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Building an Improved Internet of Things Smart Sensor Network Based on a Three-Phase Methodology

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ABSTRACT In recent years, the Internet of Things (IoT) has allowed the easy, intelligent, and efficient connection of many devices used in daily life by means of numerous smart sensors which communicate with each other using wireless signals. The rapid development of the IoT has been a result of recent advances in sensing technology. This paper proposes a three-phase methodology to improve the quality of experience for IoT system technologies. The proposed method employs the concepts of simple routing and two well-known multi-criteria decision-making method (MCDM) techniques: The Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). First, all simple routings are obtained using the proposed depth-first search technology (DFS). AHP is applied to analyze the structure of the problem and to obtain weights for various selected criteria in the second phase. In the third phase, TOPSIS is utilized to rank the simple routings, which are simple paths. A case study example is provided to demonstrate the proposed three-phase methodology. The results from the numerical experiments show that the proposed methodology can successfully achieve the aim of this paper.

INDEX TERMS Internet of Things (IoT), smart sensor network, Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

I. INTRODUCTION

The Internet of Things (IoT) offers easy and ubiquitous networking between many elements of daily life and real-world applications [1], [2]. It is an intelligent network of interconnected objects such as devices, buildings, vehicles and other items. In order to sample, collect, sense, analyze and exchange data, these objects are embedded with electronics, software, sensors, etc. to enhance production efficiency and offer more efficient resource consumption [1]–[3].

Low-cost, low-power, compact-size and open standard stacks of sensors have allowed for the inclusion of even the smallest objects installed in any kind of environment into the IoT at reasonable costs [3]–[15]. Wireless sensor networks (WSN) consisting of large numbers of wireless sensors are the core of the IoT, serving to gather signals and allow communication between objects, due to their greater flexibility over wired networks [3], [5]–[7], [9]–[11], [13], [15]–[23], [32]. The availability of powerful and inexpensive smart devices thus allows the optimization of information management, measurement results sharing and quality of service improvement [3]–[15].

Fig. 1 shows the topology of a drone freight WSN, and Fig. 2 is a schematic of Fig. 1. In Fig. 2, nodes are sensors and arcs are communication links. Each node is a basic unit, representing a device with an embedded processor, memory, wireless interface and local autonomous power supply. A node is able to collect signals such as heat, light, sound, location or motion, and can communicate this information for further aggregation and processing using native

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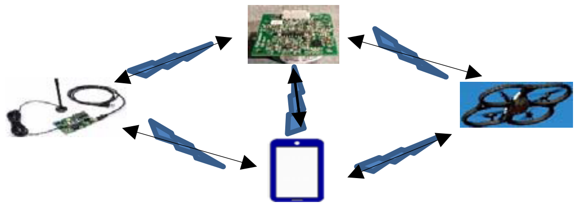

FIGURE 1. Example of a drone freight WSN network topology.

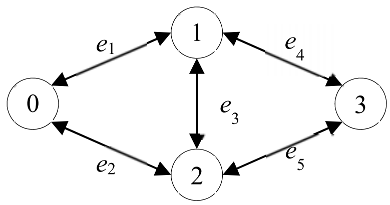

FIGURE 2. The schematic of Fig. 1.

wireless interfaces [3], [5]–[7], [9]–[11], [13], [15]–[23]. For example, node 2 could be a smartphone with an accelerometer, gyroscope, magnetometer, GPS, barometer, temperature sensor, proximity sensor, ambient light sensor, etc. The sensing capabilities of devices in WSNs may also be improved from time to time [3], [5]–[7], [9]–[11], [13], [15]–[23].

From the user perspective, service quality refers to whether a response, message or signal from the system or user is able to arrive at its destination reliably, accurately, economically, efficiently and effectively, anywhere and anytime [3]–[15]. It is thus very important that significant factors affecting signal transmission probability and power consumption be identified, in order to make smart sensor networks in the IoT more reliable, with longer lifespans [3]–[15]. The Internet of Things (IoT) is applied to systems in many fields, such as energy, medical, and transportation, and is necessary to solve the complex problems of various systems in real time. Therefore, highly reliable IoT is very important because there is zero tolerance for failure when IoT is used in each system [24].

Today, IoT systems are no longer built indoors in data centers like traditional systems. These network devices that need to connect and transfer signals to each other are exposed to various unpredictable and harsh environments such as the sun, rain, and storms because they must be built outdoors. Therefore, it is increasingly important to improve the reliability of IoT systems to prevent failure and to ensure successful operation [25]. As a result, many IoT studies are dedicated to optimizing the reliability of IoT systems. Xing et al., for instance, used the dynamic fault tree model to simulate the failure state of storage area networks of IoT to optimize the reliability of the IoT [26]. Tuan et al. conducted big data analysis to study the optimization of IoT for reliability and cost in the health care industry [27]. Sahraei et al. studied the reliability optimization of the energy transfer rate of IoT in the solar energy industry [28].

At the same time, economic efficiency must also be considered when importing IoT technology, that is, the successful operation of the IoT device function at low cost. Therefore, many IoT studies are dedicated to multidimensional optimization problems including the reliability and cost of IoT systems, such as the study by Tuan et al. on the optimization of IoT for reliability and cost in the health care industry [27], and the study by Sahraei *et al.* [28] on the reliability and low-cost optimization of IoT in the solar energy industry. Thus, there is a need to explore the reliability and cost optimization of IoT and solve related problems.

