Journal of Computing and Security

July 2017, Volume 4, Number 2 (pp. 47–61)

http://www.jcomsec.org

Multi-Constraint Optimal Path Finding for QoS-Enabled Smart Grids: A Combination Approach of Neural Network and Fuzzy System

Razieh Rastgoo [a], Vahid Sattari-Naeini [a,*],

[a] *Department of Computer Engineering, Shahid Bahonar University of Kerman, 7616914111 Kerman, Iran.*

ARTICLE INFO.

Article history:
Received: 15 March 2017
Revised: 24 June 2018
Accepted: 17 July 2018
Published Online: 02 December 2018

Keywords:
Smart Grid (SG), Routing Optimization, Neuro-Fuzzy (NF), Performance Improvement, Quality of Service (QoS).

ABSTRACT

Smart Grid (SG) is an intelligent managed network including various data networks. Due to using the two-way data and electricity flows in SG, relations among the network elements are in an efficient way. Path finding optimization is one of the important challenges in SG. In this paper, we propose a routing protocol, namely Neuro-Fuzzy Stable Optimization Multi-Constrained Routing (NFSOMCR), to investigate the optimal path between two nodes in the SG. For this purpose, seven parameters and one cost function are used to meet the important QoS requirements of SG. Depending on the different initializations applied on the parameters, some routes with their constraints are found out by Dijkstra routing algorithm that form the inputs of the Neuro-Fuzzy system. The output of this system is the optimized cost function as well as the optimal paths between two nodes. Experimental results show that the proposed method outperforms existing works in terms of power cost and throughput.

1 Introduction

The Smart Grid (SG) is used to adapt technologically the future demand growth in electrical Grids [1–4]. SG collects various communication/networking technologies into electrical power Grids to make them "smarter" [5]. Different communication networks in SG collect and transfer various information among different components of the network in order to support different requirements of SG applications [6]. Using the mutual flows of electricity and information in order to create an automated and widely distributed energy delivery network is an important goal of the SG, which is redounded to have a more reliable, secure, efficient, and environmentally interpretable electrical Grid [7]. Automated and intelligent management is a critical component that determines the efficiency of the SG [8].

SG copes with different challenges that routing optimization based on the Quality of Service (QoS) guarantee is one of them [7–9]. QoS concept is much related to the network performance in routing optimization of the communication systems. Different network services require different QoS functionalities that cannot be supplied by the current QoS-unaware routing protocols [8]. Various QoS metrics and optimization techniques can be considered in QoS assessment of SG.

Using the innovation of Artificial Intelligence (AI) is suitable to develop complex tasks such as path discovery in routing schemes [9]. In the recent years, some routing protocols have been suggested that use the AI for optimization of the network performance [10–

* Corresponding author.

Email addresses: rrastgoo@eng.uk.ac.ir (R. Rastgoo), vsnaeini@uk.ac.ir (V. Sattari-Naeini)

https://dx.doi.org/10.22108/jcs.2018.106871.0
ISSN: 2322-4460

16]. We introduce some of the recent research works and protocols in the next section in order to have a suitable understanding of shortages and infects of the routing challenge in SG. Considering the defects and incompleteness of the existent routing protocols for SG, we propose a routing protocol, Neuro-Fuzzy Stable Optimization Multi-Constrained Routing (NFSOMCR), by using seven parameters to show the QoS requirements in the SG. In addition, a cost function has been defined to collect the suggested parameters and optimize it by using the Neuro-Fuzzy technique. Sections 3 and 5 show the details of the NFSOMCR.

The rest of this paper is arranged as follows. Section 2 reviews some literatures in routing optimization of SG. In Section 3, we introduce system model. A brief overview of neural network as well as fuzzy systems has been expressed in the Section 4. We present our method for path finding, path selection based on the constraints in the paths, and details of the Neuro-fuzzy system used to optimize the routing protocol in Section 5. In Section 6, we provide the details of the experimental results of the proposed protocol and compare it by the recent research works. Eventually, with Section 7 we conclude the work.

2 Related Works

In this section, we review some literatures in routing optimization of the SG. In one of these literatures, Li and Zhang use the delay metric to verify the QoS routing requirements in the SG. They use only two QoS requirements along with greedy routing algorithm in their Optimized Multi-Constrained Routing (OMCR) protocol [13]. OMCR uses a greedy routing algorithm, which is not suitable for some conditions that the SG may experience. In addition, OMCR doesn't consider different situations and challenges in SG routing due to use only two parameters to show the QoS routing requirements. In another literature, Saputro et al., consider all of the QoS requirements of various applications to support the QoS in the network that is too expensive and complicated [14]. A routing protocol, namely Genetic Algorithm with TBR Algorithm for Smart Grids (GATAS), is designed by Zaballos et al. GATAS is a combination of the Genetic algorithm (GA) and Ticket-Based Routing (TBR) [17]. However, GATAS protocol decreases the routing packets and minimizes the network communication delay of SG [17]; there are several limitations in the GATAS. First of all, the probe distribution is not optimized. Second, the variation of the delay between two nodes in the network cannot be approximated precisely. Third, the choosing of the final probes at the destination node does not take into account the load balancing. Jahromi and Rad, introduce an optimization model (PC/ISO) by using GA, which is focused on the topological design of a power communication network rather than the routing approach of the network [15]. Ebrahimi et al., propose a fuzzy-based adaptive routing algorithm to decrease congestion in the network, which in some cases their algorithm leads to non-optimal decisions [16]. Sahin et al., suggest a routing approach to prepare the service differentiation in reliability and timeliness domains in different SG environments [18]. However, they evaluate the network performance in single-path and multi-path environments; the power consumption of the network is not studied. Hou et al., present a multicast tree routing algorithm to minimize the transmission delay in Wide Area Control Systems (WACS) [19]. Since this routing algorithm is suggested to specific application, it cannot be used in general applications. Lin et al., suggest two protocols, Local Optimal Energy Routing Protocol (LOER) and Global Optimal Energy Routing Protocol (GOER), for SG. Due to high computational overhead of the GOER, it is not suitable for large-scale networks. LOER uses the layer optimal strategy to decrease the overhead of the network [20]. In other study, a Hybrid Wireless Mesh Protocol (HWMP) based Neighbor Area Network (NAN) QoS-aware routing scheme, namely HWMP-NQ, is studied that uses an integrated routing metric to route decision. To decrease the impact of routing oscillations of the HWMP-NQ, Deng et al., suggest a multi-gateway backup routing scheme along with a routing reliability correction factor [21].

After studying the existent routing protocols and understanding their defects, we proposed a Neuro-Fuzzy routing protocol [10], namely Neuro-Fuzzy-based Optimization Multi-Constrained Routing (NFOMCR), by only two parameters that may be insufficient to cope with the different situations of the SG. After that, we decided to consider more parameters and situations for SG. In this regard, we suggested seven network parameters such as path loss, packet loss, criticality, effective throughput and the others, to evaluate the network behavior. We applied the GA to optimize the proposed routing algorithm, namely Genetic-Algorithm Stable Optimization Multi-Constrained Routing (GASOMCR), with these suggested parameters [11]. After that, we decided to propose a routing algorithm by using the innovation of the Neuro-fuzzy approach, which is redounded to a considerable result in the SG. For this purpose, we introduce seven parameters to meet important QoS requirements of SG. After that, we develop a cost function based on these parameters. Depending on the different initialization of the parameters, some routes are found out by Dijkstra routing algorithm. These routes form inputs of the Neuro-Fuzzy system. The optimized cost function as well as optimal paths between to nodes are the outputs of the proposed Neuro-Fuzzy system.

