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EMS: An Energy Management Scheme for Green IoT Environments

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ABSTRACT The Internet of Things (IoT) has important applications in all aspects of our lives in areas such as business, military, security, and health. It is known that most IoT node designs are energy constrained. Therefore, maintaining an ideal energy consumption rate has become one of the most important challenges in the IoT research field. In this paper, an IoT Energy Management Scheme (EMS) is proposed. In this system, heterogeneous types of energy-constrained nodes are considered. The proposed EMS comprises three strategies. The first strategy minimizes the volume of data that may be transmitted through the IoT environment. The second strategy schedules the work of the critical energy IoT nodes. The third strategy provides a fault tolerance scenario that can be applied to address inevitable energy problems faced by IoT nodes. Finally, to test the proposed EMS, the NS2 network simulator is used to construct an intensive simulation of the IoT environment. The simulation results proved that the proposed EMS outperformed the traditional IoT system with respect to the following performance metrics: energy consumption rate, number of failed nodes due to energy loss, throughput, and network lifetime.

INDEX TERMS Green IoT, green communication, IoT, IoT energy, IoT simulation.

I. INTRODUCTION

In recent years, the Internet of Things (IoT) has changed the world like the Internet did. The IoT has been considered to be one of the most important research topics. The IoT can be defined as billions of passive and active networked devices communicating with each other [1]–[3]. The communication between IoT devices can be achieved anytime and anywhere using services by any links. The IoT is a heterogeneous environment that incorporates many different nodes such as sensors, RFID tags, RFID readers, and mobile devices. In addition, there are many IoT applications in all aspects of our lives, such as military, security, marketing, and healthcare [4]–[6]. The IoT is not only a network for data transmission but also can be described as a system containing protocols, events, and big data processing. Furthermore, the IoT was not intended to require human intervention; this means the artificial intelligent applications could be implemented in this type of environment. The IoT technology evolution offers opportunities but also has risks. There are many challenges in the IoT research topics such as data processing and storage, routing, multimedia transmission, security, communication, and energy management [8]–[10].

It is well known that IoT applications often require battery-based nodes working for long intervals without human intervention after their initial adaptations. In the absence of energy management methodologies, these nodes would drain their batteries within short periods. In addition, an IoT application can only achieve its mission as long as its nodes are considered alive [11]–[13]. Hence, the goal of any energy supply and management technique is to maximize the network lifetime. This goal is coupled with the single node lifetime. Therefore, energy consumption is one of the most critical and multidimensional challenges in the IoT environment. This challenge can be abstracted to the problem of conserving node energy without affecting the IoT efficiency [14]–[16].

The IoT nodes that are energy based have different types of applications, such as the wireless sensor network (WSN), radio-frequency identification (RFID) network, and the mobile ad hoc network (MANET). Unfortunately, most researchers try to design protocols or techniques to minimize the energy consumption rates only for individual

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or special networks. This is cannot be applied to the IoT environment due to its heterogeneous nature. Consequently, finding one technique to minimize the energy consumption rate is difficult (if not impossible). This is can be explained by the different software and hardware requirements and the functions of each energy-based node. Therefore, in this study, an IoT Energy Management Scheme (EMS) is proposed. This system comprises three main strategies. The first strategy involves techniques that reduce the amount of data which are transmitted or received by the energy-based nodes. The second strategy comprises a work methodology to save the energy consumed at each IoT node. The third strategy comprises a fault tolerance scenario to compensate for failures of energy-based nodes.

The key contributions of this study can be summarized as follows:

- Use of data reduction techniques in the IoT environment;
- Development of a methodology to save the energy of IoT energy-based nodes;
- Design of a fault tolerance scenario for IoT energy-based nodes;
- Construction of a simulation testbed for the IoT environment;
- Presentation and discussion of the simulation results.

The reminder of this paper is organized as follows: Section II reviews the related works. The aim of Section III is to propose an EMS solution. In Section IV, the simulation testbed is constructed and the results are shown and discussed. The paper is concluded in Section V.

II. RELATED WORKS

Most of the related works in this research topic are considered special purpose solutions and cannot be implemented directly to the IoT environment. Salman, *et al.* introduced an energy system for smart homes. This system is not considered to be applicable to the heterogeneous nature of the IoT environment and was proposed only for sensors and cameras. In addition, it is not adapted for systems that can transmit large numbers of gigabytes such as the IoT environment [17]. Ku *et al.* proposed a smart energy service for IoT. This service is based on energy information gathering. The primary weak point in this service is neglecting the fault tolerance issue in addition to the weak experiments that consider the IoT infrastructure [18]. Choi *et al.* proposed an energy monitoring system. This system is considered to be a special purpose system because it is constructed only for a specific type of open platform. In addition, its experiments are not intensively constructed to provide accurate results which support the researchers claim [19]. Prathik *et al.* introduced a system to scale the energy using IoT technology (i.e., the IoT technology is used as a tool in this research). The research did not propose a solution for the energy problem in the IoT [20]. Srinivasan *et al.* introduced a smart technology to adapt the energy methodologies which are IoT-based using smart plugs, but did not face energy-critical levels which may occur in energy-based nodes in the IoT environment. In addition, the implementation itself did not reflect the nature of the IoT [21]. Kumar *et al.* introduced a system to harvest the energy using IoT. It is not considered to address the IoT energy consumption challenge, especially for unrenewable energy nodes [22]. Chaouch *et al.* used machine-to-machine communication for construction of an Energy Management Scheme to monitor and reduce the energy consumption. This is considered to be a special purpose system due to its infrastructure [23]. Panahi *et al.* proposed a smart strategy in a practical manner to charge mobile sensors wirelessly using IoT technology. The simulated testbed of this smart strategy is not adequate to represent the IoT environment due to its stress on the WSN environment only, while neglecting of other energy-based nodes such as RFID [24]. Alaudin *et al.* proposed only a real-time monitoring system for energy levels in the IoT system [25]. Tcarenko *et al.* demonstrated a hardware design which can adjust the energy consumption rate. This is considered to be a special purpose solution because it is designed for only mobile nodes in the IoT environment. Furthermore, it did not have a powerful testbed to prove the research claim [26]. Suresh *et al.* proposed a theoretical technique to decrease the energy consumption of sensor nodes in the IoT environment. In addition, this considered that the WSN is an entire IoT system which is an inaccurate definition [27]. Yaghmaee *et al.* used the IoT technology to design a smart energy metering system that consists of a cloud server and smart plugs in addition to a gateway. The implementation of this system has a deficiency in terms of the IoT specifications, and the results are considered inaccurate and insufficient [28]. Pan *et al.* proposed an energy monitoring system and decreased energy consumption rates in the IoT environment. This system is also considered to be special purpose. Moreover, its implementation testbed did not reflect the nature of IoT in an accurate manner [29]. Ding *et al.* proposed a scheduling model for energy loss optimization. This model is tested in a WSN environment, not an IoT environment; thus, its results cannot be applied in IoT [30]. Ejaz *et al.* proposed an optimized and scheduled energy-efficient framework for smart cities in addition to energy harvesting which extended the lifetime of low power devices. The performance analysis of this framework is weak because it depends on four appliances. It neglected the large quantity of data that may be transmitted in the smart city or through the IoT environment [31]. Yu *et al.* introduced an IoT-based energy management platform. It considered a small number of energy-based nodes in the IoT environment. However, there is no implementation, simulation, or results reported in this research [32]. Hu *et al.* focused only on maximizing the node's energy and optimizing the network throughput by proposing an energy harvesting cooperative system for WSN. The number of nodes, which is used in the simulation of this system, is too small to make its results accurate [33]. Iqbal *et al.* controlled the energy consumption in the smart homes. Because the smart home is considered to be a small component of the IoT, the results of this research cannot be applied in the IoT environments [34]. Oma *et al.*

introduced an energy-efficient model that is based on fog computing, and tried to distribute the sensor data processing among fog nodes. The work neglected the energy consumption for sensor nodes in addition to other IoT energy-based nodes such as RFIDs [35]. Anzanpour *et al.* proposed a model to decrease the energy consumption in wearable devices. It is considered as a special purpose solution and cannot be applied for the IoT environment due to the heterogeneous energy-based nodes [36]. Al-Kofahi *et al.* introduced a micro-controller that may help the designers to construct embedded systems that are energy efficient. This research considered the energy problem only from the hardware point of view; however, the IoT environment comprises both hardware and software energy related systems. Therefore, it is considered to be a special purpose solution [37]. Bouaziz *et al.* proposed a new routing protocol that considers mobility and energy issues in the IoT environment. It did not consider the challenge of decreasing energy consumption [38]. Sun *et al.* proposed a method to compose the IoT service as regards the requests by clients which may occur in the IoT systems. It is not considered as a long-term solution for the IoT energy consumption problem [39]. Azar *et al.* introduced a technique which is based on edge computing to avoid data compression processing which may consume high energy rates. The data compression is considered as essential process to decrease the size of transmitted data in the IoT environment. Thus, this technique may be applied in some IoT applications while failing in other applications [40]. There are also many other paths, such as [41]–[43], which are considered to be special purpose solutions for energy consumption.