Routing is the process by which a signal is forwarded using Wi-Fi, Bluetooth, NFC, ZigBee, Infrared, 4G/LTE, Thread or Whitespace TV technologies via a series of nodes and arcs from the source node to the sink node in a WSN [3], [5]–[7], [9]–[11], [13], [15]–[18]. The series of nodes and arcs from the source node to the sink is called a path [3], [5]–[7], [9]–[11], [13], [15]–[23], and shows how an application's endpoints respond to client requests, e.g., node 0 to node 1 to node 3, in Fig. 1. Routing therefore plays an important role in improving service quality. The six factors, reliability [16]–[23], energy consumption [5]–[8], transmission time [3], [9], signal transmission quality (including the strength and accuracy rate) [10], coverage ratio [11]–[13], and use-cost [15] are therefore considered in this study in order to construct an integer planning model to improve the service quality of IoT system technologies.

Battery powered smart sensors or devices, like BLE beacons, smart wears, parking sensors, phones, laptops etc., are very convenient, popular and common WSN devices which allow objects to interact, which is the major goal of the IoT [3]–[9]. Battery life is a primary concern when deciding which devices and combinations of devices, and which communications technologies to use in IoT WSNs, as battery life affects the lifespan of a node (device) and thus of the overall network [3]–[9]. For example, Bluetooth 4.0 uses a lightweight access method to offer ultra-low power standby mode operation to guarantee extremely low power consumption in both standby and operating mode [3].

Because the deployment of IoT sensor networks is important, there are several protocols already in-play for sensor networks, many of which are deployed and being used successfully. For example, Chen *et al.* [29] proposed a gap-mending algorithm to effectively improve barrier gaps in the deployment of IoT sensor networks. Lin *et al.* [30] proposed magnetic induction (MI)-based localization to detect low- and high-noise positions correctly and quickly to improve signal transmission rate by the deployment of sensor networks for underground environments. Mekki *et al.* [31] discussed the performance of some low-power wide area network (LPWAN) methods in terms of cost, battery life, range, communication rate, latency, etc., in the deployment of IoT.

From the previous research above, we found that simultaneously optimizing reliability and cost in the deployment of IoT sensor networks remains an open issue. This is the reason why we are investigating the main multidimensional objectives of the paper.

This study therefore focuses on the above multi-objective problem derived from real-world applications by proposing a systematic approach to understanding and managing issue in practice. The proposed problem-solving approach is based on the three-phase methodology: the depth-first search technology (DFS) [21], [22], originally from Graph Theory, the analytic hierarchy process (AHP) [32]–[39], and The Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) [37]–[39].

First, all simple routings must be found using DFS. Secondly, the AHP is implemented to obtain the weights of both qualitative and quantitative factors in the IoT. Finally, TOPSIS is used to analyze and optimize in terms of the weights obtained by AHP in order to find the most suitable routing from all simple routings found in the DFS.

By introducing the three-phase methodology, this study aims to improve IoT service quality by, for example, systematically and efficiently reducing power consumption and increasing successful signal transmission probability to provide a better IoT environment.

II. PROBLEM DESCRIPTION

This study considers a multi-objective problem to improve IoT service quality [4], focusing on six significant factors: reliability [16]–[23], energy consumption [5]–[8], transmission time [3], [9], signal transmission quality (including the strength and accuracy rate) [10], coverage ratio [11]–[13] and use-cost [15]. Let C, E, Q, R, S and T be the functions of the use-cost, energy consumption, transmission quality, reliability, signal strength, and transmission time of the arc e, respectively, with six corresponding goals:

$$\text{Min} \sum_{\forall e \in p} C(e) \tag{1}$$

$$\text{Min} \sum_{\forall e \in p} E(e) \tag{2}$$

$$\text{Max} \sum_{\forall e \in p} Q(e)/|p| \tag{3}$$

$$\text{Max} \prod_{\forall e \in p} R(e) \tag{4}$$

$$\text{Max} \sum_{\forall e \in p} S(e)/|p| \tag{5}$$

$$\text{Min} \sum_{\forall e \in p} T(e) \tag{6}$$

where, for all, p is a routing from the source node to the sink node. For example, the signal can be transmitted from nodes 0 to 1 to 3, or from nodes 0 to 2 to 3, in Fig. 1. The better of the two routings must be determined using the above six factors simultaneously.

Eqs. (1), (2) and (6) in this multi-objective problem are shortest path problems by letting $C(e)$, $E(e)$ or $T(e)$ be the distance of arc e, and they are able to solve the problem using a shortest path algorithm, e.g., the Dijstra algorithm, in polynomial time if such equation is considered individually [19], [20]. However, both Eqs. (3) and (5) are NP-hard [19], [21], even considered independently, since the longest path is an NP-Hard problem and cannot be solved in polynomial time [19]. Thus, traditional shortest path algorithms are unable to solve this problem.

If all paths from the source node to the sink node in the above mathematical model are known [19], [21], it may be possible to solve this multi-objective problem by substituting each path into Eqs. (1)–(6). Unfortunately, there are many paths in the above mathematical model, and their number will increase with the size of problem [19], [21]. There is thus also a need for a new, more efficient algorithm to solve this important multi-objective problem in IoT networks.

