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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 2 | Pages 623-630 | e-ISSN: 2347-470X

IARMTS: Design of an Interference-Aware Routing Model with Time Synchronization Capabilities for Dense Wireless Sensor Network Deployments

Ritesh Shrivastav[1*] and Swapnili Karmore[2]

[1]*Department of Computer Science and Engineering, Research Scholar, G. H Raisoni University, Saikheda, India, riteshar sh15@gmail.com*

[2]*Department of Data Science, GHRIET, Nagpur, India, Swapnili.karmore@raisoni.net*

***Correspondence:** Ritesh Shrivastav; riteshar sh15@gmail.com

ABSTRACT- Performance of dense wireless sensor networks is often degraded due to communication interference and time synchronization issues. Existing machine learning & deep learning models that propose bioinspired & pre-emptive packet-analysis solutions for these tasks either have high complexity, or high deployment costs. Moreover, these models cannot be scaled for heterogeneous node & traffic types, which limits their applicability when applied to real-time scenarios. To overcome these issues, this text proposes design of an interference-aware routing model with time synchronization capabilities for dense wireless sensor network deployments. The network initially collects temporal clock states & packet delivery performance of different nodes on heterogeneous traffic scenarios. These traffic patterns are converted into frequency, entropy, Gabor, and Wavelet components. The converted components are used to train an ensemble set of Naïve Bayes (NB), k Nearest Neighbour (kNN), Multilayer Perceptron (MLP), and Support Vector Machine (SVM) classifiers. These classifiers assist in identification of optimal clock deviations and set of routing paths. These routing paths are further fine-tuned via use of a Bacterial Foraging Optimization (BFO) Model, which assists in identification of interference-aware paths. The BFO Model uses a temporal fitness function that fuses throughput, communication delay, energy levels, and packet delivery performance for different set of contextual communications. Due to which, the model is able to showcase lower end-to-end delay, higher throughput, lower energy consumption, and higher packet delivery performance when compared with existing routing methods under high density nodes & heterogeneous network scenarios. The model showcases 99% PDR, 18.3% lower delay, 19.5% higher energy efficiency and 10.4% lower delay levels when compared with existing methods.

General Terms: Wireless sensor network, routing model.

Keywords: Wireless, Interference, Time Synchronization, Delay, Throughput, Energy, Packet, Delivery, Scenarios.

ARTICLE INFORMATION

Author(s): Ritesh Shrivastav and Swapnili Karmore;

Received: 06/03/2023; **Accepted**: 13/06/2023; **Published**: 30/06/2023;

e-ISSN: 2347-470X;

Paper Id: IJEER-2023_151;

Citation: 10.37391/IJEER.110252

Webpage-link:

https://ijeer.forexjournal.co.in/archive/volume-11/ijeer-110252.html

This article belongs to the Special Issue on **Mobile Computing assisted by Artificial Intelligent for 5G/ 6G/ Radio Communication**

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1. INTRODUCTION

The term "time synchronization" is used to describe the process of adjusting the clocks of all the devices that are connected to a wireless network so that they are set to the same point in time. Systems such as GPS are very reliant on accurate time data; hence, it is essential that this information be accurate in order to keep everyone on the same page and reduce the risk of communication problems via use of delay- and interference-aware routing (DIAR) [1, 2, 3, 4]. Tools such as network time protocols (NTP), precision time protocols, and global positioning systems (GPS) may be used to synchronize time (PTP). Therefore, time synchronization is required for the continuing operation of appropriate data transmission and reception in order to avoid any disruptions via segment routing to wireless mesh networks (SR-WMN) [5, 6]. A direct outcome of ensuring that all components of a network are functioning on the same time scale is the elimination of communication mistakes and delays. This is of the utmost importance when working with material that is time-sensitive, such as streaming music or video sets. There are several methods that are used in wireless networks to synchronize the clocks of the devices that are connected to the networks [7, 8, 9]. One of these methods is the Global Positioning System (GPS), which uses signals from satellites to deliver accurate time to the devices that are connected to the network. Second, Network Time Protocol, sometimes known as NTP, is a technique that is commonly used to synchronize clocks across different networks. It does this by using a server-client configuration to send time information out across a network. PTP, which stands for Precision Time Protocol, is a protocol that was established to perfectly synchronize the time in industrial and automation networks. It is accurate to within microseconds, and it is capable of supporting wired as well as wireless communications [10, 11, 12, 13].