III. THE PROPOSED ENERGY MANAGEMENT SCHEME (EMS)

The proposed EMS is designed specifically for the IoT environment. The main objective of the EMS is to consider the energy problem for wholly heterogeneous energy-based nodes in the IoT environment. To achieve this objective, the proposed EMS design should consider many alternative solutions and ideas. This is because the IoT energy-based nodes are different in their nature and specifications. The concept of the EMS is based on the application of three basic strategies. These strategies are: minimizing transmitted data in the IoT environment, scheduling of the processes of energy-based nodes, and providing fault tolerance. The EMS concept is built on the categorization of energy-based nodes into classes depending on their types such that each class comprises a special type of node (i.e., sensors, RFID, and mobiles). The EMS strategies can then be applied to each class. One or more strategies may be applicable for one class depending on its specifications and nature. The sub-sections below discuss each EMS strategy in addition to the general EMS algorithm which defines how the proposed EMS works.

A. STRATEGY 1: DATA MINIMIZATION

In the IoT environment, there are many relationships that couple the energy issue with data. The data is considered to be one of the foremost factors which consume the nodes' energy. This is because there are many forms of data processing, such as gathering, processing, and transmission, that contribute to the level of energy consumed in the IoT nodes. Reducing the volume of data in the IoT environment will, of course, have a positive impact on energy usage. The implementation of the data minimization process differs from one energy-based node class to another. Each class has its own functions and data to deal with. For example, the sensor class has the ability to gather, process, and transmit its data, but the RFID class mostly has the ability only to transmit its data. To consider this issue in the data reduction model, each class should be identified or each node identification should comprise its class. Furthermore, diversity in the use of data reduction methods is due to the diversity in the IoT energy-based nodes. Therefore, the process of data minimization in the EMS comprises data prioritization, data compression, and data fitting. The data fitting process can be used for the class which has data transmission and gathering capabilities. The data prioritization process can be used for classes which have data gathering, processing, and transmission capabilities. The data compression process is used for the class which has data transmission and processing capabilities. This is depicted in Fig. 1.

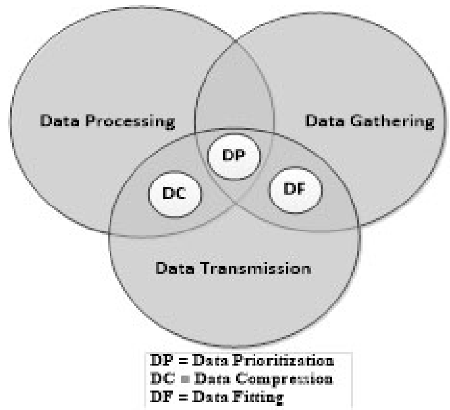


FIGURE 1. Relations between data reduction methods and capabilities of energy-based nodes.

1) DATA PRIORITIZATION

It is important to clarify that, in the case of IoT network congestion problems, the IoT data should be prioritized. The data prioritization method which is used in the EMS is based on queuing theory. The data is prioritized into 'n' classes. Each data class will be processed in a different queue. If the data is prioritized into more than two classes, the size of the data, for which its service may be delayed (or neglected), will increase; that, in turn, results in the reduction of the data which will be served, thereby reducing the amount of data that will be transferred through the IoT network. For simplicity, a two-queue model (i.e., n = 2) is used to prioritize the data [44]. This model can be extended to become more than two queues, such as in [35]. Hence, the IoT data are classified into two classes; namely, C1 and C2. The most important IoT data is assigned to C1. The assignment operation depends on the predefined conditions that are required by different types of applications. The less important IoT data is assigned to C2. The C1 data is enqueued to the first queue, which has a high quality of service (QoS) that makes this class of data have a higher service priority. The second queue service for the C2 IoT data has a low priority. The next-generation routers should be updated and adapted to this prioritization model. In the two-queue model, the linear data system is used. The formula $P_{\mathrm{ij}} = \lambda_{\mathrm{i}} + \mu_{\mathrm{j}}$ is used, where P_{ij} is the probability of transition from i (birth state) to j (death state). The model represents C1 and C2 by corresponding queues Q1 and Q2, respectively. Over time, the data classifier can distribute the IoT data among the two queues. There are seven steps that are used to summarize how the proposed two-queue model works. In step 1, within a time period that is determined by the EMS server, the IoT data are classified each according to its priority. The selection by the classifier has initial probabilities: Pr_1 and Pr_2, where $\sum_{i=1}^{2} Pr_i = 1$. In step 2, in the case of low bandwidth while servicing the data, the service controller should provide the QoS to the next IoT data in the same queue. In step 3, the incompletely processed data should be transferred from Q1 to Q2. In step 4, the processing of data in Q1 continues, even if Q2 is empty, provided that the QoS is available in Q1. In step 5, as soon as Q1 became empty, the service controller starts the processing of data in Q2. While the data is being serviced in Q2, and if a new piece of data arrives at Q1, the service controller should jump to Q1 and start the service process. A further description of the two-queue model and its state transitions are stated in [44].

2) DATA FITTING

The second data minimization method of the EMS is data fitting [45]. As stated above, this technique is used by the energy-based nodes such as sensors which can gather and transmit information. In the data fitting methodology, the data can be abstracted into a small size and sent to the destination. The abstraction process depends on finding relations between the IoT data, so this relation can be sent with some other parameters which help the destination to extract the original data. To describe the data fitting methodology in a simple manner, the sensor state can be taken as an example. Suppose that each sensor gathers its data and organizes it into a pair (a, b). The data fitting methodology can now be applied to the gathered data pairs. The data fitting methodology has many techniques. In the proposed EMS, the least square technique is applied as a data fitting methodology. In this area, there are two methods, linear [46] and nonlinear [47]. In the linear method, the interval between each data item, which is gathered by the IoT sensors, should be regular. The regular intervals between data are considered as a special situation in the IoT environment. For simplicity, the linear method is applied to the proposed EMS.

Let the sensor gathered data be organized as $\{S_1\,[i]\,[2]_{m_1}, S_2\,[i]\,[2]_{m_2}, \ldots\ \ldots\ \ldots, S_n\,[i]\,[2]_{m_n}\}$, where $\mathrm{m} = 1$ to 'n,' which indicates to size of the array of pairs at each sensor, $\mathrm{i} = 1$ to m_j, $\mathrm{j} >= 1$, and 'n' is the number of sensors. The relation between 'x' and the n-vector 'y' is determined in (1).

$$\mathrm{X} \approx \mathrm{f(y)}, \tag{1}$$

where the independent variable is represented by 'y' and the response variable is represented by 'X.' The relationship between 'X' and 'y' is determined by 'f': $\mathrm{R}^{\mathrm{n}} \to \mathrm{R}$. If 'y' is a feature vector, and 'a' is predictable data, then the approximation of function 'f' ($\mathrm{f_{app}}$) is required. The term "$\mathrm{f_{app}}$" is determined depending on the sensor data observations. The relationship between 'f' and "$\mathrm{f_{app}}$" is determined by (2).

$$\mathrm{f_{app}} = \theta_1 f_1(y) + \theta_2 f_2(y) + \theta_3 f_3(y) + \ldots\ldots \theta_n f_n(y), \tag{2}$$

where 'n' is the number of sensors, $f_1(y)$, $f_2(y)$, and $f_3(y)$ are functions for $S_1\,[i]\,[2]_{m_1}$, $S_2\,[i]\,[2]_{m_2}$, and $S_3\,[i]\,[2]_{m_3}$, respectively, and θ_1, θ_2, and θ_3 are the parameters which are determined depending on the input and output sensor data. The data approximation function is determined by (3). The primary target is determined by (4). Equation (5) is used to determine the prediction error.

