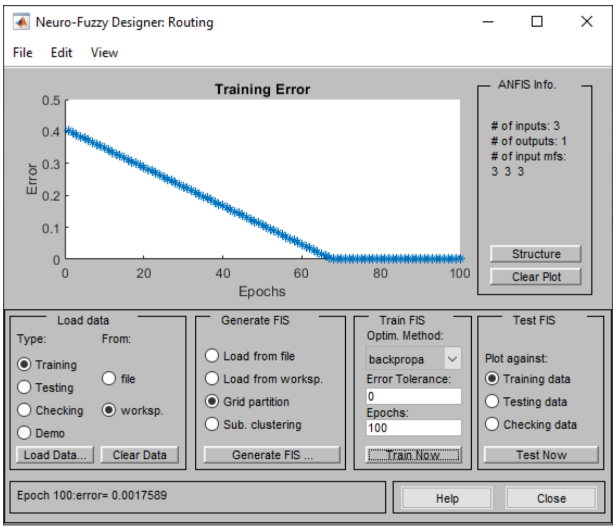

Fig. 13. Training error

The genetic algorithm model begins with a set of solutions, referred to as chromosomes. A new population is formed by building upon the previous one. The fitness of newly created solutions, which are selected as offspring, is then determined. This process is repeated until a condition, such as the advancing of the optimal solution, is met [28].

This study takes the ANFIS parameters, which are the input and output parameters, as the variables of the GA.

Inputs and outputs of the ANFIS are encoded into genes according to Table I and Table II.

TABLE I
INPUTS ENCODING

Energy			Load			Distance		
Lo	Av	Hi	L	N	He	Cl	M	F
0000	0001	0010	0011	0100	0101	0110	0111	1000

TABLE II
OUTPUT ENCODING

0	0.1	0.2	0.3	…	0.9	1
0000	0001	0010	0011		1010	1011

Each fuzzy rule is defined by a set of 16 genes that identify fuzzy sets for each of three input and one output variables.

Thus, for the proposed genetic neuro-fuzzy inference system a chromosome looks so:

P1	P2	P3	…	P12	C1	C2	C3	C4

The genetic algorithm is shown in fig.14.

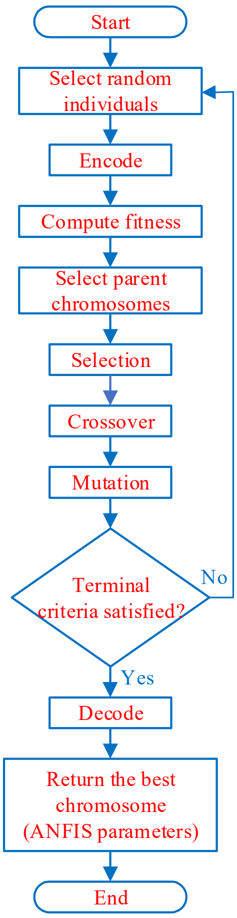

Fig. 14. Genetic algorithm

In this case the mean square error (MSE) function is used as the fitness function of the GA. The objective is to minimize the fitness function by adapting the ANFIS parameters through training. The MSE is calculated using the following formula:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y(i) - \hat{y}(i))^2 \,. \qquad (15)$$

Conclusion

This study presents the neuro-fuzzy inference system for improving the routing process in Industrial IoT 5G networks. The proposed approach has the advantage of combining three soft-computing techniques: fuzzy system, artificial neural network, and genetic algorithm.

ANFIS structure combining a neural network with a fuzzy system allows adjusting membership functions, thus the system becomes suited for dynamic environment of Industrial IoT. The genetic algorithm improves the rule base, making the proposed genetic ANFIS suitable for real network environments.

Simulation in Matlab has confirmed performance of the proposed system.

