Mobility and energy prediction models: Approach toward effective route management in mobile wireless sensor networks

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Abstract
Mobile wireless sensor network (MWSN), as a backbone of most communication and embedded systems, is characterized by low data delivery as a result of the energy constraint and in-deterministic movement of the nodes. To select optimal route path for a reliable data routing, protocols need to select neighbouring nodes with low mobility and residual energy parameters along the route. However, obtaining these parameters from the targeted nodes may encourage mischievous nodes to manipulate their energy and mobility parameters in their favor, leading to the selection of non-optimal route path and/or exposing the network to other attacks. Rather than depending on the targeted nodes for these parameters, they can be accurately and securely obtained by sink node or base station using effective predictive models. However, most of the existing predictive models engaged by MWSN routing protocols either provide only the energy level or mobility factor of the nodes for optimal route path selection. This, therefore, reduces the reliability of the obtained optimal route paths in terms of data delivery. In this article, we propose predictive models for an accurate prediction of mobility and residual energy parameters of nodes in MWSN for efficient route management. The models are simulated on an existing MWSN protocol to determine their performance. The simulation results show that the adoption of these models in the development of routing protocol will not only lead to optimal route paths’ selection but also enhance data delivery rate in MWSN.

Keywords
dynamic network, mobile ad hoc networks, model, multihop, route management

1 | INTRODUCTION

Mobile wireless sensor networks (MWSNs) play a vital role in the development of different communication and embedded system networks such as in vehicular ad hoc network (VANET), mobile telephony network, and wireless body area network for achieving smart city, intelligent transportation, and e-health systems. Most MWSNs are both self-forming...
and self-healing, thereby enabling peer-level communications between their mobile nodes without relying on centralized resources or fixed infrastructure. Their nodes, with in-built controllers and batteries as shown in Figure 1, are characterized by low energy, computation power constraint, and in-deterministic topology due to their random mobilities, which contribute to the nonstability of MWSNs and lead to the low data delivery rate and general poor performance of MWSNs. Several routing protocols had been proposed for WSNs, some of these protocols as proposed in consider different factors to achieve reliability, increase routing speed, and low transmission energy. For example, to achieve reliable data delivery, many MWSN routing protocols select multiple optimal multihop paths instead of single optimal path for data routing in the network by using these characteristics to determine the optimal multihop paths. Therefore, at present, more research efforts are being toward how to obtain the characteristics of the network topology for developing routing protocol for a reliable data delivery. Some existing protocols determine the reliable link using the stability of their neighbouring nodes by requesting them to supply their energy levels and mobility patterns, while some engage residual energies of their neighbouring nodes, along the route, and distance to determine reliable link(s) between the source and destination nodes as done in Reference. Although several research efforts had shown that residual energy and mobility factor of nodes are the major parameters needed for determining effective routing in MWSNs, however, the major issue is how to obtain these parameters. Are they to be requested from the targeted nodes (direct approach) or predicted by the sink based on some intrinsic factors (predictive approach)? In the direct approach, nodes report their residual energy at every interval to the sink node or base station. Its major drawbacks are communication overheads incurred from building energy map and its susceptibility to different forms of attacks. For example, elevation of privilege attack, where malicious node tries to change its energy and mobility status in order to be considered as the best intermediary node. Elevation of privilege attack can easily compromise the selection of optimum route path.

Meanwhile, predictive approach involves a centralized entity predicting the behavioral parameters of the nodes from their intrinsic information through effective predictive models. Thus, reducing communication overheads incurred from periodical report of residual energies and mobility factors of sensor nodes. This will not only reduce attacks but also provide accurate values for optimal path selection. Meanwhile, for all of these to be feasible, predictive approach requires an effective predictive model capable of predicting optimal route selection parameters using intrinsic information from nodes. However, most of the existing predictive models either provide energy level or mobility factor of nodes for optimal route path selection, and some of them still require targeted nodes to supply their residual energies to compute link weight and other parameters as being done in References 5 and 6, which will definitely affect the ability of the protocol to determine optimal route paths for data routing.

