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Network selection based on chi-square distance and reputation for internet of things

Said Radouche, Cherkaoui Leghris
Laboratory of Mathematics, Computer Science and Applications, FST Mohammedia, Hassan II University, Mohammedia, Morocco

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ABSTRACT

The internet of things (IoT) has become one of the most important technologies of the 21st century. The IoT environment is composed of heterogeneous IoT communication networks. These technologies are complementary and need to be integrated to meet the requirements of different types of IoT applications that require the mobility of the IoT device under different IoT communication networks. In this paper, the vertical handover decision method is considered to select the appropriate network among different IoT technologies. So, IoT devices, equipped with several radio technologies, can select the most suitable network based on several criteria like quality of service (QoS), cost, power, and security. In this work, a multi-attribute decision-making algorithm (MADM) based on techniques for order preference by similarity to an ideal solution (TOPSIS) that uses chi-square distance instead of Euclidean distance is proposed. The network reputation is added to reduce the average number of handoffs. The proposed algorithm was implemented to select the best technology depending on the requirements of the different IoT traffic classes. The obtained results showed that our proposition outperforms the traditional MADM algorithms.

Corresponding Author:

Said Radouche
Laboratory of Mathematics, Computer Science and Applications, FST Mohammedia, Hassan II University
BP 146 Mohammedia 28806, Morocco
Email: said.radouche@yahoo.com

1. INTRODUCTION

The internet of things (IoT) is an emerging technology and is the fourth industrial revolution (industry 4.0) according to scientists and experts. Nowadays, this technology has become essential in development such as massive IoT applications (like logistics, tracking and fleet management, smart buildings, smart agriculture, and smart metering) and critical IoT applications (like remote health care, traffic safety and control, smart grid automation, and industrial application and control). These applications have different requirements in terms of cost, energy, data volume, latency, availability, long-range communication, and mobility [1]. In the first, IoT aims to connect static devices. Today, IoT will need to evolve to include mobile objects internet of mobile thing (IoMT) [2], and social IoT (SIoT) [3]. Therefore, mobility is a major factor that will multiply the fields of IoT application and will allow a fulgurating development, particularly in the fields of smart cities [4], health care [5], aging society [6], automotive industry [7], and smart agriculture [8]. The increase in address space allowed by IPv6 protocol is an important factor in the development of the IoT and supports large IoT networks and applications. So, IPv6 represents an interesting feature for IoT deployments, for example, the ability to preserve the battery life of IoT devices. The IoT protocols based on IPv6 have been introduced such as IPv6 over low power wireless personal area networks (6LoWPAN), and constrained application protocol (CoAP). To meet the requirements of IoT, IoMT, and

SIoT applications, Santos *et al.* [9] developed a mobile matrix (µMatrix), a routing protocol based on a hierarchical IPv6 address to perform mobility management and any-to-any routing.

In recent years, low-power wide-area networks (LPWANs) represent a new communication paradigm to meet the diverse requirements of Internet of Things applications. LPWAN technologies complement traditional cellular and short-range wireless technologies by providing extensive connectivity for many devices spread over large geographical areas with low power and low data rates. There is a variety of low power wide area (LPWA) technologies enabling IoT connectivity [10]. These technologies can be divided into two types: proprietary LPWA technologies (like LoRa, Sigfox [11], Ingenu, Telensa and Qowisio) and standard LPWA technologies: IEEE (like 802.15.4k, 802.15.4g, and 802.11 long range low power), ETSI (low throughput networks), 3GPP (like enhanced MTC, extended coverage GSM, and NarrowBand IoT), IETF (6LPWA/LP-WAN), Weightless SIG (weightless-W/N/P), LoRa Alliance (LoRa alliance) [12], and DASH7 Alliance (DASH7). Several research works provide a comparative study of LoRaWAN, SigFox, narrowband IoT (NB-IoT), and Wi-Fi HaLow [13]–[15]. The IoT device environment is composed of different and complementary technologies. So, the integration of different technologies is needed for seamless connectivity and satisfying the user preferences. The IoT devices equipped with multiple interfaces can choose the best networks according to several criteria such as quality of service (QoS), energy, bandwidth, and cost. In this context, we present a network selection algorithm that allows IoT devices to select the network that meets the requirements of IoT services. This problem is also called vertical handover and it is a multi-attribute decision making problem.

Heterogeneous wireless networks have many different characteristics. This heterogeneity creates challenges when selecting the best network. This makes the network selection phase in vertical handover a complex decision problem. Hence, the need for a robust network selection algorithm that can identify the optimal network. A non-optimal network selection can lead to undesirable effects on the network, such as energy consumption, and poor quality of service. In the literature, many approaches have been proposed to select the optimal network among several available ones. The vertical handover decision is based on the network characteristics and the requirements of the applications, which leads to a multi-attribute decision-making (MADM) problem Figure 1.