References

[1] A. K. M. Bahalul Haque, Md. Oahiduzzaman Mondol Zihad, and Md. Rifat Hasan, “5G and Internet of Things—Integration Trends, Opportunities, and Future Research Avenues,” 5G and Beyond. Springer Nature Singapore, pp. 217–245, 2023. https://doi.org/10.1007/978-981-99-3668-7_11

[2] R. Dallaev, T. Pisarenko, Ş. Ţălu, D. Sobola, J. Majzner, and N. Papež, “Current Applications and Challenges of the Internet of Things,” New Trends in Computer Sciences, vol. 1, no. 1, pp. 51–61, 2023. https://doi.org/10.3846/ntcs.2023.17891

[3] S. Palarimath, P. M, T. K, M. Maqsood, M. A. Salam, and R. D. Palarimath, “Powering IoT Systems with 5G Wireless Communication: A Comprehensive Review,” 2023 8th International Conference on Communication and Electronics Systems (ICCES). IEEE, Jun. 2023. https://doi.org/10.1109/icces57224.2023.10192678

[4] A. Kour, “A Review: Industrial Internet of Things using 5G,” International Journal for Research in Applied Science and Engineering Technology, vol. 11, no. 1, pp. 653–657, 2023. https://doi.org/10.22214/ijraset.2023.48657

[5] B. Shah, “Fuzzy Energy Efficient Routing for Internet of Things (IoT),” 2018 Tenth International Conference on Ubiquitous and Future Networks (ICUFN). IEEE, Jul. 2018. https://doi.org/10.1109/icufn.2018.8437033

[6] J. Marietta and B. Chandra Mohan, “A Review on Routing in Internet of Things,” Wireless Personal Communications, vol. 111, no. 1, pp. 209–233, 2019. https://doi.org/10.1007/s11277-019-06853-6

[7] D. K. Shende, S. S.S, and Y. Angal, “A Comprehensive Survey of the Routing Schemes for IoT applications,” Scalable Computing: Practice and Experience, vol. 21, no. 2. Scalable Computing: Practice and Experience, pp. 203–216, 2020. https://doi.org/10.12694/scpe.v21i2.1667

[8] D. Airehrour, J. Gutierrez, and S. K. Ray, “Secure routing for internet of things: A survey,” Journal of Network and Computer Applications, vol. 66, pp. 198–213, 2016. https://doi.org/10.1016/j.jnca.2016.03.006

[9] S. D. Mali and K. Govinda, “A study on network routing attacks in IoT,” Materials Today: Proceedings, vol. 80, pp. 2997–3002, 2023. https://doi.org/10.1016/j.matpr.2021.07.092

[10] N. Rane, S. Choudhary, and J. Rane, “Artificial Intelligence (AI) and Internet of Things (IoT) - based sensors for monitoring and controlling in architecture, engineering, and construction: applications, challenges, and opportunities,” SSRN Electronic Journal, 2023. https://doi.org/10.2139/ssrn.4642197

[11] R. Kruse, S. Mostaghim, C. Borgelt, C. Braune, and M. Steinbrecher, Computational Intelligence. Springer International Publishing, 2022. https://doi.org/10.1007/978-3-030-42227-1

[12] K. C. Park and D.-H. Shin, “Security assessment framework for IoT service,” Telecommunication Systems, vol. 64, no. 1, pp. 193–209, 2016. https://doi.org/10.1007/s11235-016-0168-0

[13] M. Collotta and G. Pau, “Bluetooth for Internet of Things: A fuzzy approach to improve power management in smart homes,” Computers & Electrical Engineering, vol. 44, pp. 137–152, 2015. https://doi.org/10.1016/j.compeleceng.2015.01.005

[14] M. Jutila, “An Adaptive Edge Router Enabling Internet of Things,” IEEE Internet of Things Journal, vol. 3, no. 6, pp. 1061–1069, 2016. https://doi.org/10.1109/jiot.2016.2550561

[15] P. N. Mahalle, P. A. Thakre, N. R. Prasad, and R. Prasad, “A fuzzy approach to trust-based access control in internet of things,” Wireless VITAE, 2013. https://doi.org/10.1109/vitae.2013.6617083