Furthermore, there may be many non-dominated solutions in multi-objective problems, and it is always inconvenient and difficult for decision-makers themselves to select one as an answer for the problem from all non-dominated solutions [22], [23], [32]–[39].

This study therefore proposes a new three-phase algorithm based on multi-criteria decision-making methods to overcome the above obstacles in the multi-objective problem to improve the service quality of IoT system technologies.

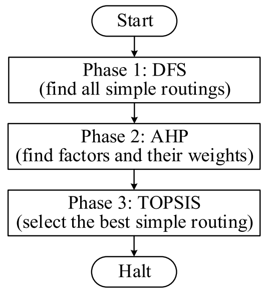

FIGURE 3. **The proposed three-phase approach.**

III. THE DFS, AHP, AND TOPSIS

This study proposes a methodology for selecting the best routing to improve IoT service quality, which consists of three phases, namely DFS [19], [20], AHP [22], [23], [32]–[37] and TOPSIS [37]–[39], as shown in Figure 3. The details of these three phases are discussed in this section.

A. SIMPLE ROUTINGS AND DFS

In graph theory, a path is a sequence of arcs connected by a sequence of vertices. For example, there are at least four paths from node 0 to node 3, as shown in Fig. 4. In this study, a routing refers to a special path used to denote the process for traffic in a WSN.

For example, in Fig. 4(a), the signal can be transmitted from node 0, to node 1, to node 3, and this transmission path is a routing. In some routing cases, there may be redundant arcs, but these arcs can be removed without blocking the transmission from the source node to the sink node, as with

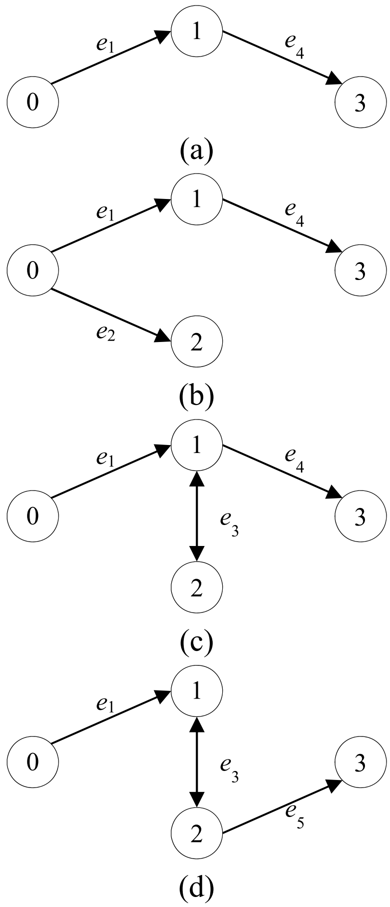

FIGURE 4. Example of paths and routings.

TABLE 1. The power and reliability of ARCS in Fig. 4 before and after removing redundant ARC(S).

	before		after	
	power	reliability	power	reliability
Fig. 4(a)	2	$.9^2$	2	$.9^2$
Fig. 4(b)	3	$.9^3$	2	$.9^2$
Fig. 4(c)	4	$.9^4$	2	$.9^2$
Fig. 4(d)	4	$.9^4$	3	$.9^3$

arc $e_{0,2}$ in Fig. 4(b), cycle $\{e_{1,2}, e_{2,1}\}$ in Fig. 4(c), and arc $e_{2,1}$ of cycle $\{e_{1,2}, e_{2,1}\}$ in Fig. 4(d). All these can be removed, while still leaving a path connecting nodes 0 and 3. For easy distinction between routings without redundant arcs and routings that include redundant arcs, routings without redundant arcs are called simple routings.

It is clear that simple routing is more reliable and results in lower power consumption than non-simple routing, since more arcs require more power, and reduce the successful signal transmission probability [16]–[23]. For example, let the power and reliability of all arcs be 1 unit of time and 0.9, respectively. Table 1 lists the required power and final reliability of the four routings in Fig. 4 below:

Thus, in order to solve the proposed problem, the first stage must be to find all simple routings. These simple routings can be found using DFS or BFS. Let all levels in the DFS tree be

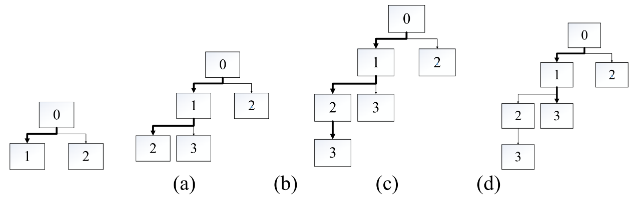

FIGURE 5. Part of the DFS-tree for Fig. 1.

numbered from 1. In conventional DFS, the DFS-tree adopted in the algorithm starts at the source node with the following three steps for each branch during the search [19], [20]:

1) THE OFFSPRING-BRANCHING STEP

a. Select and add an unvisited offspring node to the last node in the current path, e.g., nodes 1, 2 and 3 in Figs. 5(a), (b) and (c), respectively.
b. If no unvisited node can be chosen in this step, proceed to the brother-branching step, e.g., the second node 3 (in level 4) in Fig 5(d).
c. If the offspring node is the sink node, then a simple routing is found; save all ancestors in the sequence (which is the found simple routing), and proceed to the parent-branching step, e.g., the path from nodes 0 to 1 to 2 to 3 in Fig. 5(c), and from nodes 0 to 1 to 3 in Fig. 5(d).

