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High traffic communication congestion control for wireless sensor networks based on harmony search optimization

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ABSTRACT

In wireless sensor networks (WSNs), communication between the wireless nodes requires minimum response delay, minimum congestion and communication reliability. A wide variety of sensors produces a mixture of heterogeneous traffics with different reliability requirements. The article focuses on high traffic congestion which affects communication and produces latency. In the existing approaches, the congestion was controlled and the optimization was done during the time of node deployment. In the proposed method, high traffic congestion was controlled by a hop-by-hop approach which was applied in the statically deployed sensor nodes, the optimization was performed at the time of communication. To provide a uninterrupted communication to the WSNs the proposed approach analyses the occupancy ratio of the buffer and evaluates the downstream node congestion level. Here, the Harmony Search Algorithm is considered for design the optimal sensor network with Support Vector Machine (SVM). The experimental result shows the effectiveness and feasibility of the HSA-SVM environment. Also, it significantly enhances communication in diverse traffic conditions, specifically in heavy traffic areas with limited data.

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KEYWORDS
Wireless sensor networks; node deployment; communication congestion; HSA optimization

1. Introduction

A wireless sensor network (WSNs) refers to a group of spatially distributed sensors to monitor and acquire certain physical conditions of the environment and communicate the composed information to the sink [1]. These networks are applied to a wide range of regions viz military surveillance, environmental monitoring, health care and forest fire detection [2]. The most important parts of WSNs are environmental sensing, data collection and cooperation with sensor nodes processing and transmitting the packets to the sink nodes. In WSNs during communication, congestion happens when there is a dissimilarity of synchronization between the sender and the receiver [3]. In the congested network, certain packets may be lost due to the inadequacy of the node's buffer. This can degrade the quality of the network in terms of throughput and energy. Therefore, congestion is a most considerable problem in WSNs to maintain reliable communication.

To handle the critical issue as reported in [4], several control methods have used transmission rate adjustment for avoiding congestion. Congestion Detection and Avoidance (CODA) is the first study to control the congestion [5] and follows certain strategies like: Congestion detection, hop-by-hop approach, open-loop feedback and closed-loop transmission rate. In the CODA network, throughput is guaranteed by the appropriate closed-loop adjustment process. However, one of the notable problems in CODA is continuous monitoring of the channel in the constructed nodes indirectly it causes abundant energy consumption in CODA.

Enhanced CODA [6] is an effective mechanism for detecting and avoiding congestion using three strategies dual buffer thresholds, queue scheduler and bottleneck-node-based source sending are the key strategies to handle the network's congestion. For each source, the packets are sorted from high to low based on their dynamic priority. By adopting this scheme to avoid congestion, some low-priority nodes drop packets from a queue or a neighbour, which helps to minimize the latency in transmission.

Differed Reporting Rate (DRR) is also an attempt to control the congestion by adjusting the coverage rate of the sensor nodes. To achieve the aim of DRR, various flow rate components are defined. The sensor nodes close to the sink will have a minimum reporting rate, and that rate will affect the results of nodes away from the sink. This will be possible during the process of different reporting rate adjustments in DRR. Here, to obtain a better result in the high traffic environment for the evaluation purpose, the buffer occupancy ratio is considered as the performance metric [7]. Until detection of the next congestion, the node's output rate will be in the recently calculated state. Transparency of this DRR approach concludes that the single-node

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transmission rate was based on the neighbour node traffic notification. Also, increment or decrement in the two adjacent nodes will not affect the transmission rate of every single relative node.

Since many congestion control methods allow the inclusion of vague human assessment in computing problems, it can be effectively used in intelligent real-time systems and WSN's for optimization and control. Machine learning is the intelligence exhibited by the machine or software that the computer program can learn and adapt to new data without human intervention. For example, an approach presented in [8] to detect congestion using occupancy of the buffer, and the traffic rates are input parameters and the level of congestion taken as the output of the network. In this technique, congestion was evaluated at the sink level, which may approximate the level of congestion. As a result, in the source and relay nodes' congestion levels cannot be estimated.

All the other available conventional congestion control approaches have some limitations to accurately avoiding and managing the congestion. To overcome the shortcomings in the conventional methods, various classification methods have been examined to deal with the uncertain information [9–12] with subject to the SVM as a data multi-classification tool. The SVM method works with two main concepts one is based on the support vector set, and the other is kernel function [13–16]. This allows the proposed approaches to obtain a more accurate data transmission rate and a more accurate data classification through the training data testing part. Machine learning-based approaches allow the system to yield better results for the sensor nodes, and also the efficiency of the network can significantly improve in a distributed manner. The high traffic consideration and congestion control are possible by the accurate adjustment in the data transmission rate.