$$x_{app} = \mathrm{f_{app}(y_i)} \tag{3}$$

$$x_{app} \approx x_{\mathrm{i}} \tag{4}$$

$$r_i = x_{app_i} - a_i \tag{5}$$

3) DATA COMPRESSION

The third method to minimize the IoT data size is compression. Data compression is used to minimize the energy consumption rates by decreasing the number of bytes which will be transmitted from energy-based nodes to other nodes in the IoT environment. The compression mechanisms are numerous, especially for data sensors. Implementation of theses mechanisms in the IoT environment is still under research. It is very difficult to combine one mechanism with another and apply it in IoT environment. To remedy this challenge, an existing and proven compression mechanism is selected to demonstrate its impact on reducing energy consumption without considering the preference between them. In addition, it is not a requirement that the data compression mechanism be implemented only by energy-based nodes, but it can be implemented from other nodes provided that it has an effect on reducing energy consumption rates. For example, the data compression may be implemented at sensors as well as at sinks and servers. Furthermore, it is true that the greatest burden in the IoT system is the data that is collected by sensors, but also do not forget that the data for other nodes such as mobiles and RFIDs may represent a danger to their energy consumption rates. Moreover, the strategy to be implemented is not based on applying data compression only once; it is possible to recompress the collected compressed data if necessary. Moreover, because there are heterogeneous energy-based nodes in the IoT environment, applying only

TABLE 1. **The scheduling model parameters.**

Parameter	Description	priority	
Current energy level	If the level of energy is safe, moderate, or critical.	1	Alarm
Power source	If the node has a power source such as sun solar.	2	Fault Tolerant
Node alternatives	If there are overlaps between a node and other nodes such that it can be recovered in case of failure.	3	
Heterogeneity	The node belongs to which type of energy-based nodes in the IoT environment.	4	Scheduling Implementation
Importance	If this node is used in important tasks depending on the IoT application.	5	
Task frequency	The number of tasks that are assigned to a node per time.	6	
Location	To determine the distances between the node and its nearest cluster head or other nodes.	7	

one type of data compression may not be suitable for all IoT devices. Therefore, it is preferable to have more than one mechanism of data compression to choose a particular type that is suitable for each energy-based node.

Based upon the above discussion, the data compression technique which is stated in [48] is used for the sensors and MANET data in the IoT environment. However, the technique that is stated in [49] is adapted to compress the RFID data. For simplicity, the EMS design is built on many data compression techniques for different types of data, but in the simulation process, one data compression mechanism is used and tested.

B. STRATEGY 2: SCHEDULING

The second strategy to minimize the energy consumption rates is scheduling. The scheduling in the IoT means that each energy-based node can achieve its function but without a fixed or predetermined time. The proposed scheduling methodology in EMS should consider seven issues. The first issue is the current energy level at each IoT energy-based node. The second issue is the power source. The third issue is the node alternatives (overlap in covered area). The fourth issue is the heterogeneous energy-based nodes in the IoT system which leads to the heterogeneity in their functions. The fifth issue is the importance of each node. The sixth issue is the frequency of task execution. The seventh issue is the location of each node. These issues determine the relative weight of each node. These issues may be changed over time. Thus, the scheduling algorithm should work in dynamic manner.

The IoT energy-based nodes are supposed to be classified into groups of clusters for management purposes. Each cluster has a head which manages its nodes. Management here means the assignment of tasks to each node in addition to the stopping, reassignment, or pausing of these tasks. The cluster head should take into consideration the seven parameters to make a decision for each energy-based node. To extract an accurate decision, the parameters should be arranged according to their importance, as shown in Table 1. The current energy level has the first priority because it determines whether or not the scheduling technique should be implemented. The power source parameter has the second priority. The node alternatives parameter has the third priority. The heterogeneity parameter has the fourth priority. The node importance parameter has the fifth priority. The frequency of tasks has the sixth priority. The location has the last priority. The proposed order of priority gives the cluster head a clear mechanism to go directly to the node that deserves intervention if there is a capacity to rescue all energy affected nodes. These priority parameters are arranged into three groups. The first group comprises the first parameter that is defined by sending an alarm which reports energy problems to the EMS. The second group comprises the second and third parameters which are related to finding an alternative, so there is no need to apply the scheduling model if an alternative is available, as discussed in Subsection 3.3. The third group comprises the fourth, fifth, sixth, and seventh parameters which are related to the implementation of the proposed scheduling model. The location of a node may be used as an input parameter to define its importance.

The proposed scheduling model starts by receiving an alarm from an energy-based node which suffers from a severe lack of energy. The message is sent by the node to the cluster head (sink). The cluster head should determine the energy level and first determines if the available energy is critical. After that, the cluster head sends a message to the EMS server asking about an alternative for that node. It the answer is negative, the cluster head should determine the type of device: a device that can gather, process, and send data such as sensors; or a device that can only send data, such as an RFID.

In the case of a sensor, for example, the cluster head should apply the sensor scheduling algorithm, but in case of the other class of nodes, it should apply a suitable scheduling model for that class. For simplicity, sensors and RFIDs are taken as examples.

The scheduling model for sensors is based on the sensor transitioning between three states. The first state is fully active, meaning that each sensor achieves its function in the normal case. The second state is partially active, which means that the sensor is active and many tasks are assigned for it but it does not do anything, so the energy consumption rate is less than that of the fully active state. The third state is the sleep state, which means that the sensor is not ready to do anything and no task is assigned for it. Algorithm 1 and algorithm 2 describe the scheduling models for the WSN and RFID nodes, respectively. The main idea of the algorithms is to test the energy levels of the nodes periodically and reduce the overhead of the energy-based nodes depending on the priority parameters. In addition, algorithm 1 is adapted to be applied in the MANET environment.

1) MATHEMATICAL ANALYSIS

Suppose that the primary energy-based nodes in the IoT system are found in the WSN, RFID network, and

Algorithm 1

```
CEL: Current Energy Level
EL_P1 = Energy Level at time P1
EL_P2 = Energy Level at time P2
EL_P3 = Energy Level at time P3
P1: Remaining Time (Save)
P2: Remaining Time (Normal)
P3: Remaining Time (Critical)
PS: Power Source
NA: Node Alternatives
CH: Cluster Head
TF: Task Frequency
N: Number of minutes that the sensor in a full active state
H1: High Priority
H2: Middle Priority
FA: Full Active State
HA: Half Active State
S: Sleep State
Beginning of Algorithm 1
State = "FA"
CEL = Normal
PS = False
NA= False
Sensor = True
Timer:  For I = 1 to N
        Begin
            If Importance = H1
            Begin
                If TF = H
                    Begin
                    FT=M (Select the most important tasks)
                    CH sends an alarm message to the EMS server
                    End
                IF (I = P1) && (EL_P1 < CEL)
                    Begin
                    CH decreases the number of tasks to half
                    CH sends an alarm message to the EMS server
                    End
```

Algorithm 1 *Continue:*

```
                IF (I = P2) && (EL_P2 < EL_P1)
                    CH transforms the sensor state to "HA"
                IF (I = P3) && (EL_P3 < EL_P2)
                    Begin
                    CH transforms the state to 'S'
                    CH tries to transmit the sensor tasks to other surround sensors
                    CH sends an alarm message to the EMS server
                    CH saves feedback
                    End
            End
            Else IF Importance = H2
                Begin
                Decrease the number of tasks to half
                IF I = P3
                    Begin
                    CH transforms the sensor state to 'S'
                    CH sends an alarm message to the EMS server
                    CH saves feedback
                    End
                End
            Else
                Begin
                CH transforms the state to 'S'
                CH sends an alarm message to the EMS server
                CH saves feedback
                End
        End
End of Algorithm 1
```

MANET. Additionally, suppose that W[i], R[j], and M[k] represent the energy-based nodes in the WSN, RFID, and MANET networks, respectively. Let 'C,' 'D,' and 'F' represent the number of energy-based nodes in the WSN, RFID, and MANET networks, respectively. Let 'i,' 'j,' and 'k' represent counters. The current energy for each node in each network is represented by $W[i]_{cr}$, $R[j]_{cr}$, and $M[k]_{cr}$. The tasks which are assigned to nodes are T(W [i]), T(R $[j]$), and T(M [k]). The number of transmitted bits for the node

Algorithm 2

State = "FA"
CEL = Energy Borderline
EL_{P1} = Energy Level at time P1
EL_{P2} = Energy Level at time P2
EL_{P3} = Energy Level at time P3
P1: Remaining Time (Save)
P2: Remaining Time (Normal)
P3: Remaining Time (Critical)
PS = False
NA = False
RFID = True
Beginning of Algorithm 2
Timer: For I = 1 to M
  Begin
  If Importance = H1
    Begin
    If (I = P1) && (EL_{P1} < CEL)
      Decrease the number of sent out frames depends it prioritization system
    If (I = P2) && (EL_{P2} < EL_{P1})
      Increase the in-between transmission period
    If (I = P3) && (EL_{P3} < EL_{P2})
      Begin
      CH sends an alarm message to the EMS server
      CH transforms the RFID tag state to 'S'
      End'
    End
  Else Importance = H2
    Begin
    CH sends an alarm message to the EMS server
    Transforms the RFID tag state to 'S'.
    CH saves feedback
    End
  End
End of Algorithm 2

between task 'a' and task 'b' is represented by $W[i]_{ab}$, $R[j]_{ab}$, and $M[k]_{ab}$. The energy consumption for each transmitted bit between task 'a' and task 'b' is represented by $E(W[i])_T$, $E(R[j])_T$, and $E(M[k])_T$. The energy consumption for each received bit between task 'a' and task 'b' is represented by $E(W[i])_r$, $E(R[j])_r$, and $E(M[k])_r$. The energy consumed by processing depends on the type of node, its specifications, and whether it has one task or many tasks assigned at a time. Therefore, it can be represented by a two-dimensional array, $W[i][\omega_{N1}]$, $R[j][\omega_{N2}]$, and $M[k][\omega_{N3}]$, where ω represents the energy consumption at a time unit.