2) THE BROTHER-BRANCHING STEP

a. Replace the last node in the current path with one of its unvisited brother nodes, and return to the offspring-branching step. For example, if there is still an unvisited node, say node 4, after reaching the last node, say node 3, then replace node 3 with node 4, and perform the offspring-branching step.
b. If no unvisited brother node can be chosen in this step, proceed to the parent-branching step, e.g., node 3 (in level 4) returns to node 2 (in level 3) in Fig. 5(d).

3) THE PARENT-BRANCHING STEP

a. Return to the parent node of the current node and proceed to the brother-branching step, e.g., node 3 (in level 4) returns to node 2 (in level 3), and go to node 3 (level 3).
b. If there is no parent node—i.e., the current node is the source node—halt. For example, if the current node is node 0 and there are no more offspring from node 0, the DFS procedure is halted.

B. AHP

Saaty's analytic hierarchy process (AHP) is one of the most practical and useful analytical multi-criteria decision-making methods (MCDMs) because it is simple, dynamic, systematic and effective [22]. The AHP is able to solve complex and/or unstructured problems by breaking complex and non-structural circumstances into a hierarchical structure

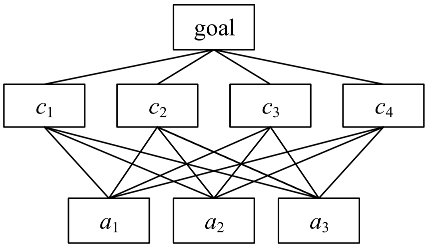

FIGURE 6. An example AHP hierarchy.

to fully present the relationship among criteria [22]–[23], [32]–[37].

The AHP is adapted here to obtain relative weights in order to distinguish the different degrees of importance among considered factors, and to reflect the decision-makers' preference for factors by giving weights. The main procedure of the AHP based on the geometric mean method for obtaining relative weights is described below [22].

STEP A1. Establish a hierarchical structure such that the goal, criteria and alternatives are at the first, second and third levels, respectively. For example, Fig. 6 is an AHP hierarchy with four criteria, c_1, c_2, c_3 and c_4 in the second level, and three alternatives, a_1, a_2 and a_3 in the third level.

STEP A2. Build the pairwise comparison for each expert in order to construct the pair-wise comparison matrix $C_k = [c_{i,j}^{(k)}]_{\mathrm{N}_c}$ of expert k for $k = 1, 2, \ldots, \mathrm{N}_e$:

$$C_k = \begin{bmatrix} 1 & c_{1,2}^{(k)} & \cdots & c_{1,\mathrm{N}c}^{(k)} \\ c_{2,1}^{(k)} & 1 & \cdots & c_{2,\mathrm{N}c}^{(k)} \\ \vdots & \vdots & \cdots & \vdots \\ c_{\mathrm{N}c,1}^{(k)} & c_{\mathrm{N}c,2}^{(k)} & \cdots & 1 \end{bmatrix}, \tag{7}$$

where $c_{i,j}^{(k)} = 1/c_{j,i}^{(k)}$ is the comparison value of criterion i according to criterion j of expert k. Note that the essence of pairwise comparisons is to determine the preferences which decision-makers expresses through Saaty's scale of relative importance.

STEP A3. Collect the data from the experts' pair-wise comparison matrix to form an aggregation pair-wise comparison matrix $C = [c_{i,j}]_{\mathrm{N}_c}$ of expert k:

$$C = \begin{bmatrix} 1 & c_{1,2} & \cdots & c_{1,\mathrm{N}c} \\ c_{2,1} & 1 & \cdots & c_{2,\mathrm{N}c} \\ \vdots & \vdots & \cdots & \vdots \\ c_{\mathrm{N}c,1} & c_{\mathrm{N}c,2} & \cdots & 1 \end{bmatrix}, \tag{8}$$

where

$$c_{i,j} = \sqrt[\mathrm{N}e]{\prod_{k=1}^{\mathrm{N}e} c_{i,j}^{(k)}}. \tag{9}$$

STEP A4. Normalize the aggregated pair-wise comparison matrix C to $C' = [c'_{i,j}]_{\mathrm{N}_c}$:

$$C' = \begin{bmatrix} 1 & c'_{1,2} & \cdots & c'_{1,\mathrm{N}c} \\ c'_{2,1} & 1 & \cdots & c'_{2,\mathrm{N}c} \\ \vdots & \vdots & \cdots & \vdots \\ c'_{\mathrm{N}c,1} & c'_{\mathrm{N}c,2} & \cdots & 1 \end{bmatrix}, \tag{10}$$

where

$$c'_{i,j} = \frac{c_{i,j}}{\sum_{k=1}^{\mathrm{N}c} c_{i,k}} \tag{11}$$

STEP A4. Determine the relative weight w_i of the i^{th} attribute for $i = 1, 2, \ldots, \mathrm{N}_c$ based on the following equations:

$$w_i = \frac{\sum_{j}^{\mathrm{N}c} c'_{i,j}}{\mathrm{N}c} \tag{12}$$

In this paper, the hierarchy structure of the AHP consists of only two levels (without using the alternative level), and the AHP is used to determine the weight coefficients, while setting priorities, i.e. ranking of alternatives will be carried out using the TOPSIS method.