Experimental results show that the proposed method outperforms existing works in terms of power cost and throughput. Appropriate training and learning of the neural network and fuzzy system, used in Neuro-fuzzy system, are very effective for convergence speed of the cost function. Our goal for using the Neuro-Fuzzy technique in NFSOMCR is comparing the power of the various Artificial Intelligence (AI) algorithms in our proposed routing protocols in order to select and use the best one of these protocols.

Contributions of this paper are listed as following:

- Proposing a routing protocol by considering the QoS guarantee,
- Using the Neuro-Fuzzy technique for optimizing the cost function of the protocol,
- Considering different initializations for parameters to have some paths with their constraints in order to form the inputs of the Fuzzy system. This step makes the network flexible to cope with the different situations and conditions for parameters as well constraints of paths in SG.

Details of the proposed model and protocol are mentioned in Section 3 and 5.

3 System Model

We propose a system model includes Home Device (HD), Smart Meter (SM), Data Aggregator Unit (DAU), Meter Data Management System (MDMS), and Control Center (CC) for SG. Description of the components of the proposed model is shown in Table 1. After sending a request from a user, the request forwards from HD to CC in order to find the optimized routes. Founded routes are sent back to user based on the NFSOMCR. Figure 1 as well as Table 1 show the proposed model and details of the components. More details of the proposed model can be found in [11].

4 Overview of Artificial Neural Network and Fuzzy System

In this section, a brief overview of artificial neural network and fuzzy system are mentioned.

4.1 Artificial Neural Network

The idea of artificial neural network is simulation of the neurons in the human brain. Neurons and their connections are defined as the neurons in the layers of the artificial neural network that connect to each other by using the weight vectors. Three types of the layers, input, hidden, and output layers, are used in these networks. Two artificial neural network topologies are as follows [22]:

- Feed forward artificial neural network: In this type of the network, the neurons of each layer is only connected to the neurons of the next layer. There is no feedback in this type of the network. Figure 2 shows a feed forward artificial neural network including three layers, two neurons in the input layer, three neurons in the hidden layer, and two neurons in the output layer.
- Feed back artificial neural network: In this type of the network, the neurons of each layer is not only connected to the neurons of the next layer but also to the neurons in the previous layers. Connecting a neuron in a layer to a neuron in the previous layer is called a feedback connection in the feed back artificial neural network. Figure 3 shows a feed back artificial neural network including three layers that has a feed back connection from the third layer to the first one.

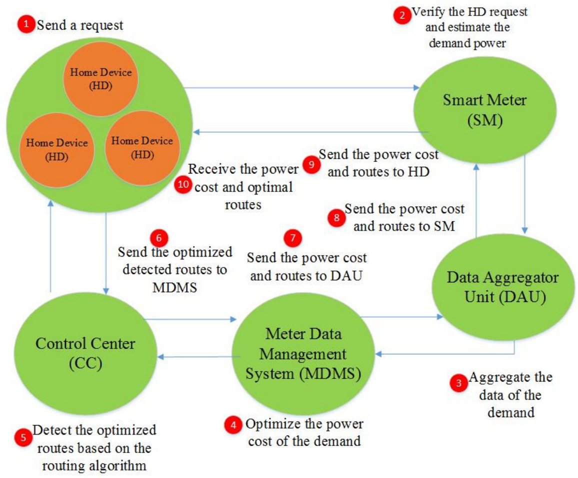

Figure 1. Suggested Model of SG, Which Contains Home Device (HD), Smart Meter (SM), Data Aggregator Unit (DAU), Meter Management System (MDMS), Control Center (CC) [11].

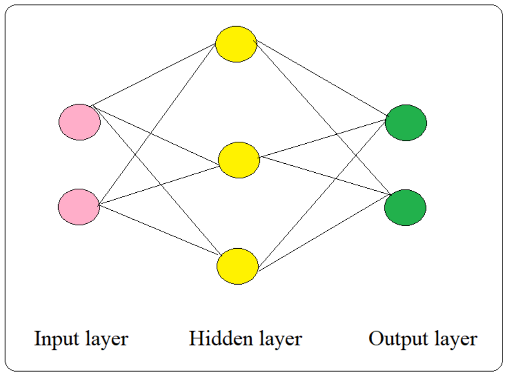

Figure 2. A Feed Forward Artificial Neural Network Including Three Layers.

Table 1. Details of the Considered Components in the Suggested Model of The SG.

Component Name	Abbreviation	Description
Home Device	HD	Devices, such as charger, TV, Laptop, etc., that users can use them for sending requests to receive the electrical energy.
Smart Meter	SM	A device that estimates the consumption of the electrical energy with the ability to record the details of the consumption.
Data Aggregator Unit	DAU	A unit that collects the data of the energy consumption of the other devices and demands.
Meter Data Management System	MDMS	A system that manage the data of the energy consumption related to other devices and optimize the power cost of the demands.
Control Center	CC	A center to detect and select the optimal routes based on the suggested routing algorithm.

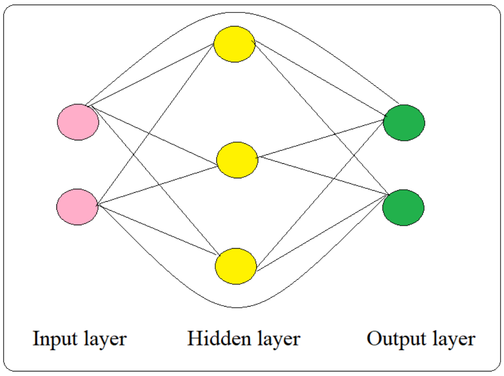

Figure 3. A Feed Back Artificial Neural Network Including Three Layers.

4.2 Fuzzy System

The idea of fuzzy system or fuzzy logic is converting the two-class outputs of the problems into multi-class outputs [23]. When we don't use the fuzzy logic in a problem or network, we only have two logical output class, true or false. In contrast, when we use the fuzzy logic, we have multi-class in the output that are expressed in the form of probability of presence each of the output class in the system. Figure 4 shows these two types of logics. While in non-fuzzy system, Boolean logic, only one of the output classes are selected and assigned to 1, in fuzzy system, the labels of the output can be in the form of probability of presence of each output in the system.

5 Proposed Protocol

We describe the details of the path finding, path selecting, and proposed Neuro-Fuzzy approach used in NFSOMCR in the following sub-sections.

5.1 Proposed Method for Path Finding

After drawing the directed graph of the SG, we assign a weight to each edge in the graph. For each edge, we consider all of the suggested QoS parameters so that we can calculate the cost function by using these parameters. Each of the suggested parameters has an effective role in the performance convergence of the network. Loss of each parameter can led to an unstable behavior for network. The suggested parameters are listed as following:

- First: packet transmission delay, d, is the delay of the packet transmission in the network that includes two types of delays: queuing and transmission delay.
- Second: connection outage probability, ζ, which is outage probability at each link of the network.
- Third: network criticality, τ, shows the network sensitivity to various changes in the network.
- Fourth: network unavailability, A, determines the delay of the components availability in the network.
- Fifth: effective throughput, ET, which is defined as the quantity of the data that is successfully transferred from the network link, divided by hop count. The number of the intermediate hops between source and destination nodes is considered as the hop count.
- Sixth: path loss, ψ, is the difference between the transmitted and received power.
- Seventh: packet loss pl, which is defined as the percentage of the total number of the transmitted packets that is lost in the network.