Also, a few of the existing research efforts focus on the changes in network topology caused by random node failures and its impact on the topology of mobile ad hoc network (MANET). Closer to our work is the work of Liu et al, where they proposed a model for calculating the average shortest path length (ASPL) after the random edge failure. Their model provides a general framework for studying the shortest path of MANET based on local-area choice of MANET with the constraints of node energy consumption and link distance. However, they did not consider other topological characteristics such as mobility of the nodes.

In view of this, we propose predictive mobility and energy models for predicting nodes' mobility factors and residual energies to determine accurate energy and mobility distribution maps of MWSNs for efficient route management in MWSNs.

The remainder of this article is organized as follows. In Section 2, the related works are examined. Section 3 discusses the predictive mobility and residual energy models. Section 4 describes how the two predictive models can be adopted in MWSNs protocols and its performance contributions to MWSN routing protocols. Finally, the conclusion is drawn in Section 5.

2 RELATED WORKS

Several route management approaches had been proposed for mobile network, while some of them focused on energy efficiency some considered efficient data delivery as their performance metric. For example, to design a reliable routing service protocol capable of selecting reliable links among vehicles in VANET, the authors in Reference 5 proposed the use of the motion or movement patterns of vehicles and justifications for past downlink to evolve a link reliability model for reliability parameter. This was used to evolve a heuristic Q-learning algorithm for dynamic adjustment of the routing path through interaction with the surrounding environment. Also, another best path selection algorithm was proposed
in Reference 17. The algorithm was developed to solve the problem of path planning for intelligent driving vehicles in the case of restricted driving, traffic congestions, and accidents. Although the algorithm might be able to ease emergency situations in path planning in autonomous vehicle, but due to the computational limitation of WSN, the algorithm is not suitable for predictive planning in WSNs.

For resource-constrained MANET, the authors in Reference 18 proposed a greedy forwarding-based routing method for MANET. Their approach computes reliable communication links by evaluating the quality of each link using the quality of the link, the distance between the source node and the destination node, and the number of the neighboring nodes. The node with the largest metric value is selected as the next hop. Also, graph theory was used in Reference 19 to model the MANETs. They proposed a routing method for vehicles based on their graph theory-based model. Although the proposed graph theory based model may be adopted for predicting routes in WSN after considering some of its computational redundances, however, their proposed protocol cannot be used for WSNs.

Meanwhile, the authors in Reference 6 proposed an energy-balanced routing method based on forward-aware factor. In the work, link weight and forward energy density derived from the residual energy and distance between the source node and the targeted node were used to determine the next-hop node. However, these two protocols in References 5 and 6 relied upon the neighboring nodes to provide their residual energy. Apart from this, Reference 6 assumed that the locations of nodes and sink are fixed, which is against the characteristics of MWSN’s nodes. These make them susceptible to different attacks from adversaries or malicious nodes who take advantage of their assumption and trust. In order to improve the control overhead of the network, we comprehensively consider the node energy information when searching the routes to the destination nodes. Zhang et al. proposed a genetic algorithm-based optimization algorithm for selecting optimal routing. To obtain optimal route, the algorithm searches for multiple routes to the destination node and uses genetic algorithm for determining the optimal paths. However, execution of genetic algorithm requires high computation which sensor nodes may not be able to provide.

Also, the authors in Reference 4 proposed a secure multipath routing protocol based on sectorization and the best neighboring nodes’ selection models to meet up the performance requirements of WSNs in mission and safety-critical systems. The protocol engaged direct approach to obtain network characteristics to generate multiple optimal route paths. However, the adoption of direct approach introduced few performance and security issues into the protocol. Verma et al. also worked on the performance analysis of energy aware routing schemes under various mobility models. They analyzed the energy cost of various energy routing schemes at different speeds of the nodes and under various mobility models such as random walk, random way point, column based, and reference point group. Their work showed that residual energy, distance, and mobility pattern are the major parameters to be considered in order to obtain reliable link for effective data delivery at low energy. Similarly, the authors in Reference 22 highlighted energy and mobility as the major parameters to be considered while making routing decision in order to provide effective connectivity among the nodes. They proposed an algorithm to determine the cumulative credit point of each node in the network and the total energy consumption of a route, which is the sum of energy consumption due to different transmissions and receptions across the edges in the route. This algorithm was used to evolve a hierarchical and cluster-based protocol, where each cluster contains one cluster head (CH) node and the CH node is assisted by two nodes. The main goal of their work is to improve the lifetime of the sensor nodes in the network. However, their algorithm adopted direct method to determine the mobility and residual energy of node, thereby making the protocol to depend on what each node offers as their mobility factor and energy level. Therefore, obtaining these parameters will in no small measure contribute to the efficiency of the protocols.