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The ability to send data between nodes in a wireless network that is both accurate and dependable is made possible by time synchronization, which is an essential component of an efficient wireless network [14, 15, 16]. This chaining together of individual components is typical in interference-aware routing schemes [17, 18, 19, 20]. Any situation in which there is a deterioration or interruption of the signals that are being transferred between devices in wireless networks is referred to as communication interference. This may result in inaccuracy or the loss of data. There are a number of elements, some of which include, but are not limited to, Walls, flooring, and even furniture have the potential to obstruct or weaken the intensity of signals that are moving through an establishment. Second, electromagnetic interference from other electronic equipment, such as radios, TVs, and microwave ovens, may sometimes interfere with wireless connections and make them less reliable. Third, if several wireless devices are using the same frequency band, the signal strength may be diminished due to interference caused by crosstalk [21, 22, 23]. The strength of a signal weakens with increasing distance, and there is a possibility that communication may break down as a result of the power constraints imposed by the transmitting apparatus [24, 25, 26]. Interference may also be generated when many wireless networks are located in close proximity to one another, as is possible in places with a high population density. This phenomenon is referred to as "interference" from other networks [27, 28, 29, 30]. Interference may slow down the speeds at which data is sent, result in mistakes during data transmission, and possibly result in the loss of the signal entirely. Wireless networks often use strategies such as channel selection, frequency hopping, and error correction in order to reduce the likelihood of interference and ensure that messages continue to flow without a hitch via Kalman Filter (KF) like models that can be used for time synchronization in networks [31, 32, 33, 34].

Thus, based on this analysis it can be suggested that the bioinspired and pre-emptive packet-analysis solutions supplied by machine learning and deep learning models are either too hard or too costly to implement. These sorts of models are not particularly effective in real-time applications due to the fact that they cannot be scaled to accommodate a variety of node types and traffic patterns. In the next section of this article, we will present our proposal for the creation of a time-synchronized, interference-aware routing model that may find extensive use in wireless sensor networks. In the 3rd section of the paper, the model was validated by comparing the outcomes it produced across a variety of communication contexts to those produced by well-established methods. This article concludes with some network-centric observations on the proposed model and some advice on how to make it even better for application in actual settings. These observations and recommendations are provided as a conclusion to this paper and can be used for different network scenarios.

1.1 Contributions of the Paper

The paper makes several contributions to the field:

1. Novel approach: The paper proposes a novel approach to address the performance degradation issues in dense wireless sensor networks caused by communication interference and time synchronization problems. By combining interference-aware routing and time synchronization capabilities, the proposed model offers a comprehensive solution to optimize network performance in real-time scenarios.
2. Ensemble of classifiers: The paper introduces an ensemble set of machine learning classifiers, including Naïve Bayes, *k* Nearest Neighbour (kNN), Multilayer Perceptron, and Support Vector Machine, to identify optimal clock deviations and routing paths. This ensemble approach enhances the accuracy and robustness of the routing decisions, enabling effective management of heterogeneous node and traffic types.
3. Conversion of traffic patterns: The paper converts temporal traffic patterns into frequency, entropy, Gabor, and Wavelet components. This conversion allows for a more comprehensive analysis of the traffic characteristics, facilitating more informed decision-making in routing and interference mitigation.

Overall, the paper's contributions lie in the development of a comprehensive interference-aware routing model with time synchronization capabilities that addresses the limitations of existing models in terms of complexity, deployment costs, and scalability for heterogeneous networks. By leveraging machine learning, ensemble classifiers, and a BFO model, the proposed approach offers a more efficient and effective solution for managing dense wireless sensor networks in real-time scenarios.