The overall network cost function of NFSOMCR, is defined as following:

$$\begin{aligned}\text{Net-Cost}(t, d, \zeta, \tau, A, ET, \mu) = p(pl).L(t, \zeta, \tau, A, \beta)\\ + p(1 - pl).C(t, d, ET, \psi, \alpha)\end{aligned}$$

where t is the time interval of the network evaluation, α shows the parameter that can be led to unavailability when packet loss is occurred due to unavailability, and β is the parameter that can be redounded to unavailability when packet loss is occurred not due to unavailability. $p(pl)$ is the probability of packet

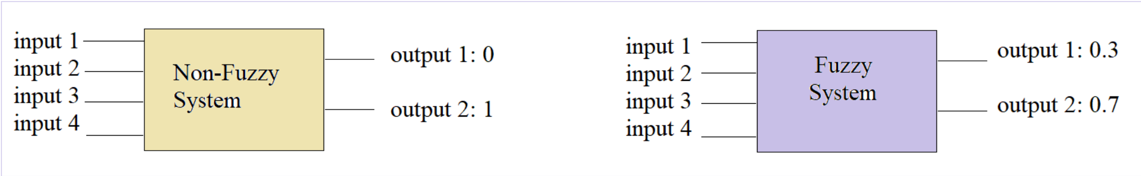

Figure 4. Non-Fuzzy System Outputs Versus Fuzzy System Outputs.

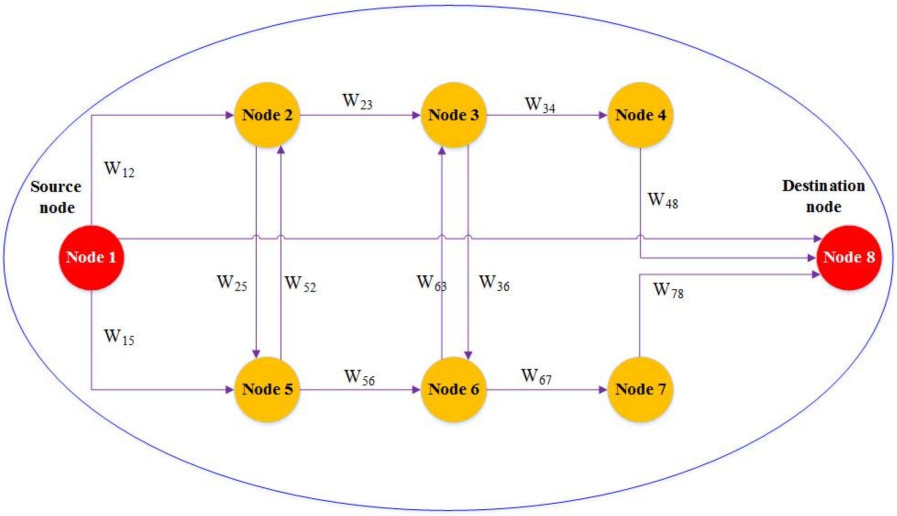

Figure 5. The Graph of the SG That Includes the Nodes, Edges, and Assigned Weights to Each Edge.

loss occurrence, L and C are the loss and cost of the parameters. All used parameters and functions in the proposed routing protocol are shown in Table. 6-14 in Appendix A. Seven parameters have been considered to define a cost function. While some of these parameters have a positive effect on the cost function, some others have a negative effect. We have defined two types of cost for these parameters:

- L defines for parameters with negative effect on the cost function. This means that when each of these parameters increases, the cost function decreases.
- C defines for parameters with positive effect on the cost function. This means that when each of these parameters increases, the cost function also increases.

Details of the parameters and functions used in the NFSOMCR can be found in [10]. Due to using the benefits of logarithm function, we used it in our cost function. The values of the parameters as well as the cost function have been scaled in the figures. All parameters are positive in order to avoid reaching to infinity. We optimize the cost function by having a trade-off among the parameters of the network cost function in the proposed Neuro-Fuzzy technique. Since we intend to use the Fuzzy system and Neural Network in Neuro-Fuzzy technique, we must have adequate training data to train the Fuzzy system and Neural Network. In this regard, we execute the Dijkstra in a loop, which the iteration numbers of the loop are selected so that we can have adequate knowledge for Fuzzy system and training data for Neural Network. In each iteration, we have the below actions:

- Initializing the suggested QoS parameters by random values,
- Assigning the edges weight by using the cost function and QoS parameters,
- Executing the Dijkstra procedure that conduces to one found path, and
- Determining the constraint of the found path.

After executing the above loop, all of the found paths of the Dijkstra algorithm are entered to the Fuzzy system to extract the If-Then rules. Then, the extracted rules are entered to Neural Network to train and find the optimal path and values of the parameters. The graph of SG, flowchart, and pseudo code of explained method are shown in Figures 5, 6 and Algorithm 1, respectively. W_ij in Figure 6 is the weight of the edge from node i to node j.

5.2 Multiple Path Selection Based on Multi-Constraint QoS Requirements

To optimize the routing protocol, we need to prepare adequate training data to learn the proposed Fuzzy system and Neural Network used in Neuro-Fuzzy tech-

Algorithm 1 Flowchart of NFSOMCR.

Start

1: Draw the **network graph**
2: Count = 0
3: Initialize the Threshold 1 and Threshold 2
4: **Loop Until Count is lower than Threshold 1**
5: Initialize the network parameters
6: Calculate the network weights
7: Dijkstra executing to find paths
8: Determine the constraints of the found paths
9: Count = Count + 1
10: **End Loop**
11: Enter found paths and constraints to **Fuzzy system**
12: Extract the **If-Then** rules
13: Enter the extracted rules to **Neural Network**
14: Train the rules
15: If the train error is lower than Threshold 2 **go to** 14 otherwise **go to** 12
16: Output the **optimal paths** and **optimal values** of the parameters after enough training

End

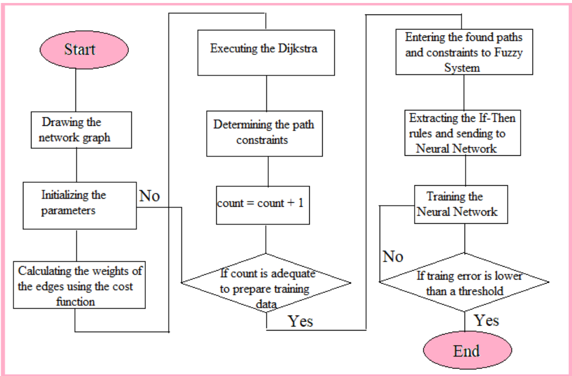

Figure 6. Flowchart of the Proposed Method for Path Finding and Optimization of the Routing Protocol by Using a Neuro-Fuzzy Technique

nique. In this regard, we find some paths by using Dijkstra routing algorithm and consider a constraint for each found path in the network. Constraints are used to bind the values of the suggested parameters as well as the network cost. Indeed, each constraint shows the boundary value of each parameter in each found path. Note that, we determine the weight of the edge in the network graph by using the network cost function considered for SG. Each constraint is a column vector including some elements, which the numbers of the elements are equal to number of the suggested parameters plus one. Latest element of the constraint vector has been used for weighting the path. For example, if we have a vector B as a constraint vector, then B includes eight elements in our work, which seven elements are the seven suggested parameters and one is the network cost calculated by cost function based on the seven parameters proposed in [11]. Each element of the B shows the boundary value for each parameter in each path of the SG. After finding the optimal path of the SG by Dijkstra, we determine the constraint of the found path. In this regard, we calculate each element of the constraint vector as Table 2.