The proposed approach utilizes the similar classification method SVM used in [3] to avoid congestion in a static environment. However, the SVM parameters are tuned by HSA algorithms since; HSA-SVM can provide better outcomes than other metaheuristics. Therefore, the proposed approach is suitable for the static types of deployment and in avoiding congestion at every hop in the WSNs by adjusting the transmission rate.

1.1. Contribution

Due to severe traffic congestion, response times were delayed and packets were lost on a regular basis and it will decrease the network reliability. While working with a large number of sensor nodes in the desired environment the designed architecture of WSN should take account of congestion control and congestion avoidance with prime concern. In the proposed method High traffic congestion was controlled by a hop-by-hop approach applied in the statically deployed sensor nodes and the optimization is executed at the time of communication. In the performance evaluation process, the proposed method uses SVM to evaluate packet loss with the adoption of HSA optimization techniques. Based on the channel information, congestion was controlled through a transmission rate adjustment to provide an uninterrupted communication for the WSNs.

1.2. Congestion types in wireless sensor networks

Network congestion arises when a network is unable to handle the flow of traffic along with it. Although, in addition, congestion degrades the overall channel capacity while network congestion is typically a temporary state rather than a permanent aspect of a network, there are circumstances where a network is continually congested, indicating a greater problem. In general, based on the behaviour, the congestion was categorized into node-level congestion and link-level congestion [17,18]. Traditionally, the buffer utilization or the mismatch between the traffic arrival rate and the traffic departure rate is evaluated in node-level congestion; conversely, channel usage is monitored in link-level congestion. The critical aspect in both cases is the timely detection of congestion and its alleviation by the network.

Node-level congestion: Congestion at the node level, which is typical in that, is common in traditional networks. It is induced by a node's buffer overflow and might result in packet loss and increased queuing delay. Node-level congestion harms the performance of the affected node in WSN. It causes energy loss due to the higher packet loss ratio and as a result, disconnects the affected node from the network, causing some routes to be unavailable. Energy depletion and unsustainable routine have an adverse impact on network performance, reducing overall network dependability and lifespan. Node-level congestion is detected by analysing buffer utilization and the gap between the consecutive data packets.

Link-level congestion: Severe collisions may occur in a specific area if numerous active sensor nodes within the range of one another attempt to broadcast at the same time. As a result of congestion, packets that leave the buffer may fail to reach the subsequent hop. Link-level congestion was monitored and examined through the channel utilization. Congestion of this type reduces connection usage and overall throughput while increasing both packet delay and energy waste. In both cases, the key element is the timely detection of congestion and its reduction from the network.

1.3. Congestion control methods

In general, congestion control is the mechanism that prevents congestion from developing in WSNs, and if

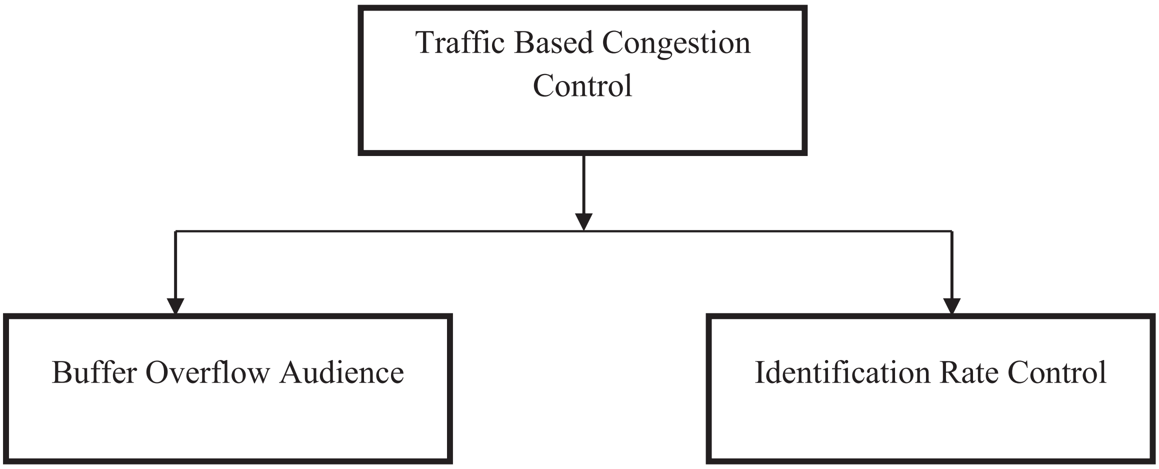

Figure 1. Congestion control methods.

congestion has already occurred, the system detects where it has happened, monitors its state and controls its consequences. In a buffer overflow scenario, data transmitting rates are reduced on the nodes whose buffers overflow or re-transmissions are performed via other alternative channels. In the proposed method, traffic was controlled at the node level. During the control process, a buffer overflow was concentrated particularly instead of individual rate control.