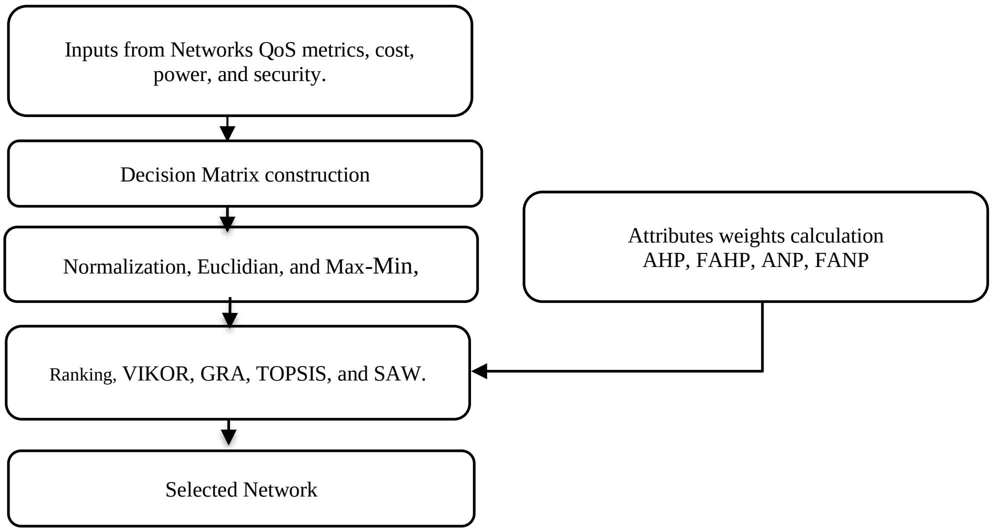

Figure 1. Vertical handover decision phase (using MADM methods)

The vertical handover is a multi-criteria decision problem and is formulated with the MADM approach. In the literature, there are several methods based on this approach used to classify the alternatives such as simple additive weighting (SAW), multiplicative exponent weighting (MEW), techniques for order preference by similarity to an ideal solution (TOPSIS), multicriteria optimization and compromise solution (VIKOR), grey relational analysis (GRA), and elimination and choice translating reality (ELECTRE) methods. The aim is to select the candidate network from a set of available ones according to different criteria. The vertical handover performance evaluation metrics are the number of handoffs and ranking abnormality to avoid ping-pong effects and preserve resources. The networks ranking begins with the decision matrix construction followed by the normalization method to unify different criteria (like Euclidean normalization, max normalization, and max-min normalization methods). Then, the assignment of weights to the criteria. Finally, the MADM method will be used to calculate a score for each alternative. Weighting criteria is an important step in the decision-making process. In this phase, decision-makers express their preferences between the criteria by the relative weight they assign to each criterion. Weight, therefore, expresses the importance given by a decision-maker to a criterion. Different weighting methods allow the calculation of the weight of each criterion. These methods can be classified into two categories. The first category represents the subjective weighting methods, the subjective determination of weights leads to several sets of weights that reflect different scales of values and opinions. This category includes analytic hierarchy process (AHP), analytical network process (ANP), fuzzy AHP, and fuzzy ANP methods. The second category contains the objective weighting methods in which decision-makers do not intervene to assign weights. The degree of importance of each criterion is calculated according to the numerical measures of all the criteria. This category contains methods such as entropy, random weighting, and bioinspired algorithms.

In the last decade, several research works based on the MADM approach have proposed network selection algorithms in a heterogeneous mobile environment. Obayiuwana and Falowo [16] presented a review and classification of the MADM algorithms widely used in the context of network selection in heterogeneous wireless environments. They also discuss the choice of criteria and its impact on decision-making. Finally, they provide the trend of research, in the application of MADM algorithms to vertical handover decision problems. Yu and Zhang [17] provided a network selection algorithm that uses TOPSIS, fuzzy AHP, and entropy methods to select the candidate network according to comprehensive utility value that combines utility values of network attributes and comprehensive utility value of user preferences. Yu and Zhang [18] proposed a hybrid MADM algorithm based on attribute weight and utility value in the vertical handover decision phase. Improvements to traditional MADM methods such as TOPSIS and GRA had also been proposed [19]–[21].

Today, IoT devices can be equipped with several network interfaces with different communication protocols more suitable for objects with energy constraints, ranging from short-range (Wi-Fi HaLow) to long-range (Sigfox, Lora, NB-IoT, and long term evolution machine [LTE-M]). In addition, a given geographical area can be covered by several access technologies with different specifications. New types of service classes have been proposed adapted to the IoT environment instead of those known in traditional mobile networks. According to 3GPP specifications, based on the quality of service (QoS) requirements, the applications are divided into four classes such as conversational, streaming, interactive and background (3GPP). The IoT applications need a new QoS architecture instead of QoS architectures widely deployed in the current networks such as integrated service (IntServ) and differentiated service (DiffServ) [22]. The basic IoT architecture includes three layers: service layer, network layer and perception layer. Duan *et al.* [23] proposed a new IoT architecture for QoS and four IoT applications (i.e. control, query, real-time monitoring, and non-real-time monitoring) based on real-time property and task type. Karagiorgo *et al.* [24] proposed three service models as open, supple, and complete service models based on interactivity, delay, and criticality. Shah and Thubert [25] proposed differentiated services in low power and lossy networks (LLNs). The network service classes are alert signals, control signals, determinists control signal, video monitoring data, query-based response data, and periodic reporting/logging, and software downloads. Recently, network selection algorithms based on MADM methods have been proposed specifically for IoT devices. Gaur [26] proposed a handover decision algorithm in heterogeneous networks based on MADM methods for IoT devices. Ayoub *et al.* [27] proposed the vertical handover decision based smart transportation systems for IoT devices. The IoT environment is composed of different technologies such as Sigfox, LoRaWAN, NB-IoT, and Wi-Fi HaLow. The MADM algorithms used to select the best technology are TOPSIS and SAW algorithms based AHP method that is used to assign weights to different parameters like cost bandwidth coverage, signal-to-noise ratio (SNR), power, loss, and rate. Three classes (eco, normal, and high performances) are identified according to the performance of the application. The simulation results show that TOPSIS outperforms SAW in the selection of the best network.