After determining some constrains in the SG, we send these constraints along by found paths to Fuzzy system to extract the If-Then rules. Note that, the number of the constraints and found paths must be such that we can have adequate training data for proposed Fuzzy system and Neural Network.

5.3 Neuro-Fuzzy Approach to Find the Optimal Path

To optimize the network cost of the proposed routing protocol, NFSOMCR, we suggest a hybrid approach. Details of the proposed fuzzy inference system and Neural Network are similar to NFOMCR [10]. Undoubtedly, the settings of the fuzzy system needs to be adjusted and specialized for the current situations. In fact, the used system in the NFOMCR is a scaled version of the system in the current model. In NFOMCR, we only had two parameters and much lower details in the cost function as well as the routing mechanism. In this regard, it is inevitable to have a system with much more settings and rules. Any appropriate membership function can be chosen in Fuzzy system. We apply the Sigmoid function due to its continuous and differential property which is effective and suitable in back propagation learning and optimizing steps in our system. The inputs of the proposed Fuzzy system are the proposed parameters and the output is the network cost. Fuzzy linguistic expressions used for inputs are 'Low', 'Medium', and 'High'. Output of the Fuzzy system is described by 'Low', 'Stable', and 'High' Fuzzy

Table 2. Constraint of the Found Path in the NFSOMCR

$$B_1 = \begin{bmatrix} \zeta_1 \\ d_1 \\ \psi_1 \\ pl_1 \\ E\Gamma_1 \\ \tau_1 \\ A_1 \\ C_1 \end{bmatrix},$$

ζ_1	ζ_1 is a max outage among the outage of the graph edges in the found path.
d_1	d_1 is a max delay among the delay of the graph edges in the found path.
ψ_1	ψ_1 is a max path loss among the path loss of the graph edges in the found path.
pl_1	pl_1 is a max packet loss among the packet loss of the graph edges in the found path.
$E\Gamma_1$	$E\Gamma_1$ is a min effective throughput among the packet loss of the graph edges in the found path.
τ_1	τ_1 is a max criticality among the criticality of the graph edges in the found path.
A_1	A_1 is a min availability among the availability of the graph edges in the found path.
C_1	C_1 is the cost of the found path.

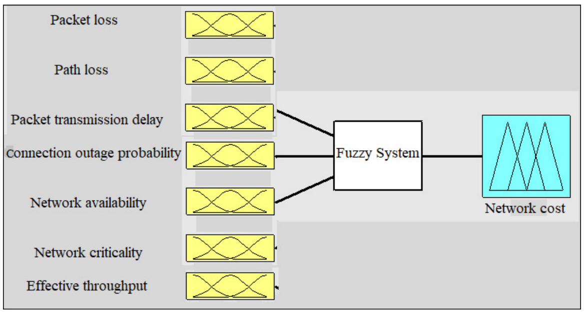

Figure 7. Fuzzy System Schematic as Well as Inputs and Output of the System.

linguistic expressions. Some of the Fuzzy rules used in our Fuzzy system are shown in Table 3. We used the If-Then rules by using the AND operator in the rules. Since the network cost function is depend on the other parameters, we used the Sugeno fuzzy inference system in the proposed model. The output of this system is a combination of the inputs. Table 4 shows some of these If-Then rules. Fuzzy system schematic as well as inputs and output of the system are shown in Figure 7.

We use a fuzzy inference system to extract the rules and send them to proposed Neural Network. The proposed Fuzzy system includes some parts, shown in the Figure 8, as the following:

- Membership function assigning: In this part, a suitable membership function is selected for inputs of the Fuzzy system.
- If-Then rule extracting: Based on the inputs and output of the system, we extract the rules of the Fuzzy system.
- Fuzzyfication: To convert the crisp values of the input parameters to linguistic expressions, uzzyfication is used. In this regard, we can extract the If-Then rules by using the linguistic expressions of the inputs.
- Decision making: In this step, we combine the extracted rules of the Fuzzy system which are suitable for proposed protocol and can optimize it. Combining some rules in order to have one rule can be useful because we test some rules and collect the result of them in one rule by the form that each parameter in the combined rule can have some values or linguistics. For example, the connection outage probability parameter can be expressed either by 'Large' or 'Medium' in one rule.
- Defuzzyfication: Converting the linguistic expressions to the crisp values is essential for us to have a suitable explanation on the achieved results. The Centroid Defuzzyfication is used.

We use a feed forward neural network with three layers. The neurons and nodes number in the first and second layer are identical. The nodes number characterizes by selecting the found path of the Dijkstra routing algorithm, in first layer. Inputs of the first layer are the nodes of the selected path found by the routing algorithm. These inputs are shown by Node1, Node2, Node3, ... parameters in Figure 9. Third layer is the output layer and computes the optimal values of the suggested parameters as well as the network cost. Training the Neural Network, we can attain the optimal values of the suggested parameters, network cost value, and optimal found path in the SG. Learning by using the back-propagation and decreasing the error are in the procedure of the learning. The goal of the proposed neural network is learning the proposed parameters and functions. Seven outputs are seven parameters and the last one is the network cost. These eight parameters are the output of the network. The network perspective of the proposed Neural Network is shown in Figure 9.

6 Results and Discussions

To examine of the network behavior of the proposed protocol, NFSOMCR, we study the network performance evaluation and Neural Network training in the following sub-sections. Also, we compare NFSOMCR with the other protocols. Details of the results are investigated in the following sub-sections.

Table 3. The Linguistic Expressions of the Inputs and Output Parameters of the Proposed Fuzzy System

Rule Number	Packet loss	Path loss	Packet Transfer Delay	Connection Outage Probability	Network Availability	Network Criticality	Effective Throughput	Network Cost
1	Low	Low	Low	Low	High	Low	High	High
2	High	Low	High	High	Low	High	Low	Low
3	low	Medium	Low	Medium	High	Medium	High	Stable
4	Medium	Low	Medium	Low	Medium	Low	Medium	Stable

Table 4. If-Then Expressions of the Extracted Rules of the Proposed Fuzzy System

Rule Number	If-Then rules
1	**If** Packet loss='Low' *and* Path loss='Low'*and* Packet Transfer Delay='Low' *and* Connection Outage Probability='Low' *and* Network Availability='High'*and* Network Criticality='Low' *and* Effective Throughput='High' **Then** Network Cost='High'.
2	**If** Packet loss='High' *and* Path loss='Low' *and* Packet Transfer Delay='High' *and* Connection Outage Probability='High' *and* Network Availability='Low' *and* Network Criticality='High' *and* Effective Throughput='Low' **Then** Network Cost='Low'
3	**If** Packet loss='Low' *and* Path loss='Medium' *and* Packet Transfer Delay='Low' *and* Connection Outage Probability='Medium' *and* Network Availability='High' *and* Network Criticality='Medium' *and* Effective Throughput='High' **Then** Network Cost='Stable'
4	**If** Packet loss='Medium' *and* Path loss='Low' *and* Packet Transfer Delay='Medium' *and* Connection Outage Probability='Low' *and* Network Availability='Medium' *and* Network Criticality='Low' *and* Effective Throughput='Medium' **Then** Network Cost='Stable'