The most popular approaches that are mainly used to avoid network congestion are: limiting the traffic from source (or) use of more resources. Buffer overflow audience and identification of rate control are the two types which help to handle the traffic based congestion shown in Figure 1.

Congestion control was implemented at the node level in the proposed work because congestion is generated by a buffer overflow in the node, resulting in packet loss and increasing the queuing latency. When a buffer overflow occurs, data packets are discarded, which negatively impacts the application because the throughput is limited to the node's maximum data sending rate. Therefore, estimating network traffic at the overloaded node is essential to ensure reliable communication between the sensor nodes in WSNs. Consequently, clear information for traffic accommodation or dropped packets must be gathered to provide the appropriate traffic load. To counter this, a transmission adjustment and re-transmission approach is to be used which can reduce the data rate of the transmitting nodes.

2. Determination of node deployment for feasible communication

The selection of deployment structure for the sensor node is extremely application and environment-oriented. Node placement schemes provide decisions to the network created for the process and Figure 2 Shows the basic deployment strategy for the sensor node. The choice of positions of the particular node usually depends on the network condition. Considering the fixed environment, deployed nodes remain unchanged for the entire life of the network. Area coverage and inter-node distance are few existing standard metrics for node deployment. Static network operation models often assume systematic data collection. Most critical environmental analyses are carried out in a static environment that helps obtain a viable solution than a random network. The optimization was carried out in the proposed method at the time of network operation.

2.1. Transmission rate adjustment

The proposed approach is suitable for the static types of deployment and in avoiding congestion at every hop in the WSNs by adjusting the transmission rate. To adjust the local channel access probability high traffic congestion control (HTCC) approach interchanges the channel information with the transport layer. When congestion occurs in the static environment, the congestion notification can be promptly rendered to the upstream nodes; by doing this constantly local congestion may be mitigated, and the local node buffer queue can be avoided being overflowed. To handle the congestion problem and to maintain network stability, the HTCC algorithm dynamically regulates the channel access priority multiplicatively or decreases the data transmission rate linearly. The reason behind the standard fluctuation in transmission rate changes from high to low or low to high, which depends on downstream node information. The traffic information about the every single node was transmitted through the upstream node. Consider normalized queue length as B, which is due to the traffic loading. The information of traffic loading is estimated based on this B congestion degree level at every sensor node. The queue length field defines the number of packets at node n.

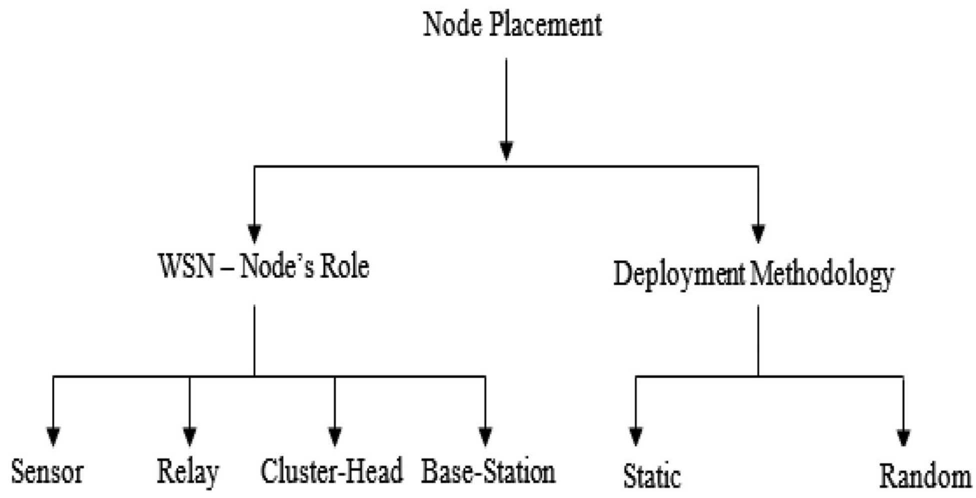

Figure 2. Node deployment methodologies.

$N_q(n) = Q(n)$. The normalized buffer occupancy ratio of n node is defined, and the buffer size of node $n\ (Q\ (n))$ is as follows:

$$B_r(n) = \frac{Queue\ buffer\ contains\ no\ of\ packets}{Size\ of\ buffer\ at\ n\ Node} \tag{1}$$

The traffic information for the node within the range of [0, 1] is denoted by a value of Br (n) and obtained by Equation (1).