The remainder of the paper is as follows: the next section presents our proposed vertical handover decision method for mobile IoT. While simulation results are presented in section 3. Finally, section 4 concludes this work and gives some future work.

2. METHOD

In this section, we describe the main contribution of this work. The network selection problem has considered us multi-attribute decision-making (MADM) problem. Based on different parameters, the most popular algorithms used to select the best technology are SAW, TOPSIS, GRA and VIKOR. The TOPSIS method is a multi-criteria decision-making method developed Hwang and Yoon [28]. The basic idea of this method is to choose a solution that is as close to the positive ideal solution (better on all criteria) and as far away as possible from the negative ideal solution (which is worst on all criteria) using Euclidean distance. This method will be the basis of the proposed method to improve the network selection problem. So, we present a new method based on chi-square distance [29] instead of Euclidian distance and to reduce the average of handoffs we added a reputation score [30]. Our proposed method will be compared with traditional MADM methods under different service classes for IoT applications.

There are eight steps performed by the proposed algorithm to rank different alternatives.

1) Determine the decision matrix D. The decision matrix D contains m rows and n columns. The rows represent the list of the candidate networks $\mathrm{A} = \{\mathrm{A}_i, \mathrm{i} = 1,2,3 \dots, \mathrm{m}\}$, the columns indicate the list of the criteria: $C = \{C_j, j = 1,2,3 \dots, n\}$ and d_{ij} represents the performance of the network A_i with the criterion C_j.

$$D = \begin{pmatrix} d_{11} & d_{12} & \cdots \cdots d_{1n} \\ d_{21} & d_{22} & \cdots \cdots d_{2n} \\ \vdots & \vdots & \vdots \ddots \vdots \\ d_{m1} & d_{m2} & \cdots \vdots d_{mn} \end{pmatrix} \tag{1}$$

2) Determine the normalized decision matrix R using the Euclidean distance method, the normalized value r_{ij} is obtained according to (2).

$$R = \begin{pmatrix} r_{11} & r_{12} & \cdots \cdots r_{1n} \\ r_{21} & r_{22} & \cdots \cdots r_{2n} \\ \vdots & \vdots & \vdots \ddots \vdots \\ r_{m1} & r_{m2} & \cdots \vdots r_{mn} \end{pmatrix} \text{ where } r_{ij} = \frac{d_{ij}}{\sqrt{\sum_i^n d_{ij}^2}} \tag{2}$$

3) Determine weighted normalized decision matrix V using the AHP method and Saaty scale to build the pairwise decision matrix. The AHP method is one of the most popular methods to resolve multicriterial decision problems. The dimension of the pairwise matrix A is nxn where n represents the attributes. The matrix element x_{ij} indicates the important factor for the i^{th} attribute over the j^{th} attribute, and x_{ji} is the reciprocal factor of x_{ij}.

$$A = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{bmatrix} \text{ where } \begin{Bmatrix} x_{ii} = 1 \\ x_{ij} = \frac{1}{x_{ji}} \end{Bmatrix} \tag{3}$$

After the construction of the pairwise comparison matrix, a consistency check must be performed. The consistency ratio (CR) must be less than 10% [31]. The matrix is normalized according to (4).

$$a_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}} \tag{4}$$

$$A_{norm} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \tag{5}$$

The attribute weights are then computed as:

$$w_i = \frac{\sum_{j=1}^n a_{ij}}{n} \text{ where } \sum_{i=1}^n w_i = 1 \tag{6}$$

The weighted normalized decision matrix V is obtained according to (7).

$$V = \begin{pmatrix} v_{11} & v_{12} & \cdots \cdots v_{1n} \\ v_{21} & v_{22} & \cdots \cdots v_{2n} \\ \vdots & \vdots & \vdots \ddots \vdots \\ v_{m1} & v_{m2} & \cdots \vdots v_{mn} \end{pmatrix} \text{ where } v_{ij} = w_j * r_{ij} \tag{7}$$

4) Determine the ideal solution A^+ and the negative ideal solution A^-.

$$A^+ = [V_1^+, V_2^+, \dots . V_n^+],\ A^- = [V_1^-, V_2^-, \dots . V_n^-] \tag{8}$$

– For the benefit criteria:

$$V_j^+ = max_i\{v_{ij}, i = 1,2,3, \dots m\}, V_j^- = min_i\{v_{ij}, i = 1,2,3, \dots m\} \quad (9)$$

– For the cost criteria:

$$V_j^+ = min_i\{v_{ij}, i = 1,2,3, \dots m\}, V_j^- = max_i\{v_{ij}, i = 1,2,3, \dots m\} \quad (10)$$

5) The similarity distances using chi-square distance between the alternatives A^+ and A^- are calculated as (11) and (12).

$$S_i^+ = \sum_{j=1}^{n} \frac{(V_j^+ - v_{ij})^2}{V_j^+ + v_{ij}} ;\{i = 1,2,3, \dots m\} \quad (11)$$

$$S_i^- = \sum_{j=1}^{n} \frac{(V_j^- - v_{ij})^2}{V_j^- + v_{ij}} ;\{i = 1,2,3, \dots m\} \quad (12)$$

6) The relative closeness to the ideal solution is given by (13).