C. TOPSIS

The Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), first proposed by Hwang and Yoon in 1981, is an MCDM widely used, in the presence of multiple and usually conflicting criteria, to evaluate and rank the performance of alternatives with respect to multiple criteria by similarity with the ideal solution [38].

There are two types of criteria: benefit and cost [37]–[39]. A lower value is better for the cost criterion, while the opposite is true for the benefit criterion. TOPSIS is based on the concept that the chosen alternative should be closest to the positive ideal solution (PIS) and the greatest geometric distance from the negative ideal solution (NIS). The PIS consists of all the best criteria values, maximizing the benefit criteria and minimizing the cost criteria. On the other hand, the NIS composed of all the worst criteria values minimizes the benefit criteria and maximizes the cost criteria. A broad survey on TOPSIS can be found in [37]–[39].

TOPSIS has been adopted to solve numerous practical topics, and has been extended for application in uncertainty situations by many researches due to its structural integrity, simplicity, and ease of operation. It is therefore adopted in this paper to select the best alternative (solution) among non-dominated solutions.

In the beginning of TOPSIS, the decision matrix $X = [x_{i,j}]_{\mathrm{N}_a \times \mathrm{N}_c}$ and the weight vector W must be known. The decision matrix X consists of alternatives and criteria, and is described by Eq. (13).

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,Nc} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,Nc} \\ \vdots & \vdots & \cdots & \vdots \\ x_{N_a,1} & x_{N_a,2} & \cdots & x_{Na,Nc} \end{bmatrix} \tag{13}$$

where $x_{i,j}$ is the rating of alternative A_i on criteria C_j, for $i = 1, 2, \ldots, \mathrm{N}_a$ and $j = 1, 2, \ldots, \mathrm{N}_c$. The weight vector $W = (w_1, w_2, \ldots, w_{\mathrm{N}_c})$ consists of weight w_j for criterion C_j, where $i = 1, 2, \ldots, \mathrm{N}_c$, and:

$$\sum_{j=1}^{\mathrm{N}_c} w_j = 1. \tag{14}$$

The main procedure of TOPSIS based on the geometric distance method representing "closeness to the ideal" is described in the following steps [38]:

STEP T1. Build the normalized new decision matrix $Y = [y_{i,j}]_{\mathrm{N}_a \times \mathrm{N}_c}$. All values of $x_{i,j}$ are from different sources and bases, and need to be normalized to transform it into a new decision matrix Z, which is a normalized and dimensionless matrix, based on the following equation:

$$y_{i,j} = \frac{x_{i,j}}{\sqrt{\sum_{i=1}^{Na} x_{i,j}^2}} \tag{15}$$

STEP T2. Build the weighted normalized decision matrix $Z = [z_{i,j}]_{\mathrm{N}_a \times \mathrm{N}_c}$ by letting

$$z_{i,j} = w_j \cdot y_{i,j}, \tag{16}$$

where $i = 1, 2, \ldots, \mathrm{N}_a$ and $j = 1, 2, \ldots, \mathrm{N}_c$.

STEP T3. Identify the PIS $Z^+ = (z_1^+, z_2^+, \ldots, z_{\mathrm{N}_c}^+)$ and NIS $Z^- = (z_1^-, z_2^-, \ldots, z_{\mathrm{N}_c}^-)$, where z_j^+ and z_j^- are the best and worst solutions obtained from criterion C_j for $j = 1, 2, \ldots, \mathrm{N}_c$, respectively, i.e., z_j^+ is the maximal (minimal) solution if C_j is needed to maximize (minimize) and z_j^- is the maximal (minimal) solution if C_j is needed to minimize (maximize).

STEP T4. Calculate d_i^+ and d_i^-, which are Euclidean distances from Z^+ and Z^- to each weighted normalized alternative $Z_i = (z_{i,1}, z_{i,2}, \ldots, z_{i,\mathrm{N}_c})$ for $i = 1, 2, \ldots, \mathrm{N}_a$ as shown in Eqs. (17) - (18), respectively.

$$d_i^+ = \sqrt{\sum_{j=1}^{Nc} (z_{i,j} - z_j^+)^2} \tag{17}$$

$$d_i^- = \sqrt{\sum_{j=1}^{Nc} (z_{i,j} - z_j^-)^2} \tag{18}$$

STEP T5. Calculate the similarity measure s_i for each weighted normalized alternative Z_i as shown in Eq. (19), where $i = 1, 2, \ldots, \mathrm{N}_a$.

$$s_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{19}$$

STEP T6. The higher value of the similarity measure is the best alternative.

IV. PROPOSED THREE-PHASE DECISION-MAKING METHODOLOGY

The proposed three-phase methodology to improve IoT service quality is discussed in this section.

A. ALGORITHM

This sub-section describes how all simple routings between node 0 and the sink node are found using the DFS, the weights of all factors listed by experts are calculated using the AHP, and the best simple routing is allocated using the TOPSIS using the three-phase methodology.

Input: A WSN in the IoT with a source node 0 and a sink node.

Output: The best routing from node 0 to the sink node with the highest similarity measure value.