The total energy that is consumed by transmitted bits is determined by (6). For the WSN, the sensing energy consumption is considered in the transmission energy consumption.

$$TE_{T(Radio)} = \left\{ \sum_{\substack{i=1\ to\ C \\ b \notin W[i]}} W[i]_{ab} * E(W[i])_T + \sum_{\substack{j=1\ to\ D \\ b \notin R[j]}} R[j]_{ab} * E(R[j])_T + \sum_{\substack{k=1\ to\ F \\ b \notin M[k]}} M[k]_{ab} * E(M[k])_T \right\} \tag{6}$$

The total energy that is consumed by the received bits is determined by (7).

$$TE_r = \left\{ \sum_{\substack{i=1\ to\ C \\ a \notin W[i]}} W[i]_{ab} * E(W[i])_r + \sum_{\substack{j=1\ to\ D \\ a \notin R[j]}} R[j]_{ab} * E(R[j])_r + \sum_{\substack{k=1\ to\ F \\ a \notin M[k]}} M[k]_{ab} * E(M[k])_r \right\} \tag{7}$$

The total processing energy consumption is determined by (8).

$$TE_P = \left\{ \sum_{\substack{i=1\ \text{to}\ C \\ \omega_{N1}=1\ to\ N1}} W[i][\omega_{N1}] + \sum_{\substack{j=1\ \text{to}\ D \\ \omega_{N2}=1\ to\ N2}} R[j][\omega_{N2}] + \sum_{\substack{k=1\ \text{to}\ F \\ \omega_{N3}=1\ to\ N3}} M[k][\omega_{N3}] \right\} \tag{8}$$

The network lifetime (NTL) is determined by (9).

$$NLT = max\left(\frac{W[i]_{cr} + R[j]_{cr} + M[k]_{cr}}{TE_{T(Radio)} + TE_r + TE_P}\right) \tag{9}$$

To maximize the NTL value, the values of $TE_{T(Radio)}$, TE_r, *and* TE_P should be minimized. The energy consumption values are based on the number of transmitted bits. Thus, the EMS is applied in the IoT system to minimize the number of transmitted bits which directly affects the energy consumption rate, as in Eqs. 10 to 12.

$$\begin{aligned}&\left(\sum_{\substack{i=1\,to\,C\\ b\notin W[i]}} \mathrm{W[i]}_{ab}*\mathrm{E(W\,[i])}_T\right)_{EMS} < \sum_{\substack{i=1\,to\,C\\ b\notin W[i]}} \mathrm{W[i]}_{ab}*\mathrm{E(W\,[i])}_T,\\ &\left(\sum_{\substack{j=1\,to\,D\\ b\notin R[j]}} \mathrm{R[j]}_{ab}*\mathrm{E(R\,[j])}_T\right)_{EMS} < \sum_{\substack{j=1\,to\,D\\ b\notin R[j]}} \mathrm{R[j]}_{ab}*\mathrm{E(R\,[j])}_T,\\ &\left(\sum_{\substack{k=1\,to\,F\\ b\notin M[k]}} \mathrm{M[k]}_{ab}*\mathrm{E(M\,[k])}_T\right)_{EMS} < \sum_{\substack{k=1\,to\,F\\ b\notin M[k]}} \mathrm{M[k]}_{ab}*\mathrm{E(M\,[k])}_T\\ &\rightarrow \left(TE_{T(Radio)}\right)_{EMS} < TE_{T(Radio)}\end{aligned} \tag{10}$$

$$\begin{aligned}&\left(\sum_{\substack{i=1\,to\,C\\ a\notin W[i]}} \mathrm{W[i]}_{ab}*\mathrm{E(W\,[i])}_r\right)_{EMS} < \sum_{\substack{i=1\,to\,C\\ a\notin W[i]}} \mathrm{W[i]}_{ab}*\mathrm{E(W\,[i])}_r,\\ &\left(\sum_{\substack{j=1\,to\,D\\ a\notin R[j]}} \mathrm{R[j]}_{ab}*\mathrm{E(R\,[j])}_r\right)_{EMS} < \sum_{\substack{j=1\,to\,D\\ a\notin R[j]}} \mathrm{R[j]}_{ab}*\mathrm{E(R\,[j])}_r,\\ &\left(\sum_{\substack{k=1\,to\,F\\ a\notin M[k]}} \mathrm{M[k]}_{ab}*\mathrm{E(M\,[k])}_r\right)_{EMS} < \sum_{\substack{k=1\,to\,F\\ a\notin M[k]}} \mathrm{M[k]}_{ab}*\mathrm{E(M\,[k])}_r\\ &\rightarrow (TE_r)_{EMS} < TE_r\end{aligned} \tag{11}$$

$$\begin{aligned}&\left(\sum_{\substack{i=1\,to\,C\\ \omega_{N1}=1\,\mathrm{to}\,N1}} \mathrm{W[i]}[\omega_{N1}]\right)_{EMS} < \sum_{\substack{i=1\,to\,C\\ \omega_{N1}=1\,\mathrm{to}\,N1}} \mathrm{W[i]}[\omega_{N1}],\\ &\left(\sum_{\substack{j=1\,to\,D\\ \omega_{N2}=1\,\mathrm{to}\,N2}} \mathrm{R[j]}[\omega_{N2}]\right)_{EMS} < \sum_{\substack{j=1\,to\,D\\ \omega_{N2}=1\,\mathrm{to}\,N2}} \mathrm{R[j]}[\omega_{N2}],\\ &\left(\sum_{\substack{k=1\,\mathrm{to}\,F\\ \omega_{N3}=1\,\mathrm{to}\,N3}} \mathrm{M[k]}[\omega_{N2}]\right)_{EMS} < \sum_{\substack{k=1\,to\,F\\ \omega_{N3}=1\,\mathrm{to}\,N3}} \mathrm{M[k]}[\omega_{N3}]\\ &\rightarrow (TE_P)_{EMS} < TE_P\end{aligned} \tag{12}$$

In case of $(NLT)_{EMS} = (NLT)_{Critical}$, the scheduling process will be applied. $(NLT)_{EMS}$ is divided into three time slots. In the first time slot, the number of tasks is decreased to approximately half, so $(NLT)_{EMS}$ will be duplicated. In the second time slot, "NLT" will be increased more than expected in the normal case of the IoT as stated in (13) because the node state is transformed to "half active," which makes the nodes ready to take a task, as in (14). In the third time slot, the state of the node is transformed to "sleep state" which increases the value $(NLT)_{EMS}$ because the energy consumption rate in case of "idle" is notably decreased. During the time slots, a chance to replace the critical energy nodes will be increased, as in (15).

$$Time\ Slot1 \rightarrow (NLT)_{EMS} = Min\left(\frac{(NLT)_{Critical}}{E_{W(HA)} + E_{R(HA)} + E_{M(HA)}}\right), \tag{13}$$

where $E_{W(Idel)}, E_{R(Idel)}, and\ E_{M(Idel)}$ represents the energy consumption rate for WSN, RFID, and MANET networks, respectively.

$$Time\ Slot2 \rightarrow (NLT)_{EMS} = Min\left(\frac{(NLT)_{Critical} - (EC)_{Slot1}}{E_{W(HA)} + E_{R(HA)} + E_{M(HA)}}\right) \tag{14}$$

$$Time\ Slot3 \rightarrow (NLT)_{EMS} = Min\left(\frac{(EC)_{Slot1} - (EC)_{Slot2}}{E_{W(idle)} + E_{R(idle)} + E_{M(idle)}}\right) \tag{15}$$