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} ;\{i = 1,2,3, \dots m\} \quad (13)$$

7) Determine the reputation score using the pseudo algorithm (14)

NBS_i=0.
if NBS_i == 0 then
$C_i^r = C_i^*$; (14)

else

$$C_i^r = \frac{C_i^* + NBS_i * C_i^r}{NBS_i + 1}; \quad (15)$$

end if

NBS_i++;

8) Ranking alternatives. To classifying the alternatives as a function of the decreasing values of C_i^*, the network with the highest value of C_i^* is selected.

$$A_i^* = arg \max_{\{i=1,2,3,\dots m\}} C_i^r \quad (16)$$

3. RESULTS AND DISCUSSION

The performance of the proposed method is examine. Firstly, heterogeneous wireless networks that are present in the IoT environment are identified. Then, the criteria and their values to construct a matrix decision is chosen. The judgment matrices are used to calculate the importance of each attribute based on the requirements of each traffic class. Finally, the networks are ranked to select the best one, can be seen in Figure 2.

The decision matrix represents the position of the IoT device. To calculate the average of the number of handovers, we consider several positions, and the IoT device can choose the best network or stay in the current network. The average ranking abnormality is calculated in each position. So, after having ranked the networks, the last network will be removed, and the calculation will be redone to know if the ranking was changed or not.

To evaluate the performance of our proposed algorithm, the simulation environment is assumed to be covered by four access networks such as NB-IoT, Wi-Fi HaLow, LoRaWAN, and Sigfox. IoT devices equipped with four interfaces can choose an appropriate access network. Different conflicting decision criteria (attributes) are used in the VHO decision process in HWNs such as delay (D), jitter (J), loss rate (L), data rate (DR), power consumption (P), bandwidth (B) and cost (C). According to the interval indicated for each attribute in Table 1, the values of these criteria (attributes) are generated randomly. The simulation is repeated 100 times (100 points).

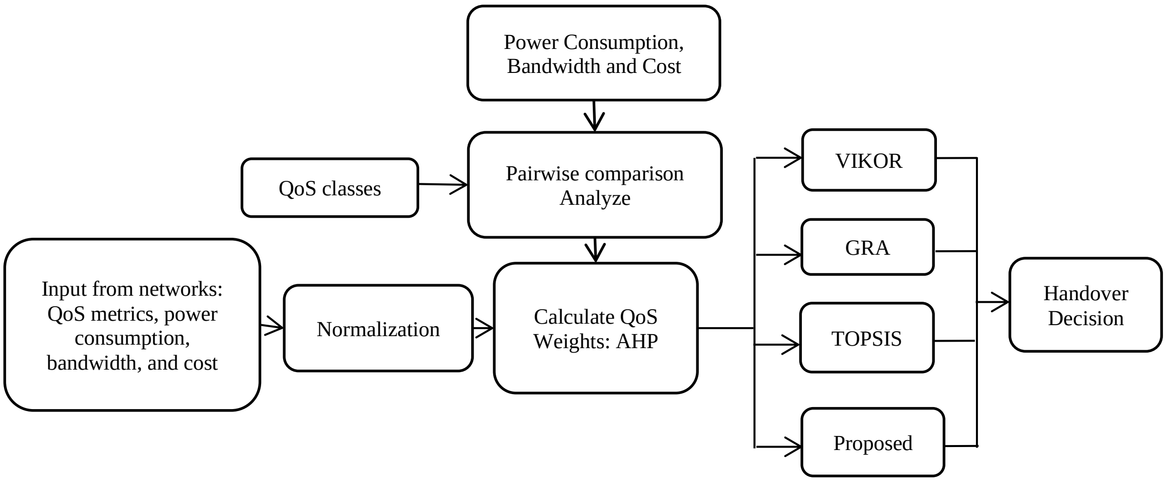

Figure 2. Functional block diagram of the simulation environment

In this section, we compare the access network selection algorithms for six types of service classes such as alert signals (S1), control signals (S2), monitoring data (S3), video data (S4), query-based response data (S5), and periodic reporting/logging, and software downloads (S6). The aim is to select the best technology in terms of QoS, bandwidth, power consumption and cost. For our simulations, the weights associated with the criteria for each service are calculated using the AHP method for each traffic class. Table 2 presents different QoS requirements for each traffic class [25]. The judgments matrix for service classes are presented in Tables 3 to 8. They are used in the AHP method to calculate the weights of QoS attributes. The weights of all attributes used in the matrix decision are presented in Table 9 based on the judgment matrix in Table 10.

Table 1. Attribute values for candidate networks

	D (s)	J (ms)	L %	DR (Kbps)	P (mW)	B %	C [1-10]
NB-IoT	1.6-10	3-10	1-5	200-200	100	20-80	10
Wi-Fi HaLow	0.6-1	3-10	1-3	600-8000	200	20-80	4
LoRaWAN	1-16	3-10	1- 4.5	0.3-50	20	20-80	2
Sigfox	1-30	3-10	1-3	0.1-1	5	20-80	1

Table 2. Traffic class characteristics

Traffic Class Name	Tolerance to		
	Loss	Delay	Jitter
Alert signals	Low	Low	N/A
Control signals	Yes	Low	Yes
Deterministic control signals	Low	Very Low	Very Low
Video monitoring/feed	Low	Low -Medium	Low
Query-based	Low	Medium	Yes
Periodic reporting/logging, software downloads	Yes	Medium-High	Yes