A few work had been done on the development of models to obtain these parameters in mobile network. Example is the work of Valikannu et al. where an energy consumption model using residual energy-based mobile agent selection scheme for MANETs is proposed. Due to the random mobility of nodes in MANET, there are chances that route failure may occur during the data transmission. In their work, they used mobile agents to dynamically choose the appropriate upper layer agents by sharing topology information among nodes for reliable data transmission. However, their model only focused on the residual energy; thus may not be useful for protocols that need distance and mobility pattern for reliable link. Meanwhile, Liu et al. focused on the ASPL and proposed a model for calculating the ASPL of the MANET after the random edge failure. The model provides a general framework for determining the shortest path of MANET. Also, Cao et al. studied the stability of network synchronization to the removal of shortcut links. They concluded that removal of a single shortcut link may destroy either completely or partially the network synchronization. They, therefore, proposed cluster-based approach to synchronize partially desynchronized network, controlling network synchronization by adjusting network topology. Similar to this is the work of Zhang et al. where a new constructing approach for a weighted topology of wireless sensor networks (WSNs) was proposed and compared with internet of things (IoT) network. Their approach is based on local-world theory taking into consideration the sensor energy, transmission distance, and flow rate.
Zhang et al.24 investigate the fixed-time synchronization (FDTS) of complex networks with stochastic perturbations. They proposed a new control scheme to achieve the synchronization in the network without the chattering phenomenon. They adopted Lyapunov functionals, using the properties of the Weiner process as well as applying a designed comparison system, to obtain FDTS criteria. Meanwhile, Wu et al.25 considered the nonfragile estimation problem for a class of complex dynamic networks with switching topologies and quantization effects. They introduced concept of nonfragility by inserting randomly occurred uncertainties into the estimator parameters and provided sufficient condition via a linear matrix inequality approach.

The major contributions of our work are the development of parametric predictive models, which can be used to obtain the residual energy and mobility factor of every node in MWSNs without direct report from the nodes. The residual energy and mobility factor of each node in the network are predicted by base station or sink node in a centralized manner. The predictive models can be adopted by any MWSN protocol to determine the topology of the MWSN topology and predict the mobility factors and residual energy of each nodes in MWSNs.

3 | PREDICTIVE MOBILITY AND RESIDUAL ENERGY MODELS

Energy constraint and indeterministic nature of nodes’ movements are the major performance bottlenecks in MWSNs, and they are the determining factors in the choice of protocol for MWSNs. The ability of protocol to predict movement pattern and residual energy of nodes enhances the performance of the MWSNs in no small means. To achieve this, two models are developed for MWSNs’ protocols to predict the current residual energy and mobility factor of each node in MWSNs. We adopted voltage of the sensor’s battery \( V_c \), permittivity of free space or vacuum, \( \varepsilon \), transmission speed \( \lambda \) (m/s), propagation time of the packet \( T_p \) (s), and previous residual energy of the source node \( E(m – 1) \) to predict the current residual energy of the node. Meanwhile, the inherent past records of nodes’ movements and the decay factor for intercluster and intracluster movements are used to model the mobility factor of the node. These variables can be independently obtained by the sink node in order to compute a node’s mobility factor and residual energy.

3.1 | Residual energy model

Wireless transmission between two sensor nodes at a unit distance is modeled as a parallel plate capacitor, where the wireless space is represented as the dielectric of the capacitor over a unit area, while the two sensor nodes are represented as the two parallel plates of the capacitor, as shown in Figure 2.