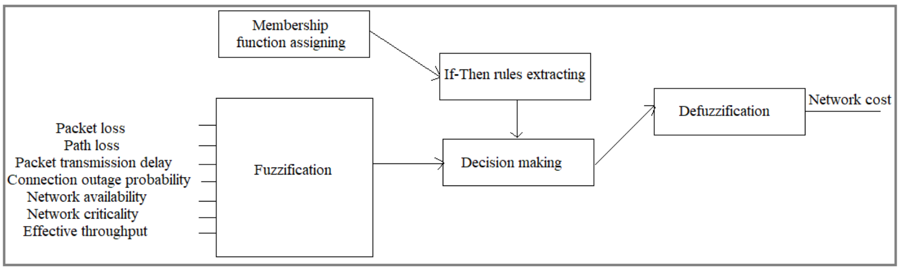

Figure 8. Parts of the Proposed Fuzzy Inference System Including Five Parts.

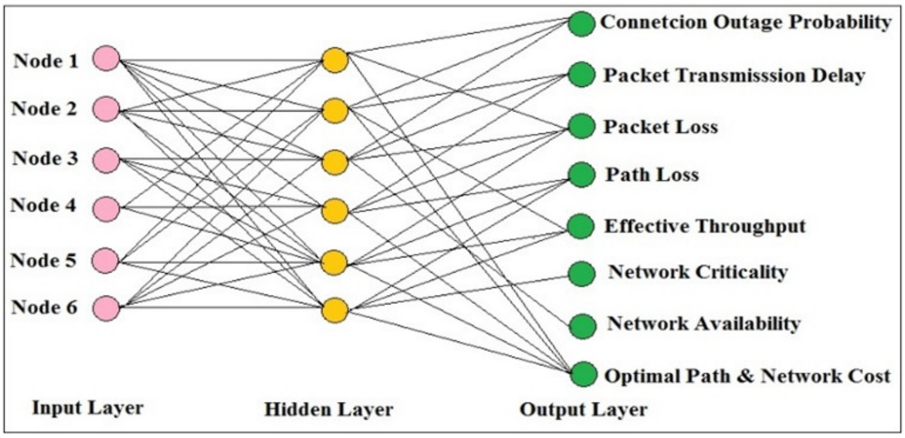

Figure 9. Network Perspective of the Proposed Neural Network Including Three Layers.

6.1 Evaluation of the Network Performance

The layer numbers are very significant in computing the network cost. In other words, we should properly determine the layer numbers to have an affordable behavior in the network. We test different values of

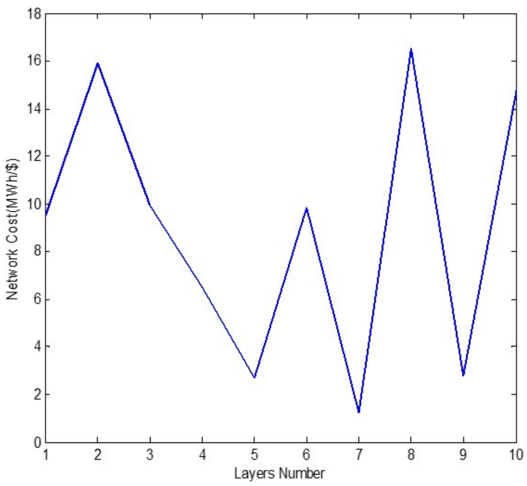

Figure 10. Network Cost Versus Layer Numbers.

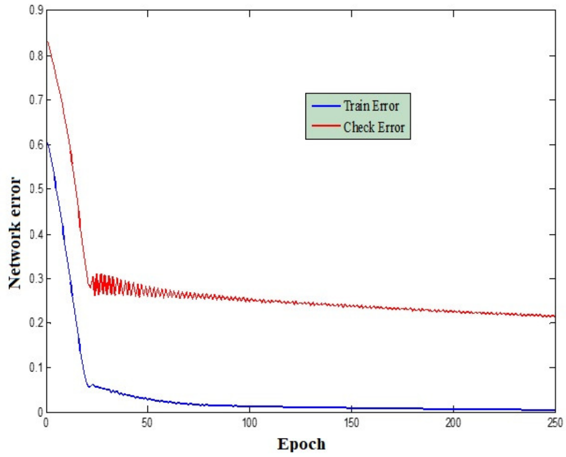

Figure 11. Train Error in Different Epochs.

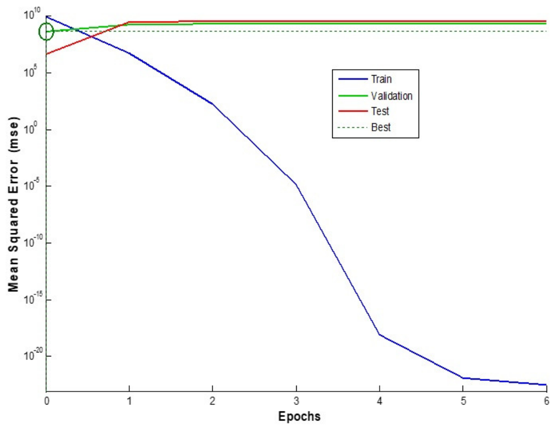

Figure 12. MSE in Different Epochs.

the layer numbers to choose the appropriate value for it. Figure 10 shows the different layer numbers versus the network cost.

6.2 Training the Network

The train error of the proposed neural network is determined in Figure 11. According to Figure 11, the train error reduces in higher epochs, which is a suitable behavior to make better the network performance. Mean Square Error (MSE) is chosen to evaluate the network performance. Figure 12 determines the MSE in different epochs for the train, test, validation, and best errors. According to Figure 12, the slop of the error curve in train error decreases, which shows that the network is near to the acceptable performance. Outputs of the proposed Neural Network are the optimal values of the proposed parameters, network cost, and path. Optimal values of the proposed parameters and network cost in training of the network are shown in Table 5. Values of the parameters are scaled in figures, for simplicity. Based on the experimental results, the feed-forward NN is converging to the proper output by suitable adjusting the network parameters. We tested different parameters for network so that the network can converge to the suitable parameters.

6.3 Comparison With Other Protocols

In this sub-section, we compare the network cost of the proposed protocols with the other protocols. In the first step, we compare the network cost of the NFSOMCR, GASOMCR [11], NFOMCR [10], and OMCR [13]. The later one is a protocol defined for SG, which is a suitable candidate solution to Multi-Constrained problems. Figure 13 shows the comparison of NFSOMCR, GASOMCR, NFOMCR, and OMCR protocols. While NFSOMCR, GASOMCR, and OMCR protocols have a similar behavior between second and seventh iterations of the figure; NFSOMCR decreases after the seventh iteration, GASOMCR has a monotonically behavior after the second iteration, OMCR increases in the last iteration, and NFOMCR decreases in the last iterations after having an increasing behavior in the first iterations. Level of the network cost in OMCR is higher than the NFSOMCR, GASOMCR, and NFOMCR. Although GASOMCR has the lower level of the network cost than the NFSOMCR protocol, NFSOMCR can also use efficiently due to decreasing behavior in last iteration as well as GASOMCR.