On the other hand, the queue length for each node is slowly becoming a reasonable measure for identifying the traffic situation. To tackle the high traffic issue congestion degree field is considered as a metric. During the communication, congestion degree is indicated the fluctuated status of the queue buffer for the specified time. Calculation of the average processing time of each packet congestion degree is considered to be a performance metric. Node congestion and buffer status changes are defined and determined by B, C and R as the increment or decrement in data transmission rate. The traffic load information helps to determine the limited amount of data to be transmitted. Concurrently values of B, C and R determined the packet loss or the packet re-transmission in the network.

2.2. *Transmission rate adjustment based on HSA-SVM*

HSA has been used for the optimal sensor network design in the proposed method, and providing the best-fit individuals is similar to the choice in genetic algorithms (GA). HSA includes the separate portion to store the Harmony Memory (HM) where the predefined harmonies (N) have been stored. Harmony Memory ensures best harmonies can always be transferred to the new HM after finding the best-fit source. In HSA, a feasible solution is called harmony, and each decision variable of the solution corresponds to a note. Previously referred to as GA, the HSA method is a random search-based approach. And this approach continuously filters the buffer space and always ensures the availability to the next transmission, which supports the networks to avoid the overflowed data transmission. Figure 3 depicts the workflow of HSA during classification. Initially, the model was constructed, and it will be tested accordingly. Since SVM performs well on small datasets; therefore, to predict the amount of packet loss based on the given data for C and R, the proposed method utilizes SVM. In general, HSA does not require any pre-domain knowledge for performance evaluation, such as objective function. If the objective is to minimize or maximize fitness with the decision (d) then the following Pseudo code explains the operation of HSA.

Algorithm HSA Pseudo code

```
Begin;
Initialize objective function
Initialize rate of Harmony Memory
Initialize required parameter & Pitch rate
Initialize random harmonies
While t = max of condition
{
    While i < = variables initialized size
{
    if rand Harmonies are less than harmony memory
{
      Select the value from initialized harmony memory
    if rand harmonies are less than the pitch rate
{
      Add the certain or required value to get satisfied
}
    end if
    else
      again choose a random value of harmonies
}
    end if
}
    end while
      Accept the new harmony solution only if better
}
end while
Analysis of the current best solution
end while
```

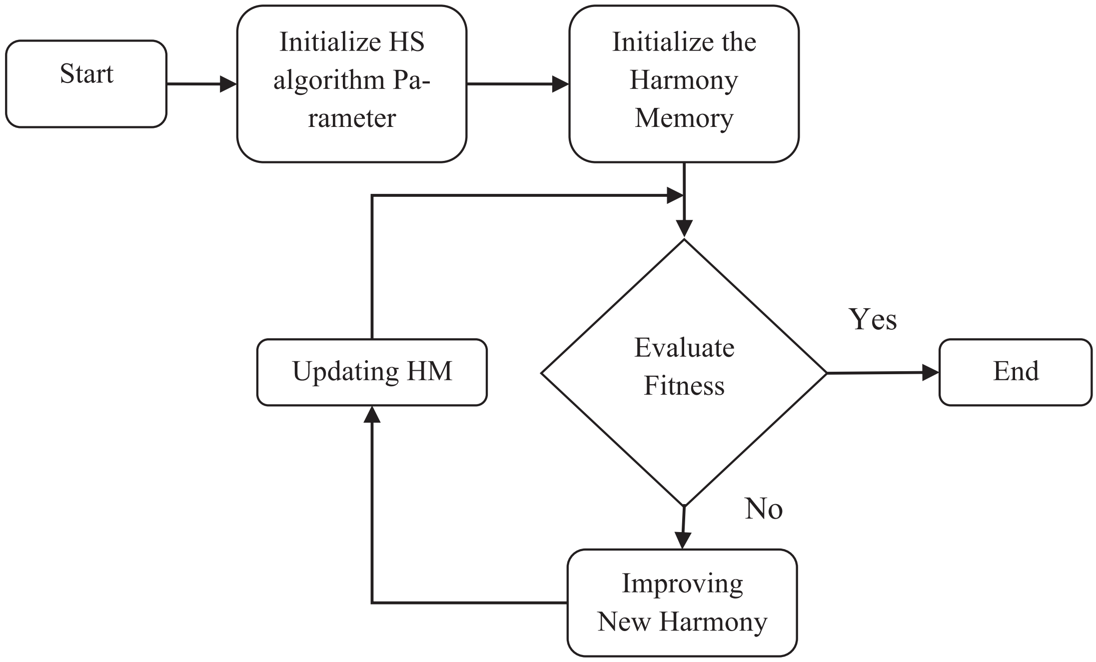

Figure 3. Generalized work flow of HSA.