1.2 Research Gaps

The major research gaps in the existing system, which the paper aims to address, can include the following:

1. Complexity and deployment costs: Existing machine learning and deep learning models that propose bioinspired and pre-emptive packet-analysis solutions for interference and time synchronization in wireless sensor networks often suffer from high complexity and deployment costs. This can limit their practical applicability and scalability in real-world scenarios. The paper aims to fill this gap by proposing a model that is less complex and more cost-effective, making it more accessible and feasible for deployment.
2. Limited scalability for heterogeneous node and traffic types: Many existing models lack the ability to scale effectively for heterogeneous node and traffic types in wireless sensor networks. This restricts their applicability in real-time scenarios where networks consist of diverse nodes and experience varying traffic patterns. The paper aims to address this gap by designing a model that can handle heterogeneous node and traffic types, improving its versatility and usefulness in real-world deployments.
3. Lack of interference-aware routing: Interference is a significant challenge in dense wireless sensor network deployments, and existing models often do not adequately consider interference in their routing decisions. This gap can lead to suboptimal routing paths and degraded network performance. The paper fills this gap by proposing an interference-aware routing model that takes interference

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into account and identifies optimal routing paths while considering interference mitigation.

By identifying and addressing these research gaps, the paper contributes to advancing the field of wireless sensor networks by proposing a model that offers a more accessible, scalable, interference-aware, and time-synchronized solution for dense network deployments with heterogeneous node and traffic types.

2. DESIGN OF AN INTERFERENCE-AWARE ROUTING MODEL WITH TIME SYNCHRONIZATION CAPABILITIES FOR DENSE WIRELESS SENSOR NETWORK DEPLOYMENTS

As per the review of interference-aware routing models, it was observed that existing deep learning and machine learning models that suggest bioinspired and proactive packet analysis approaches for these problems either have high deployment costs or high levels of complexity. These models also have limited applicability in real-time scenarios due to their inability to scale for heterogeneous node & traffic types.

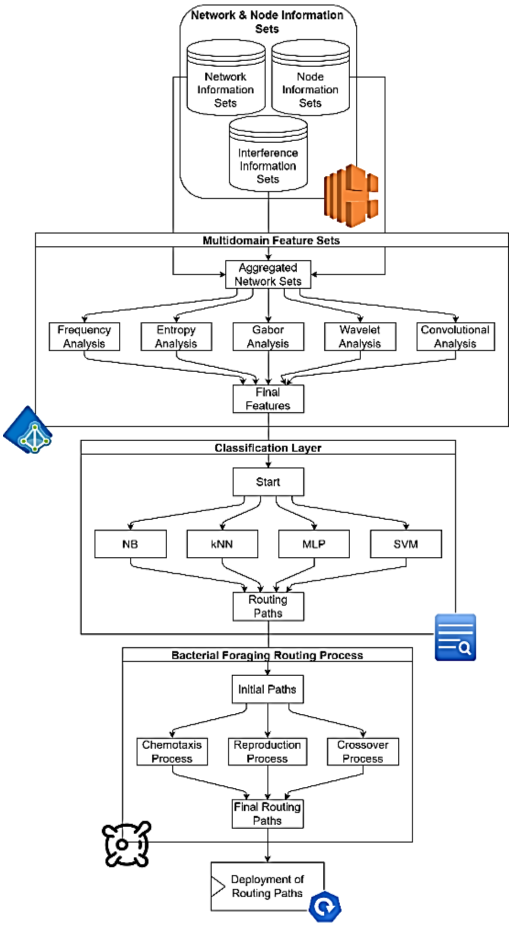

Figure 1: Design of the proposed time-synchronization & interference-aware routing process