In the second step, we compare the power cost of the NFSOMCR, GASOMCR, GOER [20], and Global Load Balance Algorithm [20]. The latter one is an algorithm for load balancing in the network. While GOER and Global Load Balance Algorithm have the decreasing behaviors, NFSOMCR decreases in the last iterations and GASOMCR have an approximately stable behavior in seven iteration of the load limitation between 3600-500 MW. This comparison is shown in the Figure 14. In load limitation between 5000-7200

Table 5. Optimized Value of the Proposed Parameters in Training of the Neural Network

Number	Packet Loss	Path Loss (dB)	Packet Transmission Delay (ms)	Connection Outage Probability	Network Availability	Network Criticality (MW)	Effective Throughput (bps)	Network Cost (MWh/ $)
1	0.2	3	2.7	0.21	0.8	3.2	9	18
2	0.18	2.8	3.2	0.3	0.87	2.81	8.7	16
3	0.8	2.3	8.3	0.84	0.2	9.1	3.4	8.03
4	0.85	3.1	8.9	0.81	0.16	8.9	2.4	8.03
5	0.23	4.1	2.6	0.41	0.81	4.5	8.1	8.03
6	0.85	3.1	8.9	0.91	0.33	8.3	2.84	8.02
7	0.26	4.3	2.8	0.41	0.85	5.2	9.2	8.01
8	0.31	3.9	3.1	0.52	0.89	5.6	8.4	8.01
9	0.47	2.9	4.6	0.21	0.51	2.1	4.5	8.01
10	0.52	2.3	5.1	0.18	0.46	3.1	5.2	8.01

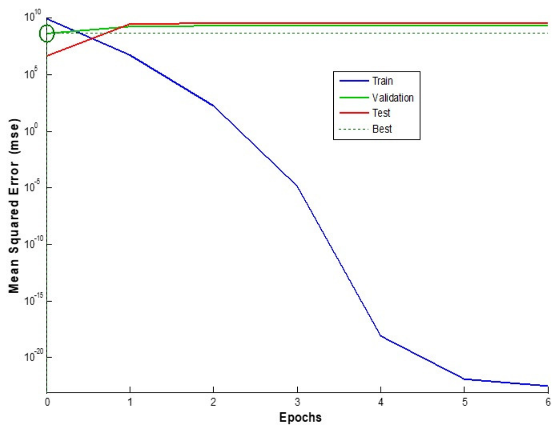

Figure 13. Comparison the Cost of NFSOMCR, GASOMCR, NFOMCR, and OMCR.

MW, however all of the protocols and algorithms have an approximately fixed and stable behavior, level of the power cost is different in these protocols and algorithms. This comparison in load limitation between 5000-7500 MW is shown in the Figure 15.

In the third step, the network throughput of the Hybrid Wireless Mesh Protocol (HWMP) [21], Neighbor QoS-aware Hybrid Wireless Mesh Protocol (HWMP-NQ) [21], Multi-gateway Routing [19], and NFSOMCR are compared in different node numbers of the network. As we can see in Figure 16, increasing mode of the protocols continues so that they reach to node number equal to 36. While HWMP decreases in this point, the other protocols increase. In the point that the node number is equal to 49, throughput of the HWMP-NQ and Multi-gateway Routing protocols decrease while NFSOMCR continues the increasing behavior. Decreasing behavior of the protocols is the result of congestion in the network due to increasing

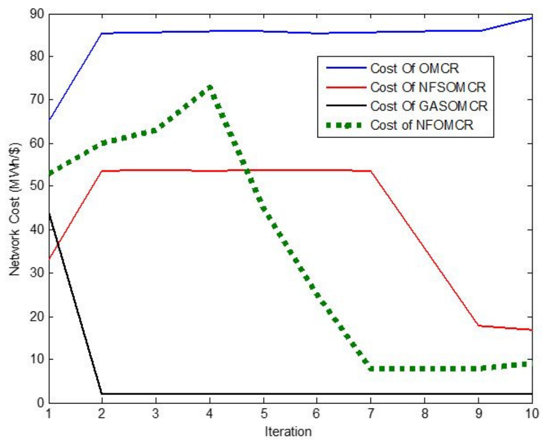

Figure 14. Comparison of the Power Cost of the NFSOMCR, GASOMCR, GOER, and Global Load Balance Algorithm in Load Limitation 3600-5000 MW.

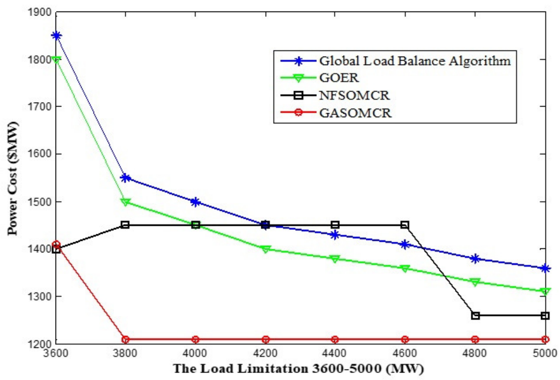

Figure 15. Comparison of the Power Cost of the NFSOMCR, GASOMCR, GOER, and Global Load Balance Algorithm in Load Limitation 5000-7500 MW.

the number of the network nodes. According to Figure 16, NFSOMCR has an increasing behavior and

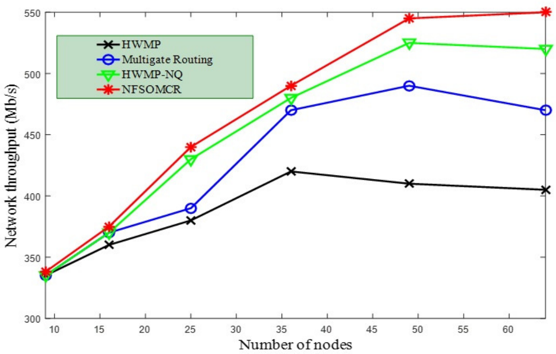

Figure 16. Comparison of the Throughput of the HWMP, HWMP-NQ, Multi-Gateway Routing, and NFSOMCR Protocols in Different Node Numbers of the Network.

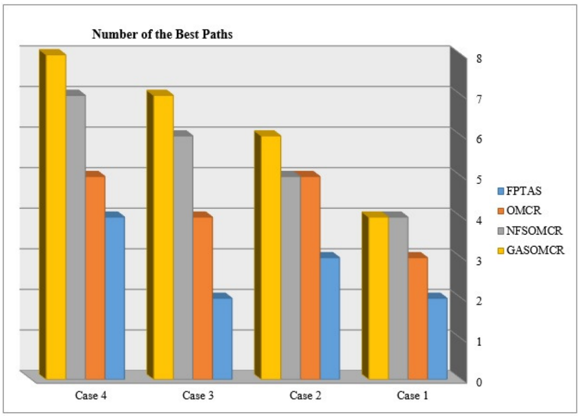

Figure 17. Comparison of the Number of the Best Paths Found by OMCR, GASOMCR, NFSOMCR, and FPTAS.

doesn't decrease till the node number equal to 64. This shows that the congestion of the network with NFSOMCR occurs in higher node numbers that has a positive effect on the network performance.