C. STRATEGY 3: FAULT TOLERANCE

The third strategy used in the EMS is fault tolerance. This strategy is used with or after applying the previous two strategies. In the case of a node's energy failure, it should be replaced with an alternative node(s). This strategy is considered as a complement of EMS trying to not lose any data or task in the IoT environment. The fault tolerance strategy depends on the classification of IoT nodes into levels as a function of the importance parameter. As stated above, the importance parameter is determined based on the nature of tasks that are assigned to the nodes in addition to the locations of the nodes. Therefore, this parameter is well known and predetermined by the IoT administrator(s). The WSN and RFID cases are consisted as examples in the fault tolerance strategy because they represent the predominant energy-based nodes in the IoT systems. For the fault tolerance issue in the WSN, there are three types of node recovery process, as shown in Fig. 2-(a), Fig. 2-(b), and Fig. 2-(c). These recovery processes are stated as follows:

Type 1: This type is used for nodes that have highest importance level. In this type, the coverage process should be achieved using more than one node. The output of the coverage process provides many coverage overlaps; this is called "Full Overlap." The fault tolerance process will be accomplished using the same WSN infrastructure (i.e. without any additional nodes). In this case, the fault tolerance process may be costly due to the importance of assigned tasks such as for military, security, and terrorism applications.

Type 2: This type is used for nodes that have a middle importance level. In this type, the coverage process should be achieved using a number of nodes less than the "full coverage" type. The middle importance level means that the entire task has mid-level importance or part of the task is important and the other part does not have the same importance level. In the case where the total task has a middle importance level, the node coverage process may be partially successful (i.e. trying to do the best effort to decrease loss of data in the

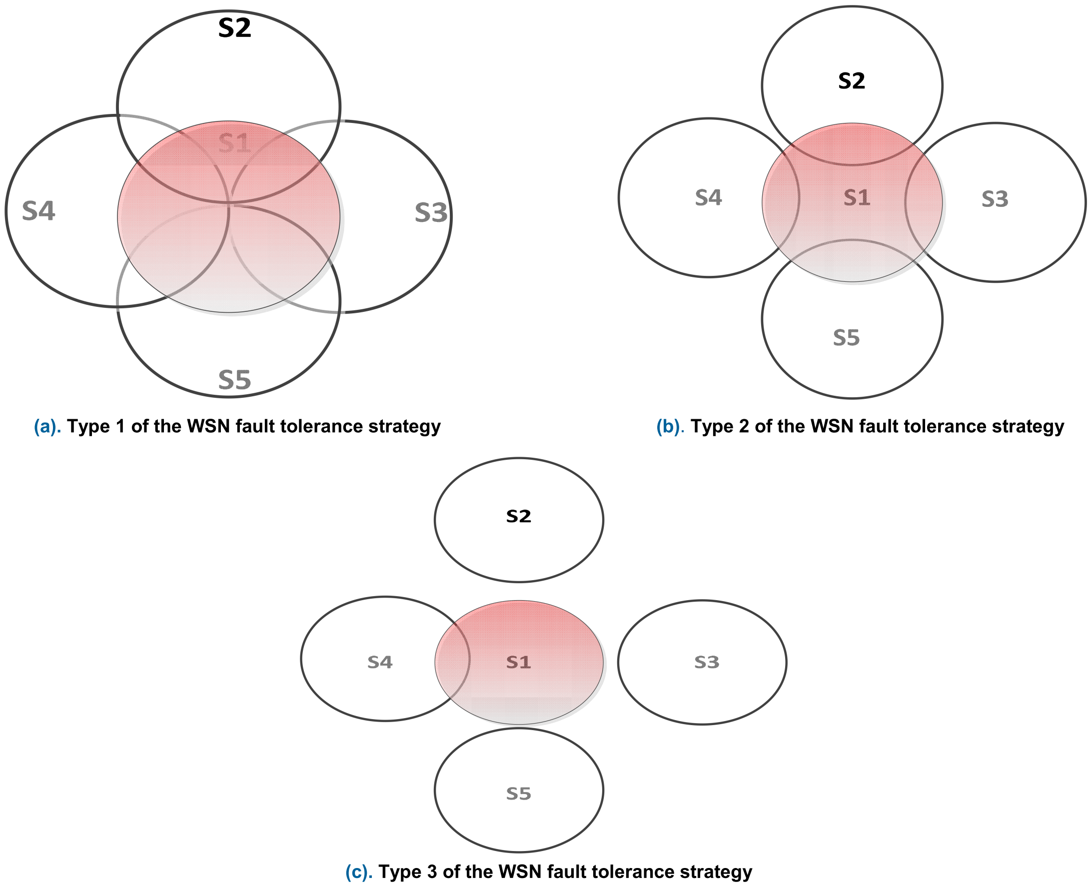


FIGURE 2. **(a). Type 1 of the WSN fault tolerance strategy. (b). Type 2 of the WSN fault tolerance strategy. (c). Type 3 of the WSN fault tolerance strategy.**

uncovered area which depends on the distribution of nodes in the WSN). On the other hand, in the case where part of the task has a high importance level and the other part has a low or middle importance level, the type 1 recovery (fault tolerance) will be applied to the important part and the other part will be covered by current alternative nodes which have areas of overlap with the energy failure node. This type of fault tolerance is called "Partial Coverage."

Type 3: This type is used for nodes which have a low importance level. In this type, the coverage process should be achieved using a low number of nodes (i.e. less than the "full coverage" and the "partial coverage" types). A low importance level means that the task(s) assigned to the node are not important which leads to low importance of the node coverage area. This type of node can be replaced, its power source can be changed, or it can be neglected. The coverage of this node is considered to be less important. Additionally, to minimize the loss of data, many prediction techniques, such as [50], may be applied to predict the required data in the case of a node failure.

As regards the fault tolerance scenario in the RFID network, it should simply comprise the RFID tags and the RFID readers. The RFID tag is used to store information about a thing in the IoT system. It is required to determine the importance of each IoT node. Based on the node's importance, the fault tolerance mechanism can be applied. In the case of the most important nodes, it can be covered by two or more tags. If the power of one tag is expired, it can be replaced by another one. In the case of the least importance of one thing, it can be recovered by only one tag. In the case of a power loss for a tag, its node can be coupled with another node to become one object and covered by one tag. This process proceeds until the failed tag is exchanged. In the case of difficulty in the process of merging things, a passive tag can be used instead of an active one, as shown in Fig. 3-(a). For the RFID reader, in the case of important tags, more than one reader can be used. The reader coverage area is calculated by determining the number of tags in its area. After that, it can be transferred to another tag when more readers cover the same set of tags. In the case of exhausting of any reader's energy, it can be replaced with another one provided that the alternative covers the same tag, as in Fig. 3- (b).

D. HOW EMS WORKS

The proposed EMS assumed that standalone server(s) observe the energy consumption rates and levels at each energy-based node in the IoT environment. The EMS mission starts when it detects information signaling a critical

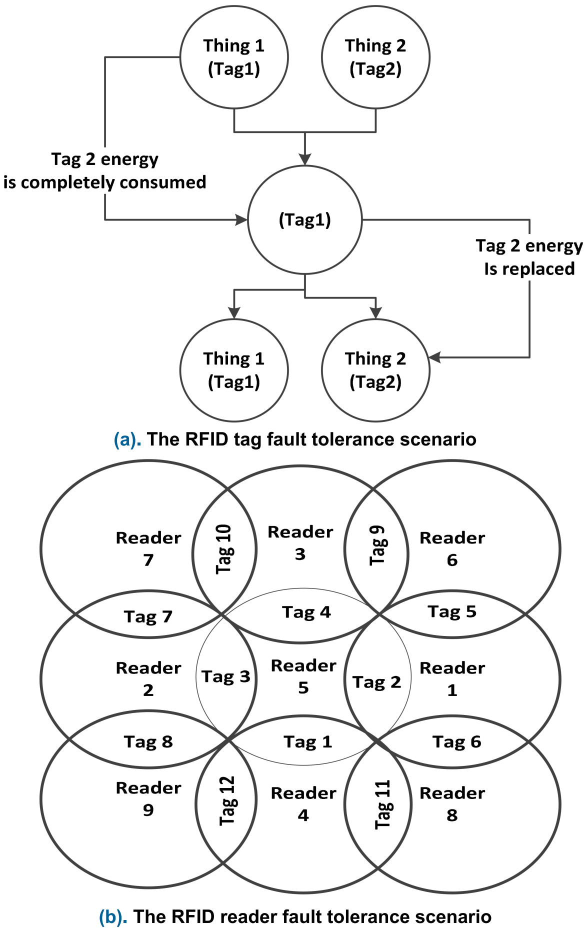


FIGURE 3. (a). The RFID tag fault tolerance scenario. (b). The RFID reader fault tolerance scenario.