The design of an interference-aware routing model with time synchronization capabilities for dense wireless sensor network deployments is suggested in this text as a solution to these problems. As per *figure 1*, it can be observed that the network first gathers the temporal clock states and packet delivery capabilities of various nodes under various traffic scenarios. These traffic patterns are transformed into Gabor, Wavelet, Frequency, and Entropy components. An ensemble of classifiers, including Naive Bayes (NB), *k* Nearest Neighbour (kNN), Multilayer Perceptron (MLP), and Support Vector Machine (SVM), are trained using the converted components. These classifiers aid in identifying the best routing paths and clock deviations. Utilizing a Bacterial Foraging Optimization (BFO) Model, which aids in the identification of interference-aware paths, further refines these routing paths. For various sets of contextual communications, the BFO Model employs a temporal fitness function that fuses throughput, communication delay, energy levels, and packet delivery performance under real-time scenarios.

The model initially collects the following information sets,

- Instantaneous Node Information,
  - Approximate Node locations
  - Energy levels for the Nodes
  - Internal clock offsets for the Nodes
- Network Information Sets,
  - Data rate of the network
  - Received Signal Strength Indicator (RSSI) levels
  - Link Quality between Nodes
- Interference Information Sets,
  - Packet Delivery Ratio of temporal communications
  - Throughput during temporal communications

These information sets are converted into multi-domain features *via* a combination of Fourier (for Frequency Patterns) estimated *via equation 1*, Cosine (for Entropy Patterns) estimated *via equation 2*, Convolutional features that are estimated *via equations 3 & 4*, Gabor components which are estimated *via equation 5*, and Wavelet components which are estimated *via equations 6 & 7* as follows,

$$DFT_i = \sum_{j=1}^{N_f} x_j * \left[cos\left(\frac{2*\pi*i*j}{N_f}\right) - \sqrt{-1} * sin\left(\frac{2*\pi*i*j}{N_f}\right)\right] \dots \quad (1)$$

Where, x represents a combination of the Network, Node and Interference data samples.

$$DCT_i = \frac{1}{\sqrt{2*N_f}} * x_i \sum_{j=1}^{N_f} x_j * \cos\left[\frac{\sqrt{-1}*(2*i+1)*\pi}{2*N_f}\right] \dots \quad (2)$$

$$Conv_{out_i} = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}} x(i-a) * LReLU\left(\frac{m+2a}{2}\right) \dots \quad (3)$$

Where, m & a represents dimensions of window & strides for different convolutional configurations, while $LReLU$ is an activation function which is estimated *via equation 4* as follows,

$$LReLU(x) = l_a * x, when\ x < 0\ , else\ LReLU(x) = x \quad (4)$$

Similarly, the Gabor components are estimated as per *equation 5*,

$$G(x,y)_s = e^{\frac{-x`^2+\partial^2 * y'^2}{2*\emptyset^2}} * \cos\left(2 * \frac{pi}{\lambda} * x'\right) \dots \quad (5)$$

Where, x & y are the parameter index & parameter values, while $\partial, \emptyset$ & λ represents the Angular & Wavelength components of the Gabor process.

$$W_a = \frac{x_i + x_{i+1}}{2} \dots \quad (6)$$

$$W_d = \frac{x_i - x_{i+1}}{2} \dots \quad (7)$$

Where, W_a & W_d represents the approximate & diagonal Wavelet components. All these components are processed by an ensemble classifier that combines Naïve Bayes (NB), k Nearest Neighbours (kNN), Support Vector Machine (SVM), and Multilayer Perceptron (MLP), which assist in identification of clock duty cycle deviations and corresponding routing paths. The clock deviation levels & routing paths used between previous source & destination nodes are used to train these classifiers. The configuration used for these classifiers can be observed from *table 1* as follows