The total capacitance of the wireless channel of length \( l \) is \( C_l \), which consists of \( n \) number of capacitors connected in parallel. The circuit in Figure 2 is, therefore, represented with the equivalent circuit shown in Figure 3.

\[
C_l = C_1 + C_2 + C_3 + \ldots + C_n.
\]  

If the wireless channel between the two sensors is uniform, then the resistance along the channel is also assumed to be uniform and is represented as \( R_w \). \( R_{\text{driver}} \) is the channel buffer resistance that is:

\[
R_{\text{driver}} = \sum_{j=1}^{l} RD_j,
\]  

**FIGURE 1** Internal architecture of sensor node
where
\[ R_{D} \in \{\text{path}_{1} \cap \text{path}_{2} \cap \text{path}_{3} \cap \ldots \cap \text{path}_{n}\} \].

Therefore, the total resistance \( R = R_{\text{driver}} + R_{w} \). For an ideal wireless channel, \( R_{w} \approx 0 \). This implies that the total wireless channel resistance is very small and the lump capacitance \( C_{l} \) of the whole channel between source and destination sensor nodes is equivalent to Figure 3.

Meanwhile, wireless channel bit energy, \( W_{\text{bit}} \), which is the energy requires to move a bit through a unit point of wireless channel is:

\[
W_{\text{bit}} = E_{d|c} \oplus E_{c|d},
\]

where \( E_{c|d} \) is energy lost when the capacitor is discharged per unit time, which is equivalent to energy consumed when a bit changes from 1 \( \rightsquigarrow \) 0. \( E_{d|c} \) is energy gain when the capacitor charged per unit time, which is equivalent to energy consumed when a bit changes from 0 \( \rightsquigarrow \) 1.

Also, the voltage across lump capacitor \( V_{c} \) is:

\[
V_{c} = E \left(1 - e^{-\frac{t}{RC_{i}}}ight). \tag{4}
\]

In Figure 2, \( V_{c} = V_{R} + V_{c} \), however, for an ideal wireless channel, \( V_{R} \approx 0 \), therefore, \( V_{s} = V_{c} = V \). \( W_{\text{bit}} \) is equal to the energy stored in any of the parallel capacitor \( C_{i} \) in Figure 2, which is:

\[
E_{c|d} = E_{d|c} = 1/2C_{i}V_{c}^{2}. \tag{5}
\]

since \( C_{i} = \frac{eA}{d} \beta \) over unit distance \( d \) and area \( A \), then \( C_{i} = C_{i}l \) and \( C_{i} = \varepsilon.l.\beta \) over a distance \( l \).

Therefore, energy consumed in transferring data packet \( \eta \) from sensor node A to sensor node B that are distance \( l = \lambda T_{p} \) apart is, therefore, given as:

\[
E_{P|C} = E_{d|c}.l, \tag{6}
\]
\[
E_{D[C]} = \frac{\varepsilon \lambda T_p \beta [E_0 - E_0 e^{-1/\lambda \varepsilon \beta m \kappa}]}{2},
\]  
(7)

where \( V_c = [E_0 - E_0 e^{-1/\lambda \varepsilon \beta m \kappa}] \).

Using Equation 7, the residual energy model of sensor node is:

\[
E_{m+1} = E_m - E_{D[C]},
\]  
(8)

\[
E_{(m+1)} = E_{(m)} - \frac{\varepsilon \lambda T_p \beta [E_0 - E_0 e^{-1/\lambda \varepsilon \beta m \kappa}]}{2}.
\]  
(9)

Equation 9 represents the proposed predictive residual energy model, where \( V_c \) is the potential difference between the two parallel plates of the lump capacitor, \( \varepsilon \) is the permittivity of free space or vacuum, \( E_0 \) is the initial energy of the sensor, \( \kappa = 10^{-9} \) is the model constant, \( \lambda \) is the transmission speed (m/s), \( T_p \) is the propagation time of the bit (seconds), \( \beta = 0.5 \) is the activity factor, and \( E_m \) is the residual energy of the node at transmission session \( m \).