energy level. First, it determines the parameters, as stated in Table 1, for a critical energy node. In the case where no alternative or other power source exists for that node, the EMS starts to apply the first strategy, which aims to minimize the data that are transmitted or received using this node. The data minimization comprises three processes: data prioritization, data compression, and data fitting. It returns to test the energy level for the critical nodes. If the state is stable, it continuous minimizing the data without affecting the IoT application mission. However, in the case of a notable decrease in the energy level, the second EMS strategy, which depends on the node importance parameter, is applied. The nodes' tasks are decreased to half to minimize their energy consumption rates over time. After that, the states of the nodes are transformed to "half active." The "half active" state means that the node currently does not do any task but it is ready to do so. Using the "half active" state provides the IoT system administrator time to replace the critical energy node with an alternative or to update its energy source. In the case where no alternatives or other power sources are available, the state of a node should be transformed to sleep. The "sleep" state will save most of the node's energy which provides the administrator with another opportunity to solve the problem. Finally, in the case of a node failure, the third EMS strategy should be applied. The important node should be covered by multiple alternate nodes. In addition, the middle importance node should be partially covered. After that, the least important node should be neglected if there is no alternative or power source, and its data can be predicted. Algorithm 3 describes how the proposed EMS works. Fig. 4 shows the general view of the proposed EMS.

Algorithm 3

M: Number of energy-based nodes.
CE_i : Current energy level at node 'i'.
E_c : Critical energy level.
A_i : An alternative for node 'i'.
N_i : Node 'i'.
PS_i : Power source for node 'i'.
FA: Full active state.
T: Time counter.
$ST1_i$: Apply the first EMS strategy on node 'i'.
$ST2_i$: Apply the second EMS strategy on node 'i'.
$ST3_i$: Apply the third EMS strategy on node "i".
$D_{Ni}(T)$: The size of data (transmitted, processing, and receiving) at node 'i' at time 'T'.
$D_{Ni}(O)$: The original size of data (transmitted, processing, and receiving) at node 'i'.
E_d : Dangerous energy level.

Beginning of Algorithm 3

```
For i = 1 to M
        Begin
        If CE_i = E_c
            If A_i = True
                    N_i = N_{A_i}
            Else If PS_i = True
                    State − N_i = FA
            Else
                    Begin
                    Timer: For T = 1 to R
                    ST1_i = True
                    If D_Ni(T) ≥ D_Ni(O)
                         ST1_i = True
                    Else If CE_i ≤ E_d
                         ST2_i = True
                    If CE_i = Zero
                         ST3_i = True
                    End
        End
```

End of Algorithm 3

IV. SIMULATION AND EVALUATION

The proposed EMS should be tested to prove its claim. This section describe how the proposed EMS is evaluated. It comprises two main sub-sections. The first sub-section demonstrates the simulation of the IoT environment, describing its components, parameters, and scenarios. The second

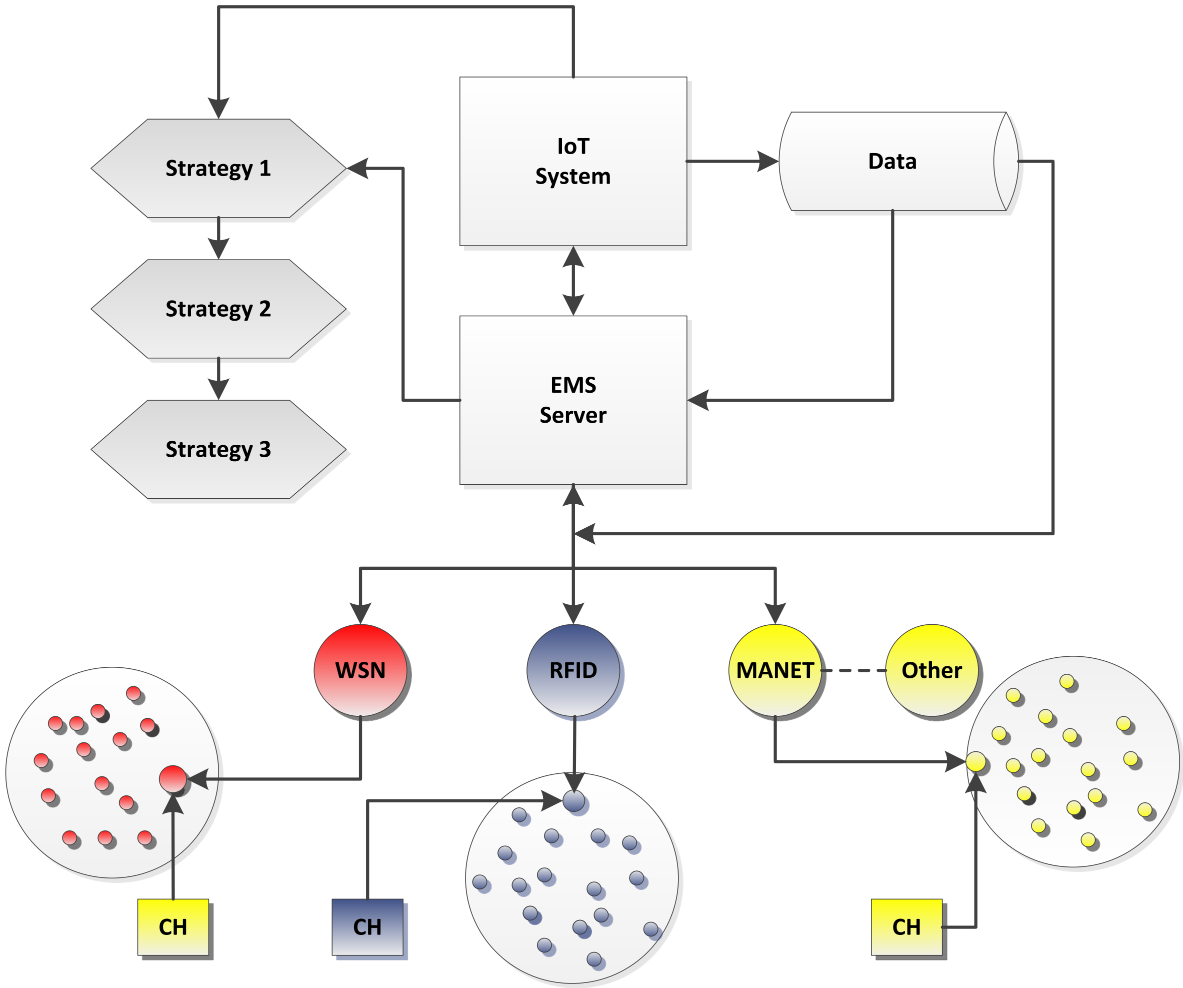


FIGURE 4. General view of EMS.

sub-section introduces the performance metrics and the simulation results with their discussion.

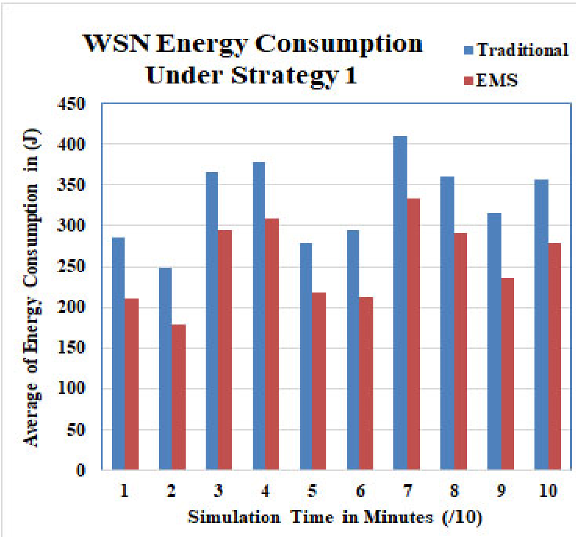
A. IOT ENVIRONMENT CONSTRUCTION

The simulation infrastructure of the IoT environment comprises five different types of networks: satellite, high altitude platform (HAP), WSN, RFID, and MANET. These networks are selected to reflect the real specifications of the IoT environment. The satellite and HAP networks are used as secondary recovery tools as an alternative to the Internet. The simulation concept that is described in [51] is used for construction of the simulated environment in which each network is described in addition to the general view of the simulation model. Additionally, the simulation parameters for the five networks are stated in [51]. The primary differences in simulation parameters are in the number of nodes and the coverage areas for the WSN, RFID, MANET, and HAP. Here, the number of nodes in the WSN equals 5,000. The number of nodes in the RFID network equals 7,000. The number of nodes in the MANET equals 650. To increase the coverage area, the number of HAPs used equals 200. The coverage area for the WSN equals 2 km $\times$ 2 km. For the MANET, the network area equals 3 km $\times$ 3 km.