Table 1: Parameters used for different classifiers

Classifier used for clock deviation analysis	**Parameters used for the classifiers**
Naïve Bayes (NB)	*Priors (P)* are estimated as per equation 8, $P = \frac{\left(\sum_{i=1}^{N_c}\left(\sum_{j=1}^{N_c}\frac{x_i - x_j}{N}\right)^2\right)}{N_c}$ (8) Where, N_c represents number of previous communications, while x are the extracted vector of features. Smoothing Value (S_v), is set to L_r, as per the BFO routing process.
Support Vector Machine (SVM)	Regularization constant ($C = \frac{1}{N_c}$) Tolerance of error $tol = L_r$
k Nearest Neighbours (kNN)	k = 1, for feature-to-feature classification operations
Multilayer Perceptron (MLP)	Total Hidden Neurons are estimated as per equation 9, $N(Hidden) = N_c * L_r * N_a$ (9) Where, N_a represents average number of nodes in the network during previous communications.

Once individual classifiers are trained, then the output class is estimated for different routes & clock deviations *via equation 10*,

$$c_{out} = c(NB) * A(NB) + c(kNN) * A(kNN) + c(MLP) * A(MLP) + c(SVM) * A(SVM) \quad (10)$$

This assists in identification of initial routes between nodes, and their corresponding clock deviation levels. These routes & deviation levels are tuned by a Bacterial Foraging Optimizer (BFO) that works as per the following operations,

- A set of iterations (NI), set of Bacterium (NB), and learning rate of bacterium (L_r) were initialized for setting up the optimization process
- Reference distance between source (s) & destination (d) was evaluated via equation 10,

$$d_{ref} = \sqrt{(x_s - x_d)^2 - (y_s - y_d)^2} \dots \quad (10)$$

Where, x & y represents locations of these nodes.

- All nodes that satisfy *equation 11* were selected and their routes were shortlisted from the classified routes,

$$d(src, node) < d_{ref}\ \&\ d(node, dest) < d_{ref} \dots \quad (11)$$

Where, $d(i,j)$ is the Euclidean distance between nodes i & j that can be placed stochastically for real-time scenarios.

- From this set of routes, a route was stochastically selected via equation 12,

$$N_{sel} = L_{sel}\left[STOCH\left(1, Size(L_{sel})\right)\right] \dots \quad (12)$$

Where, L_{sel} is a list of selected nodes that are classified by the ensemble classification process.

- Due to removal of nodes due to *condition 11*, the selected route might have communication gaps, which are filled by nodes that satisfy *equation 11*, thereby maintaining higher connectivity levels.
- Based on the selected path, calculate bacterium fitness *via equation 13*,

$$f_b = \frac{1}{N_{sel} - 1} \sum_{i=1}^{N_{sel}-1} \left[\frac{d_{ref}}{d_{i+1,i}} + \frac{E_i}{Max(E)} + \frac{THR(i)}{Max(THR)} + \frac{PDR(i)}{100}\right] \dots \quad (13)$$

Where, d, E, THR & PDR represents distance between nodes, energy levels, through put and packet delivery ratio of the selected nodes.

- Similar to this route, NB different routes were selected, their fitness was estimated, and a fitness threshold was evaluated *via equation 14*,

$$f_{th} = \sum_{i=1}^{NB} f_{b_i} * \frac{L_b}{NB} \dots \quad (14)$$

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- Bacterium with $f > f_{th}$ were passed directly to the next iteration, while others are discarded and reproduced in the next set of iterations.

After repeating this process for NI iterations, Bacteria with highest fitness levels was selected, and used for routing operations. Due to which, the clock deviations were optimized, and interference-aware routing was deployed in the network, even for larger network scenarios. Performance of this model was evaluated on different network scenarios, and compared with existing models in the next section of this text.