STEP 1. Search for all simple routings using DFS and let N_a be the number of simple routings.

STEP 2. Construct the pair-wise comparison matrix $C_k = [c_{i,j}^{(k)}]_{\mathrm{N}_c}$ for each expert for $k = 1, 2, \ldots, \mathrm{N}_e$, where N_c and N_e are the numbers of criteria and experts, respectively.

STEP 3. Aggregate C_k into the pair-wise comparison matrix $C = [c_{i,j}]_{\mathrm{N}_c}$.

STEP 4. Normalize C to C' based on Eq. (11).

STEP 5. Determine the relative weight w_j of the j^{th} attribute based on Eq. (12), where $j = 1, 2, \ldots, \mathrm{N}_c$.

STEP 6. Build the decision matrix $X = [x_{i,j}]_{\mathrm{N}_a \times \mathrm{N}_c}$ of which each alternative is a simple routing obtained from STEP 1.

STEP 7. Build the normalized new decision matrix $Y = [y_{i,j}]_{\mathrm{N}_a \times \mathrm{N}_c}$ based on Eq. (15).

STEP 8. Build the weighted normalized decision matrix $Z = [z_{i,j}]_{\mathrm{N}_a \times \mathrm{N}_c}$ based on Eq. (16).

STEP 9. Identify the PIS $Z^+ = (z_1^+, z_2^+, \ldots, z_{\mathrm{N}_c}^+)$ and NIS $Z^- = (z_1^-, z_2^-, \ldots, z_{\mathrm{N}_c}^-)$.

STEP 10. Calculate d_i^+ and d_i^- for i =1, 2, …, N_a based on Eqs. (17) and (18).

STEP 11. Calculate the similarity measure s_i for i =1, 2, …, N_a based on Eq. (19).

STEP 12. Find the alternative with the highest similarity measure value.

The flow chart of the above algorithm is depicted in Fig. 7.

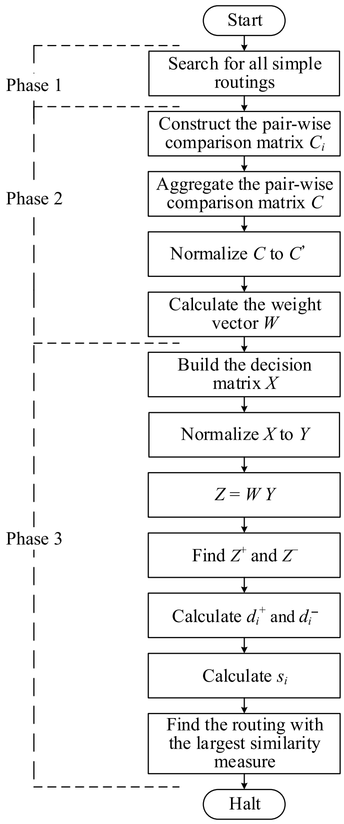

FIGURE 7. The flowchart of the proposed algorithm.

B. AN ILLUSTRATIVE EXAMPLE

The general procedures of the proposed three-phase methodology are best demonstrated with examples. For expediency, the example shown in Fig. 1 is selected to illustrate the step-by-step procedure to find the best routings between nodes 1 and 4.

The information of the six factors of each arc is listed below, where C, E, Q, R, S and T denote the use-cost, energy consumption, transmission quality, reliability, signal strength and transmission time.

It is assumed that there are five experts are assigned to analyze the system, to find out which factor has caused the most service quality problems, and to construct their own pair-wise comparison matrix in STEP 1.

The whole procedure of implementing the proposed three-phase methodology is described below.

Solution:

STEP 1. Four simple routings are identified in Fig. 1 using the DFS (see Fig. 5) (see Fig. 8): $p_1 = \{e_{0,1}, e_{1,2}, e_{2,3}\}$, $p_2 = \{e_{0,1}, e_{1,3}\}$, $p_3 = \{e_{0,2}, e_{2,1}, e_{1,3}\}$, and $p_4 = \{e_{0,2}, e_{1,3}\}$ in the first phase.

STEP 2. Construct the pair-wise comparison matrix $C_k = [c_{i,j}^{(k)}]_{N_c}$ for each expert as shown in Table 3.

STEP 3. Obtain the pair-wise comparison matrix $C = [c_{i,j}]_{N_c}$ by aggregating experts' pair-wise comparison matrices based on Eq. (9), as shown in Table 4.

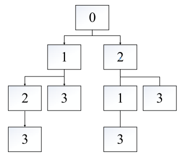

FIGURE 8. The DFS tree of Fig. 1.

TABLE 2. The information of the six factors of each ARC.

	e_1	e_2	e_3	e_4	e_5
C	2	5	3	1	2
E	3	2	2	2	4
Q	3	2	4	1	3
R	0.9	0.8	0.95	0.88	0.9
S	3	2	3	2	2
T	1	3	3	4	2

TABLE 3. The experts' positive reciprocal matrices.