Finally, we compare the number of the best paths found by OMCR, GASOMCR, NFSOMCR, and FPTAS [24]. FPTAS is the best estimate result of the OMCR problem [13]. Four test cases are used to compare the ability of the protocols in order to find the best paths in routing of the network. In these test cases, SG is simulated by randomly generated topology and some pairs of the source-destination nodes in the network. Different numbers of nodes (from thousands, dozens, and more) have been tested to evaluate the model. For evaluating the larger numbers of nodes, the powerful processors are needed in order to decrease the processing time and parallel executing. Figure 17 shows this comparison.

7 Conclusion and Future Works

SG is an intelligent managed network, which utilizes the two-way flows of the data and electricity to have the efficient relations among various components. In this work, we propose a QoS routing protocol, NFSOMCR, which uses the novelty of the Neuro-fuzzy technique to improve the network performance. Seven parameters are suggested to show the QoS requirements in the SG. Trading-off among the proposed parameters leads to minimize the network cost. To improve the path selecting of the NFSOMCR, we consider a loop that including some actions, which are: initializing the parameters value, assigning the weights of the edges in the network graph, executing the Dijkstra routing algorithm, determining the optimal path, determining the constraint of the found path. After execution of the loop, we have some paths along with their constraints. Fuzzy system extracts the If-Then rules from the found paths and constraints. Fuzzy rules are sent to Neural Network to train and extract++ the optimal values of the parameters, network cost, and optimal cost. Suitable designing and training of the Fuzzy system and Neural Network, utilized in the Neuro-Fuzzy system, have an important role in the convergence speed of the network performance to optimum value. Our comparison results of the proposed protocol with the other protocols shows the performance improvement in the network. We will continue our study on NFSOMCR protocol in order to optimize and decrease the network cost level more and more. Although having the seven parameters in our proposed protocol can be expensive; the network behavior is sufficiently appropriate with these suggested parameters cost functions.

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A Appendix

Table A.1. First Part of the Parameters Used in the Proposed Routing Protocol.

Variable	Description	Variable	Description
C_i	The weight of link i	d_{trans}	transmission delay
pl	Packet loss	L	packet length
ρ	$\rho = \frac{\lambda}{\mu}$	R	link bandwidth
N	Queue capacity in each network node	ζ	Connection outage probability
λ	Arrival rate in the queue	η	threshold
μ	Mean service rate of the queue in node	I_{ag}	aggregate interference power
f	frequency	I_{th}	$I_{th} = \frac{P_d}{\eta - P_0}$
h	antenna height	P_d	noise power
dis	path length between each two nodes	P_0	desired signal power
ψ	Hata path loss	α	The effect of the parameters that is not comprised in the suggested parameters, when packet loss happens.
Γ_i	throughput on link i	β	The effect of the factors that are not comprised in the suggested parameters, when unavailability happens.
Γ	Minimum of the throughputs in the network links	$\overline{A}$	Network unavailability
n	Number of the links	L	Penalization function
LR	transmission rate of the link	$g(t)$	utility function
p_i	collision probability of link i	L_{outage}	Penalization of connection outage
x_i	normalized channel airtime allocated to link i	L_{packet_loss}	Penalization of packet loss
$E\Gamma$	effective throughput	$L_{1-availabality}$	Penalization of unavailability
K	hop count between source and destination nodes in the network	$L_{criticality}$	Penalization of network criticality
E	set of links	L_{β}	Penalization of β
m	the number of links	C_{delay}	Cost of packet transmission delay
b_i	betweenness of link i ,	$C_{throughput}$	Cost of effective throughput
W_i	weight of link i	C_{path_loss}	Cost of path loss
$I_i^{(st)}$	current flow transmitted through ith vertex, from node s to node t	C_{α}	Cost of α
A_{ij}	an element of the adjacency matrix	t	Spent time from the beginning time of the network evaluation
$V_i^{(st)}$	voltage at vertex i from node s to node t	L_{packet_loss}	penalization made by packet loss
n_e	edges number in the network	L_{β}	penalization made by packet loss, because of the parameter β happening
A	Network availability	Net_Cost	Network cost
$MTBF$	Mean Time Between Failure (MTBF)	P_{delay}	Tax of packet transmission delay
$MTTR$	Mean Time To Repair (MTTR)	$P_{troughput}$	Tax of effective throughput
d	Packet transmission delay	P_{path_loss}	Tax of path loss
d_{ϱ}	queuing delay	T_{packet_loss}	Tax of packet loss
L_s	average number of the packets in the queue	T_{outage}	Tax of connection outage
P_{n_p}	probability that there are n_p packets in the queue of each node in the network	$T_{criticality}$	Tax of network criticality
n_p	Number of the packets in the queue	$T_{unavailability}$	Tax of unavailability

Table A.2. Second Part of the Parameters Used in the Proposed Routing Protocol.

Variable	Description	Variable	Description
P_N	probability that there are N packets in the queue of each node in the network	C	Cost function
λ_e	effective arrival rate	τ	Network criticality
Count	Counter of loop	Train Error	Error of the training in the proposed Neural Network.
Neurons number	The number of the neurons in the proposed Neural Network.	Check Error	Error of the proposed Neural Network in test data.
Validation Error	Error of the e proposed Neural Network in validation data.	Best Error	Minimum error of the proposed Neural Network.
Test Error	Error of the proposed Neural Network in test data.	Epoch	One iteration in evaluating the proposed Neural Network.
ζ^*	Optimal value of connection outage	ψ^*	Optimal value of path loss
pl^*	Optimal value of packet loss	$\overline{A}^*$	Optimal value of network unavailability
τ^*	Optimal value of network criticality	$E\Gamma^*$	Optimal value of effective throughput
d^*	Optimal value of packet transmission delay		

Table A.3. Loss Functions Used in the NFSOMCR

$L_{outage}\ (t,\zeta) = \frac{1}{\lVert\zeta\rVert} \cdot \mathrm{g(t)}$	$C_{delay}\ (t,\mathrm{d}) = \frac{1}{\lVert d\rVert} \cdot \mathrm{g}(t)$
$L_{packet\_loss}\ (t,\ pl) = \frac{1}{\lVert pl\rVert} \cdot \mathrm{g}(t)$,	$C_{throughput}\ (t,\ \mathrm{E}\Gamma) = \lVert E\Gamma\rVert .\ \mathrm{g}(t)$,
$L_{criticality}\ (t,\ \tau) = \frac{1}{\lVert\tau\rVert} \cdot \mathrm{g}(t)$,	$C_{path\_loss}\ (t,\ \psi) = \frac{1}{\lVert\psi\rVert} \cdot \mathrm{g}(t)$,
$L_{1-availability}\ (t,\ \overline{A}) = \frac{1}{\lVert\overline{A}\rVert} \cdot \mathrm{g}(t)$,	$C_{\alpha}\ (t,\ \alpha) = \lVert\alpha\rVert \cdot \mathrm{g}(t)$,
$L_{\beta}\ (t,\ \beta) = \frac{1}{\lVert\beta\rVert} \cdot \mathrm{g}(t)$,	$\mathrm{g}(t) = 1000\log(t)$