3. STATISTICAL ANALYSIS

This paper proposed the design of an interference-aware routing model with time synchronisation capabilities for dense wireless sensor network deployments to address scalability and communication issues. The network first gathers the temporal clock states and packet delivery capabilities of various nodes under various traffic scenarios. These traffic patterns are transformed into Gabor, Wavelet, Frequency, and Entropy components. An ensemble of classifiers, including Naive Bayes (NB), k Nearest Neighbor (kNN), Multilayer Perceptron (MLP), and Support Vector Machine (SVM), are trained using the converted components. These classifiers aid in identifying the best routing paths and clock deviations. Utilizing a Bacterial Foraging Optimization (BFO) Model, which aids in the identification of interference-aware paths, further refines these routing paths. For various sets of contextual communications, the BFO Model employs a temporal fitness function that fuses throughput, communication delay, energy levels, and packet delivery performance. As a result, the model, when compared to existing routing techniques, can demonstrate lower end-to-end delay, higher throughput, lower energy consumption, and higher packet delivery performance in high density node & heterogeneous network scenarios. Performance of this model was tested on Network Simulator-2 (NS2.34) under the conditions as depicted in *table 2*,

Table 2: Configuration of the network & nodes for simulation purposes

Parametric Network Settings	Value for the settings
Communication Model used during simulations	Multiple Ray Communication Antennas
MAC Model	802.16a
Queuing Model	Priority Queuing with Drop Tails
Network Nodes	2500
Routing protocol used to perform time synchronizations	DSR (Dynamic State Routing)
Dimensions of the Network	1.5km x 1.5km
Energy Model Used	Idle: 0.05 mW Reception: 1 mW Transmission: 2 mW Transition: 0.5 mW Initial: 1000 mW

Based on these parameters, the network was simulated with varying number of communications. For each of these communications, end-to-end delay (D), energy consumed (E), throughput (THR) and Packet Delivery Ratio (PDR) were estimated, and compared with DAIR [3], SR WMN [6], and KF [33], which are recently proposed time synchronization models. This performance was evaluated w.r.t. different Number of Communication (NC), with 10% nodes out of clock synchronization, and can be observed from *figure 2* as follows

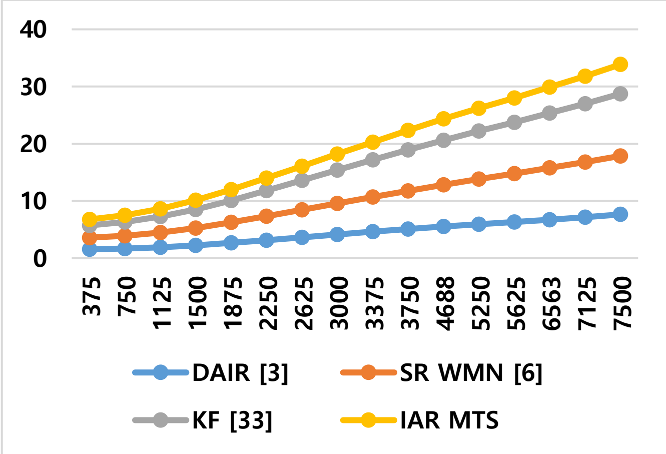

Figure 2: Average communication delay under 10% clock synchronization scenarios

As per this evaluation, and its visualization in *figure 2*, it can be observed that even under large-scale scenarios and multiple synchronization issues, the proposed model is capable of reducing the delay needed for communication by 10.5% when compared with DAIR [3], 14.9% when compared with SR WMN [6] and 16.2% when compared with KF [33] under different communications. This delay is reduced due to use of multi-domain features for identification of clock deviations, and use of BFO for selection of optimal routing paths. Due to which, the model is useful for a wide variety of high-speed communication scenarios. Similarly, the energy consumed during these communications can be observed from *figure 3* as follows,

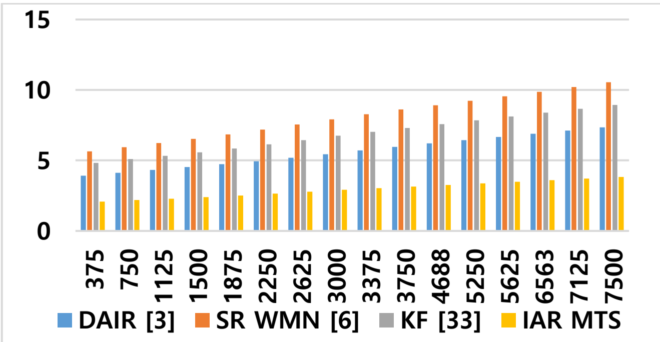

Figure 3: Average communication energy needed under 10% clock synchronization scenarios