Expert ID		C	E	Q	R	S	T
1	C	1	6	5	2	1	4
	E	1/6	1	1	1	2	1
	Q	1/5	1/1	1	2	2	2
	R	1/2	1/1	1/2	1	1/1	1/1
	S	1/1	1/2	1/2	1	1	1/1
	T	1/4	1/1	1/2	1	1	1
2	C	1	6	5	2	3	4
	E	1/6	1	1	1	1	2
	Q	1/5	1/1	1	1	2	2
	R	1/2	1/1	1/1	1	1/2	1/2
	S	1/3	1/1	1/2	2	1	1/2
	T	1/4	1/2	1/2	2	2	1
3	C	1	6	4	2	3	3
	E	1/6	1	3	1	2	2
	Q	1/4	1/3	1	1	1	3
	R	1/2	1/1	1/1	1	1/2	1/2
	S	1/3	1/2	1/1	2	1	1/1
	T	1/3	1/2	1/3	2	1	1
4	C	1	6	4	2	2	3
	E	1/6	1	1	2	1	2
	Q	1/4	1/1	1	1	2	2
	R	1/2	1/2	1/1	1	1/2	1/1
	S	1/2	1/1	1/2	2	1	1/1
	T	1/3	1/2	1/2	1	1	1
5	C	1	6	5	3	3	3
	E	1/6	1	1	1	1	1
	Q	1/5	1/1	1	2	2	2
	R	1/3	1/1	1/2	1	1/4	1/1
	S	1/3	1/1	1/2	4	1	1/1
	T	1/3	1/1	1/2	1	1	1

STEP 4. Normalize C to $C' = [c_{i,j}]_{N_c}$ based on Eq. (11), as shown in Table 5.

STEP 5. The average of six factors in each row is the weight of each factor, i.e., the weights of C, E, Q, R, S and T are 0.40, 0.13, 0.15, 0.10, 0.13 and 0.10 (see the last column in Table 5).

STEP 6. The decision matrix $X = [x_{i,j}]_{N_a \times N_c}$ is shown in Table 6. Note that each alternative is a simple routing obtained from STEP I.

STEP 7. Build the normalized new decision matrix $Y = [y_{i,j}]_{N_a \times N_c}$ based on Eq. (15), as shown in Table 7.

STEP 8. Build the weighted normalized decision matrix $Z = [z_{i,j}]_{N_a \times N_c}$, as shown in Table 8.

TABLE 4. The five experts' aggregated score.

	C	E	Q	R	S	T
C	1.00	6.00	4.57	2.17	2.22	3.37
E	0.17	1.00	1.25	1.15	1.32	1.52
Q	0.22	0.80	1.00	1.32	1.74	2.17
R	0.46	0.87	0.76	1.00	0.50	0.76
S	0.45	0.76	0.57	2.00	1.00	0.87
T	0.30	0.66	0.46	1.32	1.15	1.00

TABLE 5. The values of the normalized aggregated pair-wise comparison matrix.

	C	E	Q	R	S	T	Average
C	0.39	0.59	0.53	0.35	0.28	0.24	0.40
E	0.06	0.10	0.14	0.16	0.17	0.13	0.13
Q	0.08	0.08	0.12	0.22	0.22	0.15	0.15
R	0.11	0.07	0.05	0.10	0.14	0.15	0.10
S	0.17	0.08	0.07	0.09	0.13	0.22	0.13
T	0.18	0.09	0.09	0.08	0.06	0.11	0.10

TABLE 6. The elements of *X*.

	$p_1=\{e_{0,1}, e_{1,2}, e_{2,3}\}$	$p_2=\{e_{0,1}, e_{1,3}\}$	$p_3=\{e_{0,2}, e_{2,1}, e_{1,3}\}$	$p_4=\{e_{0,2}, e_{2,3}\}$
C	7	3	8	7
E	9	5	8	6
Q	3.3333333	2	2	2.5
R	0.7695	0.792	0.6336	0.72
S	2.6666667	2.5	2	2
T	6	5	9	5

TABLE 7. The elements of *Y*.

	$p_1=\{e_{0,1}, e_{1,2}, e_{2,3}\}$	$p_2=\{e_{0,1}, e_{1,3}\}$	$p_3=\{e_{0,2}, e_{2,1}, e_{1,3}\}$	$p_4=\{e_{0,2}, e_{2,3}\}$
C	0.535303	0.229416	0.611775	0.535303
E	0.627060	0.348367	0.557386	0.418040
Q	0.661903	0.397142	0.397142	0.496428
R	0.526112	0.541496	0.433197	0.492269
S	0.576975	0.540914	0.432731	0.432731
T	0.464294	0.386912	0.696441	0.386912

TABLE 8. The elements of *Z*.

	$p_1=\{e_{0,1}, e_{1,2}, e_{2,3}\}$	$p_2=\{e_{0,1}, e_{1,3}\}$	$p_3=\{e_{0,2}, e_{2,1}, e_{1,3}\}$	$p_4=\{e_{0,2}, e_{2,3}\}$
C	0.214121	**0.091766**	0.244710	0.214121
E	0.081518	**0.045288**	0.072460	0.054345
Q	**0.099286**	0.059571	0.059571	0.074464
R	0.052611	**0.054150**	0.043320	0.049227
S	**0.075007**	0.070319	0.056255	0.056255
T	0.046429	**0.038691**	0.069644	**0.038691**

TABLE 9. Values of d_i^+, d_i^-, and s_i for i =1, 2, …, N$_a$.