### 3.2 Mobility model

Mobility factor \( M_f \) determines the stability of MWSN’s topology, for example, MWSN with nodes with high \( M_f \) would undoubtedly have low stability, which affects the data delivery rate in the network. \( M_f \) can be used to predict the nodes’ movements and network topology, and therefore, with an effective \( M_f \) model, stable nodes can be easily determined. This can be used by MWSN protocol to select cluster head (CH) for a cluster. In a cluster-based MWSN, node can move outside its cluster or within its cluster. To take account of this, we represent the effect of intercluster and intracluster movement as decay rate \( \delta \)

\[
F = \delta M_f(m),
\]  
(10)

\[
\delta = \delta \exp \left(-\frac{\varepsilon^2}{r^2}\right),
\]  
(11)

\[
M_f(m + 1) = \left(\delta M_f(m) - \delta \exp \left(-\frac{\varepsilon^2}{r^2}\right)\right).
\]  
(12)

Equation 12 is the proposed predictive mobility model, where decay factor \( \delta = 1.0 \) if a node moves from one cluster to another cluster, and \( \delta = 0.5 \) if its movement is within its cluster, and \( r \) is the mobility reset duration. Mobility reset duration is the number of location changes performed by a node before its mobility factor (MF) is reset back to 1. As node changes position, its MF at instant \( m \) reduces to reflect its movement pattern.

### 4 Adoption and Performance Analysis of the Predictive Models

In this section, the two models in Equations 9 and 10 are used in the MWSN’s protocol proposed in Reference 26 to select CH and determine optimal route path for a reliable data delivery. The MWSN protocol through the sink node or BS computes the residual energies and mobility factors of all nodes in the MWSN using Equations 9 and 12 to generate distribution map for the MWSN and selects CH as the node with the highest \( E_m \) but lowest \( M_f(m) \).

To obtain the best route path between the source and destination nodes during multihop routing, source node selects its intermediate node (IN) from the distribution map, which is node with high \( E_m \) but low \( M_f(m) \). The selected best intermediary node (BIN) becomes temporary source node and selects its own best intermediary node. This is repeated
until the best intermediary nodes’ list of the primary source node is generated. This list forms the best route path between the primary source and the base station.

4.1 Experimental analysis

We performed experiments to evaluate the performance of the two predictive models by using them to predict the residual energies and stabilities of the heterogeneous sensor nodes in two 21-heterogenous node MWSNs’ clusters. To evaluate the performance of the predictive models, we introduced it in the protocol proposed in Reference 16 and developed a MATLAB-based MWSN simulating platform consisting of a base station (BS) and two 21-node heterogeneous sensor node clusters on 150 m × 60 m scaled deployment area. Each sensor node in the clusters has the following specifications: IEEE 802.15.4 compliant RF transceiver and 8-MHz microcontroller with 10-kB RAM and ROM. The platform was then used to evaluate the efficiency of the proposed predictive models based on the following:

- Effect of the transmission distance on the residual energy of sensor nodes.
- Effect of intracluster and intercluster movements on the mobility factor of sensor nodes.
- Impact of the proposed predictive models on the data delivery rates and computation latency of MWSN protocol.

4.2 Mathematical analysis

To analyze the mean waiting time (MWT) for each source node, we considered a hop as 1-1-M system with random hop requests from the source to n number of possible neighbouring nodes. A typical 1-1-3 system is shown in Figure 4. We characterized these random hop requests arrivals to source node using queue size distribution $P_z$, which is given by

$$P_z = Pr_{z=0}(\lambda T_s)^z.$$  \hspace{1cm} (13)

For m number of nodes in the network, we determine the probability of no neighbouring node involved in hopping $Pr_{z=0}$ using Equation 1 as follows:

$$\sum_{z=0}^{N} P_z = \sum_{z=0}^{N} Pr_{z=0}(\lambda T_s)^z = 1,$$

$$\therefore Pr_{z=0} \sum_{z=0}^{N} (\lambda T_s)^z = 1,$$

$$= Pr_{z=0} \left( \frac{1}{1 - \lambda T_s} \right),$$

$$\therefore Pr_{z=0} = 1 - \lambda T_s.$$  \hspace{1cm} (14)