As per this evaluation, and its visualization in *figure 3*, it can be observed that even under large-scale scenarios and multiple synchronization issues, the proposed model is capable of reducing the energy needed for communication by 19.4% when compared with DAIR [3], 26.2% when compared with SR WMN [6] and 23.5% when compared with KF [33] under different communications. This energy consumption is reduced

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due to use of multi-domain features for identification of clock deviations, and use of residual energy for selection of optimal routing paths. Due to which, the model is useful for energy-aware communication scenarios. Similarly, the throughput obtained during these communications can be observed from *figure 4* as follows;

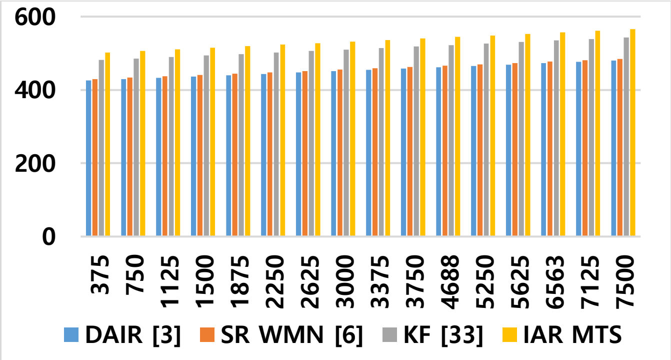

Figure 4: Average communication throughput needed under 10% clock synchronization scenarios

As per this evaluation, and its visualization in *figure 4*, it can be observed that the proposed model is capable of improving the throughput obtained during communication by 8.3% when compared with DAIR [3], 8.5% when compared with SR WMN [6] and 1.9% when compared with KF [33] under different communications. This throughput is improved due to use of ensemble classification for identification of clock deviations, and use of BFO that incorporates temporal throughput for selection of optimal routing paths. Due to which, the model is useful for high data rate communication scenarios. Similarly, the PDR obtained during these communications can be observed from *figure 5*.

As per this evaluation, and its visualization in *figure 5*, it can be observed that the proposed model is capable of improving the PDR obtained during communication by 5.5% when compared with DAIR [3], 6.5% when compared with SR WMN [6] and 8.3% when compared with KF [33] under different communications. This PDR is improved due to use of ensemble classification for identification of clock deviations, and use of BFO that incorporates temporal PDR for selection of optimal routing paths. Due to which, the model is useful for high efficiency communication scenarios.

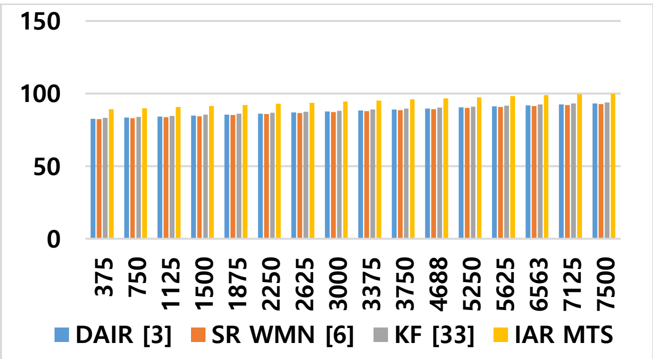

Figure 5: Node average communication PDR achieved under 10% clock synchronization scenarios