Table 3. Judgment matrix for alerts/alarms traffic

	Delay	Jitter	Loss	Data rate
Delay	1	3	1	5
Jitter	1/3	1	1/3	5
Loss	1	3	1	5
Data rate	1/5	1/5	1/5	1
Weights	0.3797	0.1786	0.3797	0.0620
CR	0.058731			

Table 4. Judgment matrix for control signals traffic

	Delay	Jitter	Loss	Data rate
Delay	1	3	3	5
Jitter	1/3	1	1	5
Loss	1/3	1	1	5
Data rate	1/5	1/5	1/5	1
Weights	0.5005	0.2189	0.2189	0.0616
CR	0.057831			

Table 5. Judgment matrix for deterministic control signals traffic

	Delay	Jitter	Loss	Data rate
Delay	1	1	3	5
Jitter	1	1	2	5
Loss	1/3	1/2	1	5
Data rate	1/5	1/5	1/5	1
Weights	0.3904	0.3500	0.1976	0.0619
CR	0.044255			

Table 6. Judgment matrix for video monitoring /feed traffic

	Delay	Jitter	Loss	Data rate
Delay	1	1/2	1/3	5
Jitter	2	1	1	5
Loss	3	1	1	5
Data rate	1/5	1/5	1/5	1
Weights	0.1976	0.3500	0.3904	0.0619
CR	0.044255			

Table 7. Judgment matrix for query-based data download traffic

	Delay	Jitter	Loss	Data rate
Delay	1	3	1/2	5
Jitter	1/3	1	1/3	5
Loss	2	3	1	5
Data rate	1/5	1/5	1/5	1
Weights	0.3145	0.1774	0.4468	0.0613
CR	0.081756			

Table 8. Judgment matrix for Periodic reporting /log, software download traffic

	Delay	Jitter	Loss	Data rate
Delay	1	3	3	5
Jitter	1/3	1	1	5
Loss	1/3	1	1	5
Data rate	1/5	1/5	1/5	1
Weights	0.5005	0.2189	0.2189	0.0616
CR	0.057831			

Table 9. Attribute weights for all services using the AHP method

	D	J	L	DR	P	B	C
S1	0.1696	0.0798	0.1696	0.0277	0.3145	0.1774	0.0613
S2	0.2236	0.0978	0.0978	0.0275	0.3145	0.1774	0.0613
S3	0.1744	0.1564	0.0883	0.0277	0.3145	0.1774	0.0613
S4	0.0883	0.1564	0.1744	0.0277	0.3145	0.1774	0.0613
S5	0.1405	0.0793	0.1996	0.0274	0.3145	0.1774	0.0613
S6	0.2236	0.0978	0.0978	0.0275	0.3145	0.1774	0.0613

Table 10. Judgment matrix for all attributes

	QoS	Power	Bandwidth	cost
QoS	1	2	3	5
Power	1/2	1	3	5
Bandwidth	1/3	1/3	1	5
Cost	1/5	1/5	1/5	1
Weights	0.4468	0.3145	0.1774	0.0613
CR	0.081756			

The network selected times for each type of service are shown in Tables 11 to 16. The simulation results show that Sigfox and LoRaWAN networks are the most selected by the proposed, TOPSIS, and VIKOR methods. The GRA method selects the NB-IoT and Wi-Fi HaLow. The reputation added to our developed method increases the percentage selection of Sigfox network selection that has the lowest power consumption and cost values according to Table 1. The importance of each parameter changes depending on the requirements of each application (traffic class). The network selection algorithm employed the subjective method (AHP method) for assigning weights to each criterion. Each type of the six classes has its weight vector. For the IoT applications (LLN applications) considered in this work, the priority is QoS, power and cost. As a result, the NB-IoT and Wi-Fi HaLow methods have been omitted. These technologies are penalized by their cost and energy consumption.

Table 11. The selected times for alert signals traffic

S1	NB-IoT	Wi-Fi HaLow	LoRaWAN	Sigfox
Proposed	0	0	12	88
TOPSIS	0	0	59	41
GRA	46	45	8	1
VIKOR	7	0	43	50

Table 12. The selected times for control signals traffic

S2	NB-IoT	Wi-Fi- HaLow	LoRaWAN	Sigfox
Proposed	0	0	35	65
TOPSIS	0	0	62	38
GRA	48	42	8	2
VIKOR	10	0	48	42

Table 13. The selected times for monitoring data traffic

S3	NB-IoT	Wi-Fi HaLow	LoRaWAN	Sigfox
Proposed	0	0	16	84
TOPSIS	0	0	61	39
GRA	47	52	1	0
VIKOR	6	0	40	45

Table 14. The selected times for video traffic

S4	NB-IoT	Wi-Fi HaLow	LoRaWAN	Sigfox
Proposed	0	0	3	97
TOPSIS	0	0	37	63
GRA	41	56	3	0
VIKOR	0	0	31	65

Table 15. The selected times for query-based data downloads traffic

S5	NB-IoT	Wi-Fi-HaLow	LoRaWAN	Sigfox
Proposed	0	0	6	94
TOPSIS	0	0	53	47
GRA	47	43	9	1
VIKOR	4	0	35	61

Table 16. The selected times for periodic reporting/logging, software downloads traffic

S6	NB-IoT	Wi-Fi-HaLow	LoRaWAN	Sigfox
Proposed	0	0	35	65
TOPSIS	0	0	62	38
GRA	48	42	8	2
VIKOR	10	0	48	42

The ranking abnormality is a phenomenon that characterizes the majority of MADM methods. This anomaly means that the ranking order is not stable, it can change. This change occurs when new alternatives are added or removed. This phenomenon may influence the efficiency of the decision algorithm in the context of vertical handover by producing unnecessary handovers. Therefore, the number of handoffs and the ranking abnormality are the most important metrics used to evaluate the performance of the vertical handover decision algorithms. Reducing these performance metrics allows for saving power consumption which is the most important factor for IoT devices and applications.