	$p_1=\{e_{0,1}, e_{1,2}, e_{2,3}\}$	$p_2=\{e_{0,1}, e_{1,3}\}$	$p_3=\{e_{0,2}, e_{2,1}, e_{1,3}\}$	$p_4=\{e_{0,2}, e_{2,3}\}$
d_i^+	0.127850	0.039990	0.164725	0.126668
d_i^-	0.059074	0.161176	0.009058	0.053748
s_i	0.316033	**0.801209**	0.052120	0.297910

TABLE 10. All best simple routings.

	0	1	2	3
0		$\{e_{0,1}\}$	$\{e_{0,1}, e_{1,2}\}$	$\{e_{0,1}, e_{1,3}\}$
1	$\{e_{1,0}\}$		$\{e_{1,2}\}$	$\{e_{1,3}\}$
2	$\{e_{2,1}, e_{1,0}\}$	$\{e_{2,1}\}$	$\{e_{3,1}\}$	$\{e_{2,3}\}$
3	$\{e_{3,1}, e_{1,0}\}$	$\{e_{3,1}\}$	$\{e_{3,2}\}$	

TABLE 11. The average runtimes of the proposed algorithm for five problems.

n	Phase 1	Phase 2	Phase 3	Total
10	0.99751	0.00000	0.31415	1.31166
20	2.04724	0.00000	0.73774	2.78498
30	17.75302	0.00000	6.25437	24.00739
40	214.02935	0.00000	115.08946	329.11882
50	7791.97735	0.00000	1876.83169	9668.80904

STEP 9. From Table 7, PIS $Z^+ = (z_1^+, z_2^+, \ldots, z_{N_c}^+) =$ (0.091766, 0.045288, 0.099286, 0.054150, 0.075007, 0.038691) (see these bold values in Table 8) and NIS $Z^- = (z_1^-, z_2^-, \ldots, z_{N_c}^-) =$ (0.244710, 0.081518, 0.059571, 0.043320, 0.056255, 0.069644) (see these underlined values in Table 8).

STEP 10. Calculate d_i^+ and d_i^- for i =1, 2, …, N$_a$, as shown in Table 9.

STEP 11. Calculate the similarity measure s_i for $i = 1, 2, \ldots, \mathrm{N}_a$, as shown in the last row in Table 9.

STEP 12. From Table 9, p_2 has the highest similarity measure value, 0.801209, and this information will be given to policy makers for their reference use in decision-making.

In the same way, all best simple routings are found using the proposed three-phase methodology, as shown in Table 10.

From Table 10, even if two nodes are in both sides of an arc, it be observed that it is not necessary to transmit the signal directly along that arc. For example, nodes 0 and 2 are on both sides of arc e_2, and the best routing between these two nodes is not along e_2, but rather from node 0 to node 2 via node 1. Thus, from this simple example, it is concluded that the proposed three-phase methodology is very useful in improving the service quality of IoT WSNs.

V. NUMERICAL EXAMPLES

Five set of numerical experiments were implemented to verify the performance of the proposed algorithm conducted on a moderate-size networks. In these experiments, the number of nodes were 10, 20, 30, 40, 50 generated uniformly and randomly in an area of 100m × 100m, respectively. Hence, all network structures are simulated randomly.

The proposed algorithm implemented in the C programming language run on a Windows 10 with an Intel Core i7-5960X CPU and 16 GB of RAM.

Table 11 lists the runtime for each test problem. Not unexpectedly for an NP-hard problem, the runtime growths with the number of nodes, i.e., the size of the problem. Most of the runtime is spent in searching for all simple paths, i.e., the Phase 1. The runtime for the Phase 2 is the smallest one due to the factor that there are only six factors for five experts. The runtime of Phase 3 is less than that of Phase 1 because not any path is a simple path. Also, general networks always include cycles in Phase 1. In Phase 3, only these found simple paths in Phase 1 are calculated their values of use-cost, energy consumption, transmission quality, reliability, signal strength and transmission time by multiplying the weight of each factor obtained in Phase 2.

Hence, from Table 11, the proposed algorithm is able to solve the problem for moderate-size WSNs.

VI. CONCLUSION

This study aims to systematically and efficiently improve the quality of experience for IoT system technologies, including identifying major factors affecting the quality of experience. To achieve the above goal, a three-phase methodology is proposed. In the first phase of the proposed three-phase methodology, a DFS is created to search for all simple routings. In the second phase, the AHP based on pairwise comparisons is adapted to analyze the qualitative and quantitative factors that need to be considered to improve the quality of experience of IoT system technologies. In addition, the related weights of these factors are obtained to allow this study to focus on those factors that are top priority for improvement in an environment with limited resources. In the third phase, the TOPSIS based on the weights derived from the AHP is used to choose the routing with the best similarity measure among all simple routings obtained from the proposed DFS.

The performance and applicability of the proposed three-phase methodology is illustrated through an application example of a case study. Furthermore, simulation results demonstrate the performance of the proposed algorithm to solve the problem with size up to 50 nodes. Hence, using this three-phase methodology, reasonable results and the best routing available can indeed be generated for fast decision-making.

In future work, a user-friendly software will be prepared to accelerate and simplify the computation processes of the DFS, AHP and TOPSIS with two normalizations [40] in the proposed three-phase methodology. As another future direction, the proposed methodology can include other methodologies to ensure greater reliability for IoT decision-making processes.

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