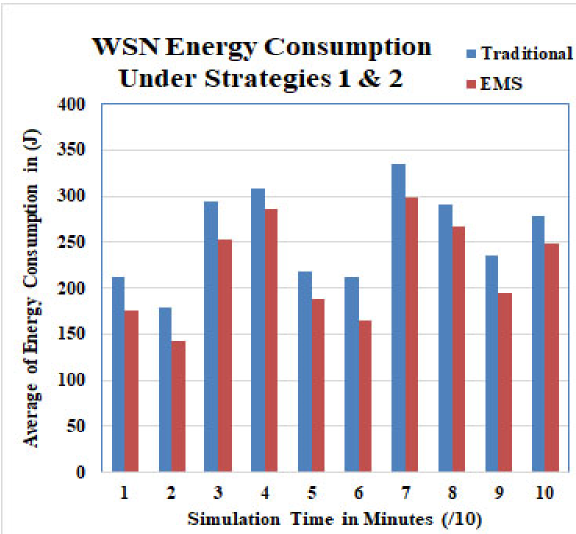
B. RESULTS AND DISCUSSION

In this sub-section, the simulation results of the proposed EMS are shown and discussed. The performance metrics which are used to evaluate the EMS are as follows: the average energy consumption rate for IoT energy-based nodes, the number of failure nodes due to energy loss, the throughput, and the network lifetime. The metrics are measured relative to the IoT traditional system. The traditional system description that is stated in [41] did not apply the EMS strategies.

The energy consumption rate is the key performance metric that should be measured in the proposed EMS due to the importance of determining its effect on the IoT system. A low energy consumption rate corresponds to good EMS performance, and vice versa. In the proposed simulation model, WSN, RFID, and MANET are considered as core IoT systems. This is because most of these networks' nodes are energy-based. Fig. 7 shows the energy consumption results

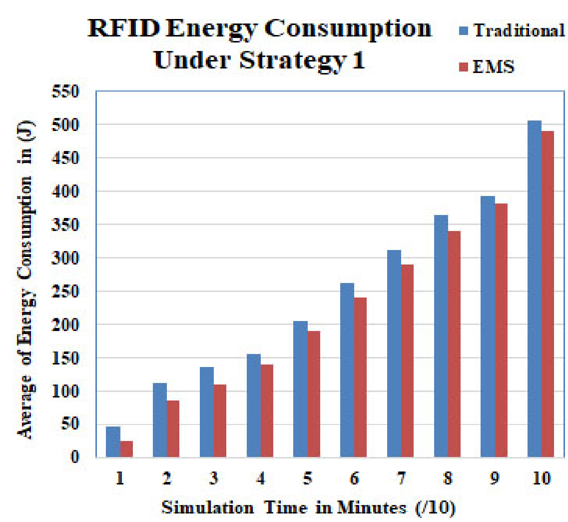


(a). Energy consumption after applying the EMS strategy 1 in WSN

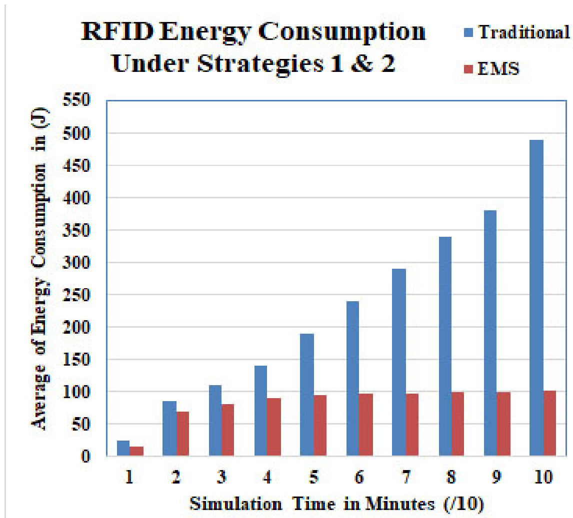


(b). Energy consumption after applying the EMS strategies 1 & 2 in WSN

FIGURE 5. **(a). Energy consumption after applying the EMS strategy 1 in WSN. (b). Energy consumption after applying the EMS strategies 1 & 2 in WSN.**



(a). Energy consumption after applying the EMS strategy 1 in RFID

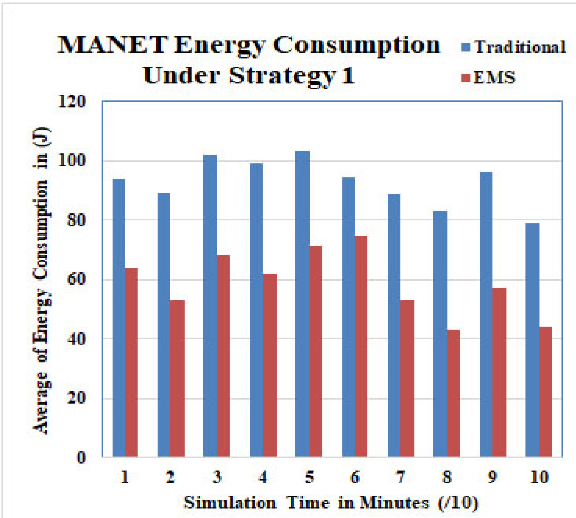


(b). Energy consumption after applying the EMS strategies 1 & 2 in RFID

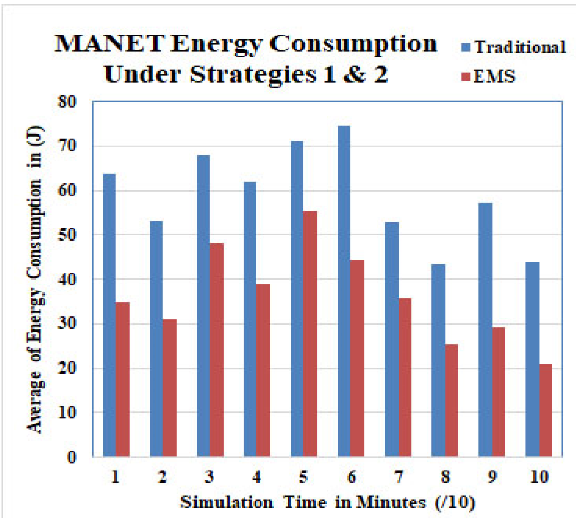
FIGURE 6. **(a). Energy consumption after applying the EMS strategy 1 in RFID. (b). Energy consumption after applying the EMS strategies 1 & 2 in RFID.**

for WSN. The X and Y axes represent the simulation time in minutes divided by 10 and the average of energy consumption rate, respectively. Fig. 5-(a) and Fig. 5-(b) present the results of energy consumption in WSN after applying the EMS strategy 1 and the EMS strategies 1 and 2, respectively. It is notable that applying the EMS strategy 1 decreases the energy consumption and applying strategy 2 decreases the energy consumption which was extracted after applying strategy 1. For energy consumption in the RFID network, Fig. 6 shows its results. Fig. 6-(a) and Fig. 6-(b) show the results of this network after applying the EMS strategy 1 and strategies 1 and 2, respectively. The positive effect of EMS strategies 1 and 2 on the RFID energy consumption rates is notable. Regarding the energy consumption rates in MANET, Fig. 7-(a) and Fig. 7-(b) show its energy consumption results. These figures prove that the EMS also decreases the energy consumption rates.

The number of nodes that have failed due to energy loss is very important parameter due to its effect on many issues in the IoT system such as routing and node functions. Measurement of this performance metric shares in the process of determining the effect of EMS on the entire IoT system. This parameter is measured after applying the EMS strategy 1, strategy 2, and strategy 3. Fig. 8, Fig. 9, and Fig. 10 show the simulation results for the number of failure nodes metric for WSN, RFID, and MANET, respectively. The X and Y axes represent the simulation time in minutes divided by 10 and the number of failed nodes, respectively. It is notable



(a). Energy consumption after applying the EMS strategy 1 in MANET



(b). Energy consumption after applying the EMS strategies 1 & 2 in MANET

FIGURE 7. Energy consumption after applying the EMS strategy 1 in MANET. (b). Energy consumption after applying the EMS strategies 1 & 2 in MANET.

that the number of failed nodes in the traditional system for WSN, RFID, and MANET is larger than that in the proposed EMS for these networks. This reflects the EMS's ability to retain power for as long as possible without disturbing any IoT function.