Figure 3 shows that our method reduces the problem of ranking abnormality to a value of 1% for the services alert signals, control signals, video data, and periodic reporting/logging, and software downloads. For the other services, monitoring data and query-based response data, the ranking anomaly is reduced to 2%. We find that the developed method provides better performance than the VIKOR, GRA, and TOPSIS methods used in this work in terms of the average of ranking abnormality. In addition, the traditional MADM methods do not provide better performance for all types of services. The ranking established by our method is less sensitive when the last alternative is removed from the candidate networks list. However, the other MADM methods are most affected. So, the IoT device can select another network among the available ones. The change of connection affects IoT devices' energy consumption and reduces battery life.

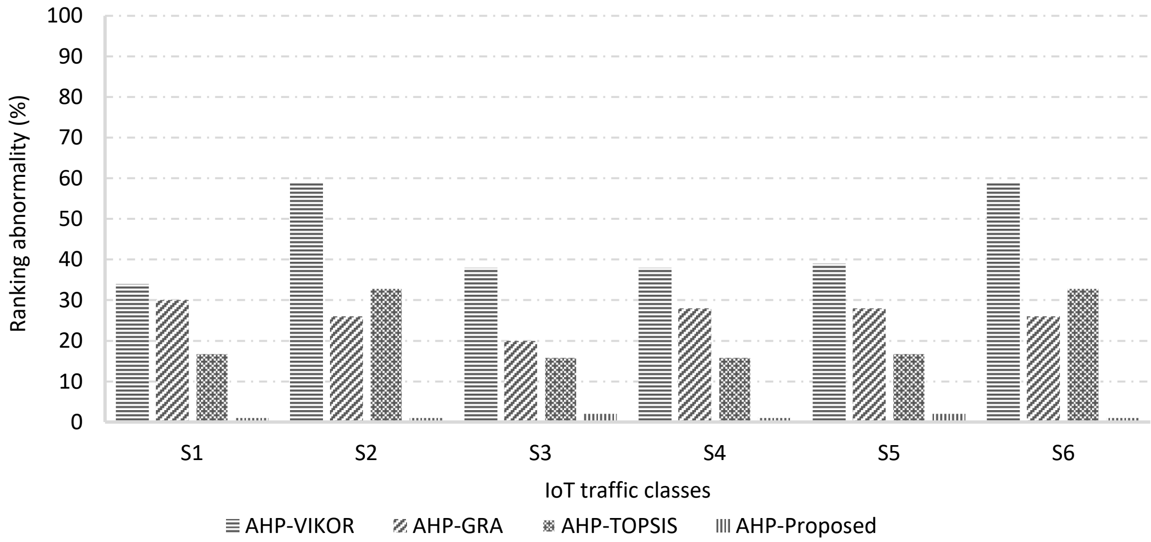

Figure 3. Average of ranking abnormality

Figure 4 illustrates the average number of handoffs for each traffic class. The simulation results show that our method reduces the average of the number of handoffs to a value of 13%, 12%, 11%, 3%, 7% and 12% respectively for the six types of services alert signals, control signals, monitoring data, video data, query-based response data, and periodic reporting/logging, and software downloads. We can deduce that for all service types, our vertical handover decision algorithm provides the best performance regarding the number of handoffs compared to other algorithms VIKOR, GRA, and TOPSIS. These methods do not provide better performance for all types of services. Finally, these results show the efficiency of our method. The reduction of this metric is important to avoid the ping-pong effect. Therefore, the IoT device stays a long time in the preferred network and saves power consumption.