**FIGURE 4** A sessional 1-1-M model for the predictive models
The source utilization $\rho$ is given by:

$$\rho = 1 - Pr_{z=0} = 1 - 1 + \lambda T_s = \lambda T_s. \quad (15)$$

The MWT is derived as service time multiplied by the mean queue size:

$$\text{MWT} = \frac{\rho}{1 - \rho} T_s, \quad (16)$$

since mean queue size is given as:

$$\sum_{z=0}^{N} z P_z = \frac{\rho}{1 - \rho}. \quad (17)$$

The MWT is the delay required before a given source hops' message to the intermediary node. This delay is due to computation and communication overheads incurred by the source node due to the execution of the predictive model. For any predictive model for WSNs, its MWT must not be too high. According to the Little theorem, $\lambda$ multiplied by MWT should be equal to the number of nodes in the network. If the computed $\lambda \times \text{MWT}$ is insignificant, then the source node will not be overwhelmed with traffic. For the purpose of analysis, we assume 50 hop requests per hour, that is, $\lambda = 50$ hops/h, while mean service time $T_s = 20$ ms as obtained from the experimental simulation. Then, MWT is computed as:

$$\rho = \lambda T_s
= 0.0139 \times 20 \times 10^{-3}
= 2.78 \times 10^{-4} \text{ seconds}$$

$$\text{MWT} = \frac{\rho}{1 - \rho} T_s
= \frac{2.78 \times 10^{-4} \times 20 \times 10^{-3}}{1 - 2.78 \times 10^{-4}}
= 5.56 \times 10^{-6} \text{ seconds.}$$

4.2.1 Results and discussion

The results in Figures 5 to 8 show the selected CHs and optimal route paths when the predictive models were used to predict the residual energies and mobility factors of nodes on an MWSN consisting of two 21-node heterogeneous clusters.

**Figure 5** The simulated mobile sensor node network with optimal route path ($M_{SN}$, $D, L, I, A, R, X, P_{CH}$) on cluster 1
FIGURE 6  The simulated mobile sensor node network with optimal route path ($I_{SN}, U, T, L, D, P_{CH}$) on cluster 1

FIGURE 7  The simulated mobile sensor node network with optimal route path ($P_{SN}, V, M, I, K, B, W_{CH}$) on cluster 2

FIGURE 8  The simulated mobile sensor node network with optimal route path ($Q_{SN}, J, O, I, H, W_{CH}$) on cluster 2
Tables 1 to 4 represent the corresponding best intermediary nodes for the selected optimal route paths in Figures 5 to 8. Figure 5 shows that the best optimal path from source node $M$ to base station consists of nodes $M, D, L, J, A, R, X$, and $P$ in cluster 1, where $P$ represents CH. Meanwhile, in the same cluster but different source nodes $I$, as shown in Figure 6, the predictive model selected optimal path consisting of nodes $I, U, T, L, D, C$, and $P$. For cluster 2 with source node $P$, as shown in Figure 7, the selected optimal path to the base station consists of nodes $P, V, M, I, K, B$, and $W$. Figure 8 shows that the optimal path from source node $Q$ to base station consists of nodes $Q, J, O, I, H$, and $W$. The similarity of the selected optimal route paths from Figures 5 to 8 and real application scenarios prove the practicability and accuracy of the predictive models.

Meanwhile, Figures 9 to 11 show the residual energies at different distances between the source node and the base station for different prediction instances. The results indicate that residual energy decreases as the number of data transmission that a node involved in increases; however, the rate of the decrement is most pronounced in Figure 11. That is, the rate at which the residual energy of the source node decreases becomes increasing as the distance between source and receiver nodes increases. This further corroborates the fact that the transmission power of a signal depends on the transmission distance.

**Table 1** Results of the predictive models on cluster 1 for selection of the best intermediary nodes' BINs for seven-hop routing

| Hop | BIN | Considered neighbors |
|-----|-----|----------------------|
| 1   | $M_{SN}$ | DKLY                |
| 2   | $D$   | LXBJ                |
| 3   | $L$   | JK                  |
| 4   | $J$   | ABK                 |
| 5   | $A$   | RK                  |
| 6   | $R$   | XBQ                 |
| 7   | $X$   | CQP<sub>CH</sub>    |
| 8   | $P_{CH}$ |                     |

**Table 2** Results of the predictive models on cluster 1 for selection of the best intermediary nodes' BINs for six-hop routing

| Hop | BIN | Considered neighbors |
|-----|-----|----------------------|
| 1   | $I_{SN}$ | UMYVH            |
| 2   | $U$   | TY                  |
| 3   | $T$   | KLS                 |
| 4   | $L$   | BDS                 |
| 5   | $D$   | RXC                 |
| 6   | $C$   | XOP<sub>CH</sub>   |
| 7   | $P_{CH}$ |                     |