Table A.4. Optimal Values of the Parameters Used in the NFSOMCR

$\zeta^* = \arg\min_{\zeta}\left(\zeta.L_{outage}(t,\zeta) + T_{outage}(\zeta)\right)$	$pl^* = \arg\min_{pl}\left(pl.L_{packet\_loss}(t,pl) + T_{packet\_loss}(pl)\right)$
$\tau^* = \arg\min_{\tau}\left(\tau.L_{criticality}(t,\tau) + T_{criticality}(\tau)\right)$	$\psi^* = \arg\min_{\psi}\left(C_{path\_loss}(t,\psi) + P_{path\_loss}(\psi)\right)$
$\overline{A}^* = \arg\min_{\overline{A}}\left(\overline{A}.L_{unavailability}(t,\overline{A}) + T_{unavailability}(\overline{A})\right)$	$d^* = \arg\min_{d}\left(C.L_{delay}(t,d) + P_{delay}(d)\right)$
$E\Gamma^* = \arg\min_{E\Gamma}\left(C_{throughput}(t,E\Gamma) + P_{throughput}(E\Gamma)\right)$	$f = p\ (pl)\ .\ L + p\ (\bar{pl})\ .\ C$
$L = L_{packet\_loss}\ (t,\ \zeta,\ \tau,\ \overline{A}) + L_{\beta}\ (t,\ \beta)$	$C = C_{delay}\ (t,\ d) + C_{throughput}\ (t,\ E\Gamma) + C_{path\_loss}\ (t,\psi) + C_{\alpha}(t,\alpha)$

Table A.5. Functions Used for Parameters of the NFSOMCR

Parameter	Defined Functions for Parameter
Packet loss	$pl = \rho^N \frac{1-\rho}{1-\rho^{N+1}}$ $\rho=\frac{\lambda}{\mu}$
Path Loss	ψ= 69.55 + 26.16 log(f) - 13.82 log(h) - $a(h)$ + [44.9 - 6.55 log(h)] log(dis) $a(h)$ = 3.2 [log(11.75h)]^2 - 4.97
Packet Transmission Delay	$d = d_{\varrho} + d_{trans}$ $d_{\varrho} = \frac{L_s}{\lambda_e}$ $L_s = \sum_{n_p=0}^{N} . P_{n_p}\ ,\ P_{n_p} = \frac{(\frac{\lambda}{\mu})^{n_p}}{\sum_{n_p=0}^{N}(\frac{\lambda}{\mu})^{n_p}}$ $\lambda_e = \lambda[1-P_N]\ ,\ d_{trans} = \frac{L}{R}$
Connection Outage Probability	$P_{out} = \Pr\{SINR < \eta\} = \Pr\ \{I_{ag} > I_{th}\ \}$
Network Availability	$A = \frac{MTBF}{MTBF+MTTR}$
Network Criticality	$\tau = \frac{1}{m-1}\sum_{i\in E}\frac{\partial b_i}{\partial w_i}\ ,\ b_i = \frac{\sum_{s\prec t} I_i^{(st)}}{(\frac{1}{2})n_e(n_e-1)}$ $I_i^{(st)} = \frac{1}{2}\sum_{j} A_{ij}\lvert V_i^{(st)} - V_j^{(st)}\rvert$ $A_{ij} = \begin{cases} 1, & \textit{if there is an edge between } i \textit{ and } j \\ 0, & \textit{otherwise} \end{cases}$
Effective Throughput	$\Gamma_i = LR \times (1 - p_i) \times x_i\ ,\ \Gamma = \min_{i=1,2,\ldots,n}\{\Gamma_i\}\ ,\ \mathrm{E}\Gamma = \frac{\Gamma}{\kappa}$
Network Cost	$Next\_Cost\ (t,\ d,\ \zeta,\ \tau,\ \overline{A},\ \mathrm{E}\Gamma,\ \psi,\ \alpha,\ \beta) = p\ (pl)\ .\ L\ (t,\ \zeta,\ \tau,\ \overline{A},\ \beta) + p\ (p\overline{A})\ .\ \mathrm{C}\ (t,\ d,\ \mathrm{E}\Gamma,\ \psi,\ \alpha)$ $L\ (t,\ \zeta,\ \tau,\ \overline{A},\ \beta) = L_{packet\_loss}\ (t,\ \zeta,\ \tau,\ \overline{A}) + L_{\beta}\ (t,\ \beta)$ $C\ (t,\ d,\ E\Gamma,\ \psi,\ \alpha) = C_{delay}\ (t,\ d) + C_{throughput}\ (t,\ E\Gamma) + C_{path\_loss}\ (t,\ \psi) + C_{\alpha}\ (t,\ \alpha)$ $p(pl) = p\ (pl\ \lvert\overline{A}\rvert)\ .p\ (\overline{A}) + p\ (pl\ \lvert A\rvert).\ p(A)\ )$ $L_{outage}\ (t,\ \zeta) = \frac{1}{\lVert\zeta\rVert}\ .\ \mathrm{g(t)}\ ,$ $L_{packet\_loss}\ (t,\ pl) = \frac{1}{\lVert pl\rVert}\ .\ \mathrm{g(t)},$ $L_{1-availability}\ (t,\ \overline{A}) = \frac{1}{\lVert \overline{A}\rVert}\ .\ \mathrm{g(t)},$ $L_{criticality}\ (t,\ \tau) = \frac{1}{\lVert\tau\rVert}\ .\mathrm{g(t)}\ ,$ $L_{\beta}\ (t,\ \beta) = \frac{1}{\lVert\beta\rVert}\ .\ \mathrm{g(t)}\ ,$ $C_{delay}\ (t\ ,\ d) = \frac{1}{\lVert d\rVert}\ .\ \mathrm{g(t)},$ $C_{throughput}\ (\mathrm{t},\ \mathrm{E}\Gamma) = \lVert E\Gamma\rVert\ .\ \mathrm{g(t)}\ ,$ $C_{path\_loss}\ (\mathrm{t},\ \psi) = \frac{1}{\lVert\psi\rVert}\ .\mathrm{g(t)}\ ,$ $C_{\alpha}\ (\mathrm{t},\ \alpha) = \lVert\alpha\rVert\ .\mathrm{g(t)}$

Razieh Rastgoo received the B.Sc. Degree in Computer Engineering, Hardware, from Shiraz University of Iran. Also, she achieved her M.Sc. degree from Shahid Bahonar University of Kerman, Iran. She currently is a Ph.D. student of Semnan University of Iran as well as the Ph.D. researcher at Barcelona University of Spain. Her interest areas are: Artificial Intelligence, Machine Learning, Deep Learning, Computer Vision, Smart Grids, Sign Language, Routing Protocols, Computer Networks.

Vahid Sattari-Naeini received his B.Sc. from Isfahan University of Technology, Isfahan, Iran, in 1999, and his M.Sc. from the University of Isfahan, Isfahan, Iran, in 2001 both from Department of Computer Engineering. He got his Ph.D. from The University of Isfahan, Isfahan, Iran, in 2012. Currently he is an Assistant Professor of Computer Engineering at Shahid Bahonar University of Kerman, Kerman, Iran. Among his research interests are wireless networks and computing, SoC design challenges, parallel and distributed communications, and applications of (Meta) heuristic methods in wireless communications.