Regarding the throughput performance metric, it is used to determine the number of bytes which are sent and received successfully within a time period. It is considered as one of the most important performance metrics to clarify the EMS efficiency in the management the energy consumption rate. This is because high energy consumption rates mean that there is a high probability of node failures which will affect the data transmission rate, and vice versa. The results of the throughput performance metric are shown in Fig. 11. The X and Y axes represent the simulation time in minutes

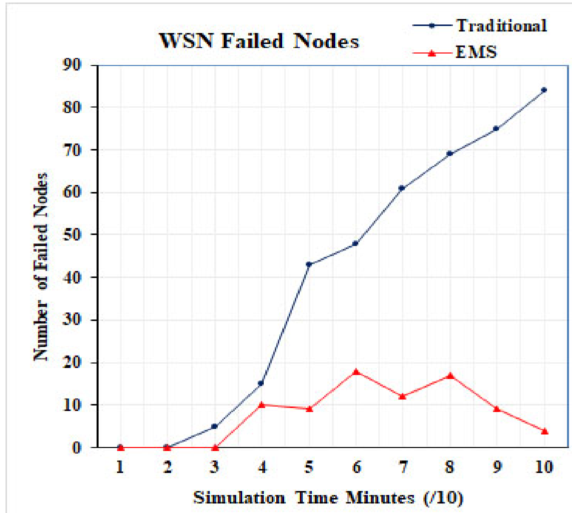


FIGURE 8. Number of WSN failed nodes.

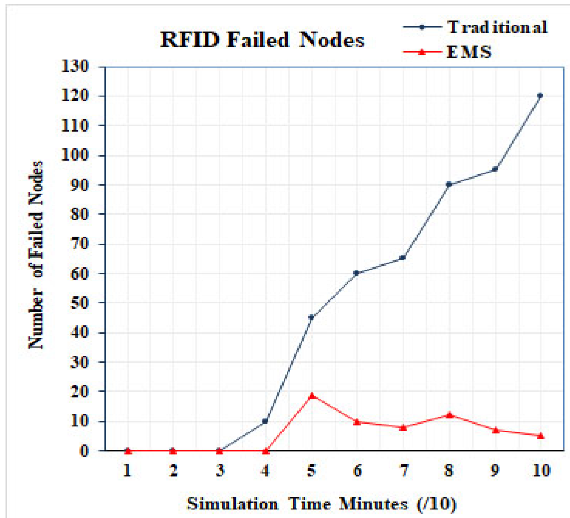


FIGURE 9. Number of RFID failed nodes.

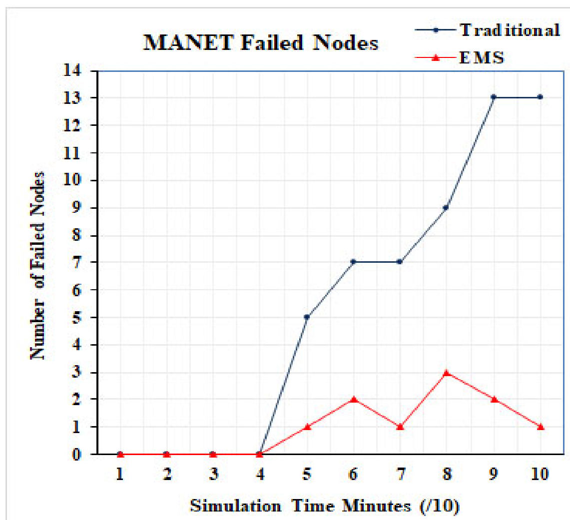


FIGURE 10. Number of MANET failed nodes.

divided by 10 and the throughput (kb/s), respectively. The transmission rate in the case of using the proposed EMS is

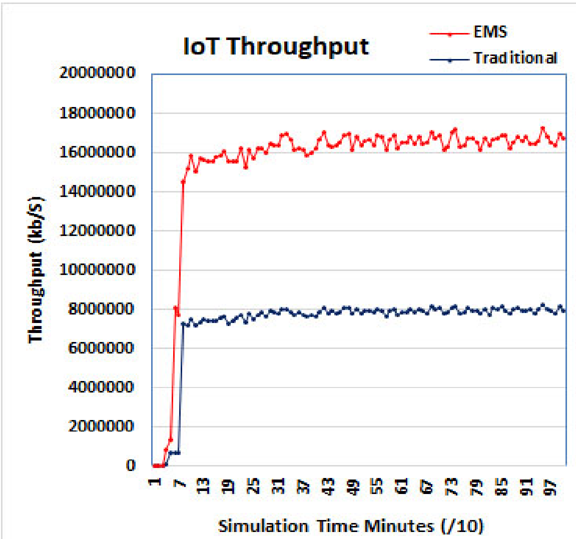


FIGURE 11. Throughput.

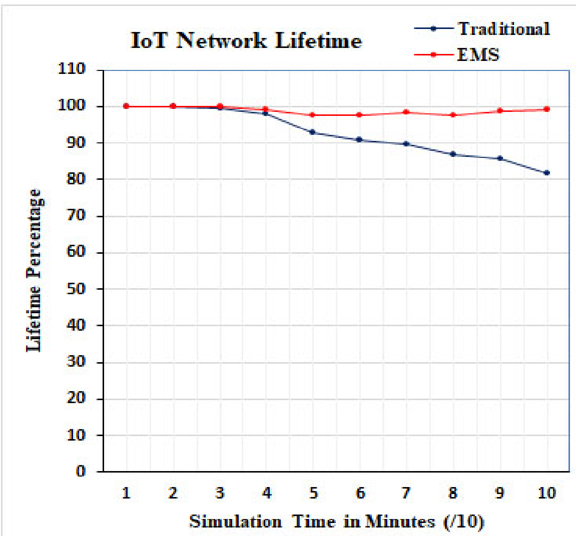


FIGURE 12. IoT Network lifetime.

higher than that in the traditional system. This is explained by the efficiency of the proposed EMS to save the energy of each IoT node; this provides a stability in the entire IoT system that leads to a decrease in the number of packets lost. On the contrary, in the traditional IoT system, the failure nodes may be increased within the time which may create a significant number of bottlenecks, resulting in congestion that, in turn, will negatively affect the transmission rate.

The network lifetime performance metric is also very important parameter due to its direct relationship to the energy consumption rates that may decrease or increase the network lifetime. To ensure that the proposed EMS increases the network lifetime, the percentage of time in which the IoT system operates without problems is measured for the EMS and compared with that for the traditional system. Fig. 12 shows the results of the network lifetime performance metric. The X and Y axes represent the simulation time in minutes divided by 10 and the lifetime percentage, respectively. The results prove that the IoT network, with the proposed EMS, has a lifetime greater than that with the traditional energy control methodologies. This is due to the large number of failure nodes which are found in the traditional system. A large number of failure nodes means a low number of transmitted bytes, leading to low throughput which clarifies the decrease in the network lifetime. On the other hand, the high IoT system lifetime that appears in the EMS plot of Fig. 12 means a low number of failure nodes are being compensated, thus decreasing their negative effect.

V. CONCLUSION

In this study, an Energy Management Scheme for IoT systems was introduced. The basic concept of the EMS is based on application of three different strategies. The first strategy decreased the volume of data which may be transmitted through the IoT system. The second strategy transformed the status of each energy-based node in the IoT system depending on a group of parameters such as energy level importance to save the node energy. The third strategy resolved the fault tolerance issue to find alternative nodes for the ones that have failed due to energy loss. Finally, the EMS was tested using a simulation environment that was constructed with the NS2 simulator. The simulation results proved that the proposed EMS outperformed the traditional IoT as follows: the energy consumption rate and the number of failure nodes for WSN decreased by 32.66%↓ and 19.75%↓, respectively. The energy consumption rate and the number of failure nodes for RFID decreased by 65.909%↓ and 87.422%↓, respectively. The energy consumption rate and the number of failure nodes for MANET decreased by 60.844%↓ and 81.481%↓, respectively. The throughput is increased by 53.137%↑. Finally, the IoT network lifetime is increased by 26.408%↑. Therefore, the EMS is recommended to control the energy consumption rates in the IoT environments.

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