[16] X. Luo, Y. Lv, M. Zhou, W. Wang, and W. Zhao, “A Laguerre neural network-based ADP learning scheme with its application to tracking control in the Internet of Things,” Personal and Ubiquitous Computing, vol. 20, no. 3, pp. 361–372, 2016. https://doi.org/10.1007/s00779-016-0916-x

[17] E. De Coninck et al., “Distributed Neural Networks for Internet of Things: The Big-Little Approach,” Internet of Things. IoT Infrastructures. Springer International Publishing, pp. 484–492, 2016. https://doi.org/10.1007/978-3-319-47075-7_52

[18] C. Razafimandimby, V. Loscri, and A. M. Vegni, “A Neural Network and IoT Based Scheme for Performance Assessment in Internet of Robotic Things,” 2016 IEEE First International Conference on Internet-of-Things Design and Implementation (IoTDI). IEEE, Apr. 2016. https://doi.org/10.1109/iotdi.2015.10

[19] T.-Y. Wu, G.-H. Liaw, S.-W. Huang, W.-T. Lee, and C.-C. Wu, “A GA-based mobile RFID localization scheme for internet of things,” Personal and Ubiquitous Computing, vol. 16, no. 3. pp. 245–258, 2011, https://doi.org/10.1007/s00779-011-0398-9

[20] S.-J. Yoo, J. Park, S. Kim, and A. Shrestha, “Flying path optimization in UAV-assisted IoT sensor networks,” ICT Express, vol. 2, no. 3. pp. 140–144, 2016. https://doi.org/10.1016/j.icte.2016.08.005

[21] V. Jain and M. Agrawal, “Applying Genetic Algorithm in Intrusion Detection System of IoT Applications,” 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI), IEEE, Jun. 2020. https://doi.org/10.1109/icoei48184.2020.9143019

[22] Y. Yang, “Optimization Strategy of IoT Sensor Configuration Based on Genetic Algorithm-Neural Network,” Journal of Sensors, vol. 2021, pp. 1–12, 2021. https://doi.org/ 10.1155/2021/5098013

[23] B. Shah, “Fuzzy Energy Efficient Routing for Internet of Things (IoT),” 2018 Tenth International Conference on Ubiquitous and Future Networks (ICUFN), IEEE, Jul. 2018. https://doi.org/10.1109/icufn.2018.8437033

[24] S. Kuwelkar and H. Virani, Enhancing the RPL Protocol Using an Artificial Neural Network for Sustainable IoT Infrastructure,” Transitioning to Sustainable Industry, Innovation and Infrastructure. MDPI, Jul. 04, 2023. https://doi.org/ 10.3390/books978-3-03897-869-5-6

[25] F. Albalas, E. Alrabee, W. Mardini and A. Sawafta, "Energy-Aware Routing Approach in Internet of Things Using Genetic Algorithms," 2022 9th International Conference on Internet of Things: Systems, Management and Security (IOTSMS), Milan, pp. 1-6, 2022. https://doi.org/10.1109/IOTSMS58070.2022.1006203

[26] M. A. Soliman, H. M. Hasanien, H. Z. Azazi, E. E. El-kholy, and S. A. Mahmoud, “Hybrid ANFIS-GA-based control scheme for performance enhancement of a grid-connected wind generator”, IET Renewable Power Generation, vol. 12, issue 7, 2018, pp. 832–843, https://doi.org/10.1049/iet-rpg.2017.0576

[27] P.-H. Weng, F.-T. Liu, Y.-J. Chen, C.-Y. Chang, and R.-C. Hwang, “A Hybrid Supervised Neural Network Learning Algorithm,” 2008 3rd International Conference on Innovative Computing Information and Control. IEEE, 2008. https://doi.org/10.1109/icicic.2008.607

[28] I. O. Olayode, L. K. Tartibu, and F. Justice Alex, “Comparative Study Analysis of ANFIS and ANFIS-GA Models on Flow of Vehicles at Road Intersections”, *Applied Sciences*, vol. 3, no. 2, p. 744, 2023. https://doi.org/10.3390/app13020744