4. CONCLUSION AND FUTURE SCOPE

This paper proposed the design of an interference-aware routing model with time synchronization capabilities for dense wireless sensor network deployments to address scalability and communication issues. The network first gathers the temporal clock states and packet delivery capabilities of various nodes under various traffic scenarios. These traffic patterns are transformed into Gabor, Wavelet, Frequency, and Entropy components. An ensemble of classifiers, including Naive Bayes (NB), k Nearest Neighbor (kNN), Multilayer Perceptron (MLP), and Support Vector Machine (SVM), are trained using the converted components. These classifiers aid in identifying the best routing paths and clock deviations. Utilizing a Bacterial Foraging Optimization (BFO) Model, which aids in the identification of interference-aware paths, further refines these routing paths. For various sets of contextual communications, the BFO Model employs a temporal fitness function that fuses throughput, communication delay, energy levels, and packet delivery performance. In terms of communication speed, it was observed that even under large-scale scenarios and multiple synchronization issues, the proposed model is capable of reducing the delay needed for communication by 10.5% when compared with DAIR [3], 14.9% when compared with SR WMN [6] and 16.2% when compared with KF [33] under different communications. This delay is reduced due to use of multi-domain features for identification of clock deviations, and use of BFO for selection of optimal routing paths. Due to which, the model is useful for a wide variety of high-speed communication scenarios.

In terms of energy efficiency, it was observed that even under large-scale scenarios and multiple synchronization issues, the proposed model is capable of reducing the energy needed for communication by 19.4% when compared with DAIR [3], 26.2% when compared with SR WMN [6] and 23.5% when compared with KF [33] under different communications. This energy consumption is reduced due to use of multi-domain features for identification of clock deviations, and use of residual energy for selection of optimal routing paths. While, in terms of data rates, it was observed that the proposed model is capable of improving the throughput obtained during communication by 8.3% when compared with DAIR [3], 8.5% when compared with SR WMN [6] and 1.9% when compared with KF [33] under different communications. This throughput is improved due to use of ensemble classification for identification of clock deviations, and use of BFO that incorporates temporal throughput for selection of optimal routing paths. When PDR was estimated, it was observed that the proposed model is capable of improving the PDR obtained during communication by 5.5% when compared with DAIR [3], 6.5% when compared with SR WMN [6] and 8.3% when compared with KF [33] under different communications. This PDR is improved due to use of ensemble classification for identification of clock deviations, and use of BFO that incorporates temporal PDR for selection of optimal routing paths. Due to which, the model is useful for high efficiency communication scenarios. In future, performance of the proposed model must be validated under large-scale scenarios, and can be improved via integration of multiple bioinspired models for pre-emption of clock deviation, and interferences.

Ethical & Practical Implications

The widespread adoption of the proposed interference-aware routing model with time synchronization capabilities for dense wireless sensor network deployments could have several ethical and social implications. Some potential implications are:

1. *Privacy concerns*: Collecting temporal clock states and packet delivery performance of different nodes in the network may raise privacy concerns. The data collected could potentially contain sensitive information about individuals or organizations, and its misuse or unauthorized access could lead to privacy breaches. Proper data protection and anonymization measures should be implemented to address these concerns.
2. *Data security*: As the proposed model involves collecting and analyzing network data, it becomes important to ensure the security of the data. Unauthorized access to the collected data or vulnerabilities in the model's implementation could result in data breaches, leading to potential exploitation or disruption of the sensor network.
3. *Bias and fairness*: Machine learning models, such as Naïve Bayes, k Nearest Neighbour, Multilayer Perceptron, and Support Vector Machine classifiers, rely on training data to make predictions and decisions. If the training data is biased or unrepresentative, it could introduce unfairness or discrimination in the routing decisions made by the model. Care should be taken to ensure the fairness of the model and mitigate biases in the training data.
4. *Dependence on technology*: Widespread adoption of the proposed model could lead to a heavy reliance on technology for network management and optimization. While this can bring benefits, it also raises concerns about potential system failures or vulnerabilities. It is crucial to have backup systems and contingency plans in place to mitigate the impact of any technical failures.

To address these ethical and social implications, it is crucial to incorporate principles such as transparency, accountability, fairness, privacy protection, and sustainability in the design, implementation, and governance of the proposed model. Regulatory frameworks and guidelines should be established to ensure responsible deployment and usage of the technology, considering the potential implications on individuals, communities, and the environments.

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