**Table 3** Results of the predictive models on cluster 2 for selection of the best intermediary nodes BINs for six-hop routing

| Hop | BIN | Considered neighbors |
|-----|-----|----------------------|
| 1   | $P_{SN}$ | VOAN            |
| 2   | $V$   | BMA                 |
| 3   | $M$   | BKI                 |
| 4   | $I$   | KUC                 |
| 5   | $K$   | BSU                 |
| 6   | $B$   | RSW<sub>CH</sub>   |
| 7   | $W_{CH}$ |                     |
### TABLE 4

Results of the predictive models on cluster 2 for selection of the best intermediary nodes BINs for five-hop routing

| Hop | BIN | Considered neighbors |
|-----|-----|----------------------|
| 1   | QSN | JOP                  |
| 2   | J   | IOP                  |
| 3   | O   | INP                  |
| 4   | I   | HET                  |
| 5   | H   | GEW\textsubscript{CH} |
| 6   | W\textsubscript{CH} |                      |

**FIGURE 9** Predicted residual energy of a node for source-base distance $d = 60$ m

**FIGURE 10** Predicted residual energy of a node for source-base distance $d = 100$ m

**FIGURE 11** Predicted residual energy of a node for source-base distance $d = 140$ m
Figure 12 shows the mobility factors for different mobility reset thresholds for intracluster movements. The results indicate that mobility factor exponentially decreases as the number of node’s intracluster movements increases. That is, as the node changes its position within the cluster, its mobility factor increases. Meanwhile, Figure 13 shows the mobility factors for different mobility reset thresholds for intercluster movements. It shows that the rate of decrement in mobility factor for intracluster movements is lower than that in intercluster movements. This indicates that intercluster movement affects the stability of the MWSN’s topology than that in intracluster movement. Also, reset threshold obviously affects the rate of decrement in mobility factor during intracluster movements. The test results show that under different conditions, the predictive models are consistent with the actual results. This clearly shows that the predictive models accurately capture the effect of the nodes’ movements and can be practically used to predict the stability of the MWSN.

Figures 14 and 15 show the computation latencies and data delivery rates, respectively, for the protocol proposed in Reference 16 with and without the propose predictive models. The data delivery rate of the protocol improves when the predictive models are used but computation latency remains unchanged. This shows that the predictive models improve the data delivery rate of the protocol without significantly increasing the protocol’s computation latency. This further shows the practical significance of the propose models.

From the mathematical analysis, the \( MWT = 5.56 \times 10^{-6} \) seconds and \( \lambda \times MWT = 7.7 \times 10^{-8} \) are insignificant, which indicates that the models do not introduce significant communication overhead.
5 | CONCLUSION

The work presented an approach that explores the usage of exponential predictive method to model the residual energies and mobility factors of MWSNs' nodes. Predictive approach is used to predict the current energy consumption of each node after transmission, which is used to obtain the residual energy of the node based on its previous residual energy. Similarly, the stability of a node is predicted through the mobility factor of the node. The mobility factor model captures both the intracluster and intercluster node’s movements in order to determine the stability of the node. The overall stability of all nodes in the network determines the stability of its topology. The simulations results showed that the models are capable of accurately determining the CH and optimal route path if adopted in MWSN protocol. However, we do not develop a protocol that employs these models but only adopted the existing protocol. In future, we intend to develop a protocol based on these models and deal with some of the security issues likely to emanate as a result of using the predictive models.

6 | CONFLICT OF INTEREST

The authors have no conflict of interest relevant to this article.

AUTHOR CONTRIBUTIONS

Oladayo Olakanmi Conceptualization-Equal, Formal analysis-Lead, Investigation-Lead, Methodology-Lead, Software-Lead, Validation-Lead, Writing-original draft-Lead, Writing-review & editing-Lead; Kehinde Odeyemi Formal analysis-Supporting, Investigation-Supporting, Methodology-Supporting, Software-Supporting, Validation-Supporting, Writing-review & editing-Supporting; Ashraf Abbas Conceptualization-Supporting, Formal analysis-Supporting, Investigation-Supporting, Methodology-Supporting, Writing-original draft-Supporting.

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