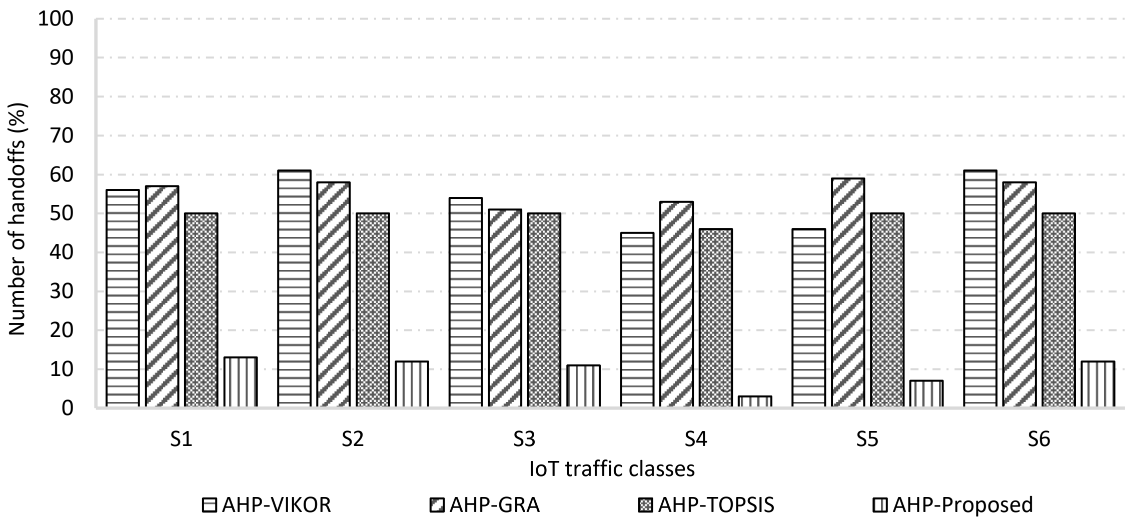

Figure 4. Average of number of handoffs

4. CONCLUSION

In this paper, we have proposed a vertical handover decision algorithm for IoT devices that move in an IoT environment composed of different IoT network technologies. The proposed method is a MADM algorithm based on the chi-square distance that is used to calculate the distance of each alternative from the worst and best alternative. The reputation is added to reduce the number of handoffs and preserve energy consumption. Several IoT traffic classes have been considered. The simulation results show that the developed method outperforms the conventional MADM methods in terms of the average of vertical handoff and ranking abnormality and the selection of the suitable network. In our future works, we plan to improve network selection algorithms for IoT devices to select the optimal network while saving battery life. Finally, we will investigate the 802.21 (MIH) standard for LPWAN networks to meet the requirements of the new IoT paradigm and IoT applications.

REFERENCES

[1] 5G Americas, "5G: The future of IoT - 5G Americas," *5G Americas white paper*, 2019. Accessed: Jul. 17, 2022. [Online]. Available: https://www.5gamericas.org/5g-the-future-of-iot

[2] K. Nahrstedt, H. Li, P. Nguyen, S. Chang, and L. Vu, "Internet of mobile things: Mobility-driven challenges, designs and implementations," in *2016 IEEE First International Conference on Internet-of-Things Design and Implementation (IoTDI)*, Apr. 2016, pp. 25–36. doi: 10.1109/IoTDI.2015.41.

[3] B. Afzal, M. Umair, G. Asadullah Shah, and E. Ahmed, "Enabling IoT platforms for social IoT applications: Vision, feature mapping, and challenges," *Future Generation Computer Systems*, vol. 92, pp. 718–731, Mar. 2019, doi: 10.1016/j.future.2017.12.002.

[4] R. Morello, S. C. Mukhopadhyay, Z. Liu, D. Slomovitz, and S. R. Samantaray, "Advances on sensing technologies for smart cities and power grids: A review," *IEEE Sensors Journal*, vol. 17, no. 23, pp. 7596–7610, Dec. 2017, doi: 10.1109/JSEN.2017.2735539.

[5] M. Arogia Victor Paul, T. Anil Sagar, S. Venkatesan, and A. K. Gupta, "Impact of mobility in IoT devices for healthcare," in *Digital Business: Business Algorithms, Cloud Computing and Data Engineering*, 2019, pp. 243–261. doi: 10.1007/978-3-319-93940-7_11.

[6] Y. Shibata and G. Sato, "IoT based mobility information infrastructure in challenged network environment toward aging society," in *2017 31st International Conference on Advanced Information Networking and Applications Workshops (WAINA)*, Mar. 2017, pp. 645–648. doi: 10.1109/WAINA.2017.126.

[7] M. A. Rahim, M. A. Rahman, M. M. Rahman, A. T. Asyhari, M. Z. A. Bhuiyan, and D. Ramasamy, "Evolution of IoT-enabled connectivity and applications in automotive industry: A review," *Vehicular Communications*, vol. 27, Jan. 2021, doi: 10.1016/j.vehcom.2020.100285.

[8] B. Miles, E.-B. Bourennane, S. Boucherkha, and S. Chikhi, "A study of LoRaWAN protocol performance for IoT applications in smart agriculture," *Computer Communications*, vol. 164, pp. 148–157, Dec. 2020, doi: 10.1016/j.comcom.2020.10.009.

[9] B. P. Santos, O. Goussevskaia, L. F. M. Vieira, M. A. M. Vieira, and A. A. F. Loureiro, "Mobile matrix: Routing under mobility in IoT, IoMT, and social IoT," *Ad Hoc Networks*, vol. 78, pp. 84–98, Sep. 2018, doi: 10.1016/j.adhoc.2018.05.012.

[10] U. Raza, P. Kulkarni, and M. Sooriyabandara, "Low power wide area networks: an overview," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 2, pp. 855–873, 2017, doi: 10.1109/COMST.2017.2652320.

[11] Sigfox, "The global communications service provider for the internet of things (IoT)," Sigfox. Accessed: May 24, 2022. [Online]. Available: https://www.sigfox.com/en

[12] LoRa Alliance, "LoRa Alliance." Accessed: May 24, 2022. [Online]. Available: https://lora-alliance.org

[13] S. C. Gaddam and M. K. Rai, “A comparative study on various LPWAN and cellular communication technologies for IoT based smart applications,” in *2018 International Conference on Emerging Trends and Innovations In Engineering And Technological Research (ICETIETR)*, Jul. 2018, pp. 1–8. doi: 10.1109/ICETIETR.2018.8529060.

[14] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, “A comparative study of LPWAN technologies for large-scale IoT deployment,” *ICT Express*, vol. 5, no. 1, pp. 1–7, Mar. 2019, doi: 10.1016/j.icte.2017.12.005.

[15] F. Muteba, K. Djouani, and T. Olwal, “A comparative survey study on LPWA IoT technologies: Design, considerations, challenges and solutions,” *Procedia Computer Science*, vol. 155, pp. 636–641, 2019, doi: 10.1016/j.procs.2019.08.090.

[16] E. Obayiuwana and O. E. Falowo, “Network selection in heterogeneous wireless networks using multi-criteria decision-making algorithms: a review,” *Wireless Networks*, vol. 23, no. 8, pp. 2617–2649, Nov. 2017, doi: 10.1007/s11276-016-1301-4.

[17] H.-W. Yu and B. Zhang, “A heterogeneous network selection algorithm based on network attribute and user preference,” *Ad Hoc Networks*, vol. 72, pp. 68–80, Apr. 2018, doi: 10.1016/j.adhoc.2018.01.011.

[18] H.-W. Yu and B. Zhang, “A hybrid MADM algorithm based on attribute weight and utility value for heterogeneous network selection,” *Journal of Network and Systems Management*, vol. 27, no. 3, pp. 756–783, 2019, doi: 10.1007/s10922-018-9483-y.

[19] B. R. Chandavarkar and R. M. R. Guddeti, “Simplified and improved multiple attributes alternate ranking method for vertical handover decision in heterogeneous wireless networks,” *Computer Communications*, vol. 83, pp. 81–97, Jun. 2016, doi: 10.1016/j.comcom.2015.10.011.

[20] M. Mansouri and C. Leghris, “New Manhattan distance-based fuzzy MADM method for the network selection,” *IET Communications*, vol. 13, no. 13, pp. 1980–1987, Aug. 2019, doi: 10.1049/iet-com.2018.5454.

[21] M. Mansouri and C. Leghris, “A use of fuzzy TOPSIS to improve the network selection in wireless multiaccess environments,” *Journal of Computer Networks and Communications*, vol. 2020, pp. 1–12, Jul. 2020, doi: 10.1155/2020/3408326.

[22] N. Lo and I. Niang, “A survey on QoS-based communication protocols for IoT systems,” in *Proceedings of the 3rd International Conference on Networking, Information Systems & Security*, Mar. 2020, pp. 1–9. doi: 10.1145/3386723.3387834.

[23] R. Duan, X. Chen, and T. Xing, “A QoS Architecture for IOT,” in *2011 International Conference on Internet of Things and 4th International Conference on Cyber, Physical and Social Computing*, Oct. 2011, pp. 717–720. doi: 10.1109/iThings/CPSCom.2011.125.

[24] S. Karagiorgo, G. Stamoulis, and P. Kikiras, “Enabling QoS in the internet of thing,” in *The Fifth International Conference on Communication Theory, Reliability, and Quality of Service*, 2012, pp. 33–38.

[25] S. Shah and P. Thubert, “Differentiated service class recommendations for LLN traffic,” *Internet Engineering Task Force*. 2015. Accessed: Jul. 17, 2022. [Online]. Available: https://datatracker.ietf.org/doc/draft-svshah-tsvwg-lln-diffserv-recommendations-04

[26] A. Gaur, “Containerized IoT solution for efficient mobile vertical handover,” Carleton University, Ottawa, Ontario, 2018. doi: 10.22215/etd/2018-12884.

[27] W. Ayoub, A. Ellatif Samhat, M. Mroue, H. Joumaa, F. Nouvel, and J.-C. Prévotet, “Technology selection for IoT-based smart transportation systems,” in *Vehicular Ad-hoc Networks for Smart Citie*, 2020, pp. 19–29. doi: 10.1007/978-981-15-3750-9_2.

[28] C.-L. Hwang and K. Yoon, *Multiple Attribute Decision Making*, vol. 186. Berlin, Heidelberg: Springer Berlin Heidelberg, 1981. doi: 10.1007/978-3-642-48318-9.

[29] H. A. Abu Alfeilat *et al.*, “Distance and similarity measures effect on the performance of K-nearest neighbor classifier-A review,” *Big Data*, vol. 7, no. 4, pp. 221–248, Dec. 2019, doi: 10.1089/big.2018.0175.

[30] T. Bi, R. Trestian, and G.-M. Muntean, “Reputation-based network selection solution for improved video delivery quality in heterogeneous wireless network environments,” in *2013 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*, Jun. 2013, pp. 1–8. doi: 10.1109/BMSB.2013.6621734.

[31] J. Malczewski, “GIS and multicriteria decision analysis,” *Geographical Analysis*, vol. 34, no. 2, 1999.

BIOGRAPHIES OF AUTHORS

Said Radouche is currently a Ph.D. candidate at FSTM Hassan II University, advised by Dr Cherkaoui Leghris. He received his M.S. degree in Computer Science and Telecommunication from Mohammed V University of Rabat, Morocco in 2003. His research activities focus on heterogeneous wireless networks. He is currently a computer teacher at CRMEF Casablanca-Settat, Ministry of National Education, Morocco. He can be contacted at said.radouche@yahoo.com.

Cherkaoui Leghris has a Ph.D. in Computer Sciences from the Ecole Nationale Supérieure d’Informatique et d’Analyse des Systèmes, Mohammed V University of Rabat in 2007. In 2003, he had the diploma of Higher Studies in ENSIAS and before the degree in Applied Computer Science from the Cadi Ayyad University of Marrakech. He is currently working as a professor of Higher Education at the Faculty of Science and Techniques, Hassan II University of Casablanca. He is responsible for various modules in the communication networks domain. He conducts research on networking at L@M Laboratory, RTM team. His main research focuses on the IoT networks based across IPv6 protocol, multi-access network technologies and IT security. He is also an active member in the Moroccan Internet Society organization, which works for openness and accessibility of the Internet for any. He can be contacted at cherkaoui.leghris@fstm.ac.ma.