Although it has distinctive features of computational simplicity for a predetermined deployed network, it mainly obtains re-transmission values based on each node's different B, C and R values.

2.3. Comparison of musical and optimization similarities

- Aesthetic evaluation determines the quality of harmony in the musical process. Likewise, the objective function value determines the quality of a solution vector in an optimization process.
- The ultimate goal of the musical process is to obtain the best (outstanding) harmony. The ultimate objective of an optimization process is to obtain the global optimum.
- During the musical process, musicians modify the pitch of their instruments, whereas an optimization algorithm modifies the decision variables values.
- In the musical process, any attempt to play a harmony is referred to as practice. Each effort to update a solution vector in optimization is referred to as iteration.

These rules are the main body of the HS algorithm Figure 3 depicts the workflow of HSA during classification; initially, the model was constructed, and it will be tested accordingly. Since SVM performs well on small datasets; therefore, to predict the amount of packet loss based on the given data for C and R. In general, HSA does not require any pre-domain knowledge for performance evaluation, such as objective function.

3. Performance evaluation

This section verifies the reliability of the proposed scheme through simulation and comparison of the performance with several known methods.

3.1. Simulation environment

Simulation studies were carried out to evaluate the proficiency of SVM, and the comparison of other classification techniques was evaluated by using MATLAB. The modified data sets [3] are used for reading purposes. For the simulation purpose, 80 percent of a training phase and 20 percent of the testing phase have been taken respectively with 400 inputs. Subsequently, the proposed method rewrites the training phase data by using SVM. Packet loss values are calculated on the basis of values B, C and R during the maximum process iteration, and the numbers of search agents taken are 50 and 5, respectively. Initially, the data values are labelled as 1 for zero re-transmission, and for further transmission, other data are labelled as -1.

Since the data complexity is high in most complex situations, only the SVM classification tool can provide the boundary for the different classes to provide a viable solution. Figures 4 and 5 shows the result of training data and the actual data obtained by HSA-SVM. The red lines represented the actual data matched by HSA-SVM, respectively. Figures 6 and 7 display the test compliance and the actual data by red and blue lines. The horizontal axis denotes the available data and the vertical axis displays the amount of the packet loss.

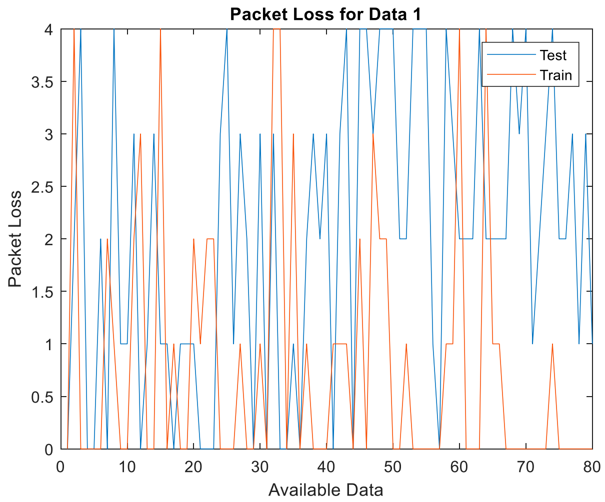

Figure 4. Data compliance in HSA-SVM.

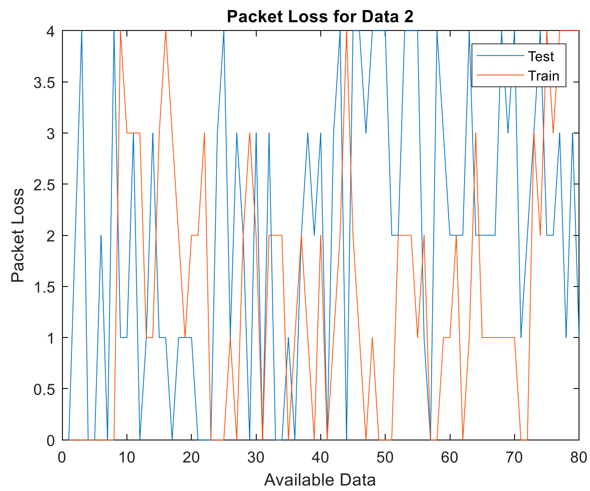

Figure 5. Data compliance in HSA-SVM.

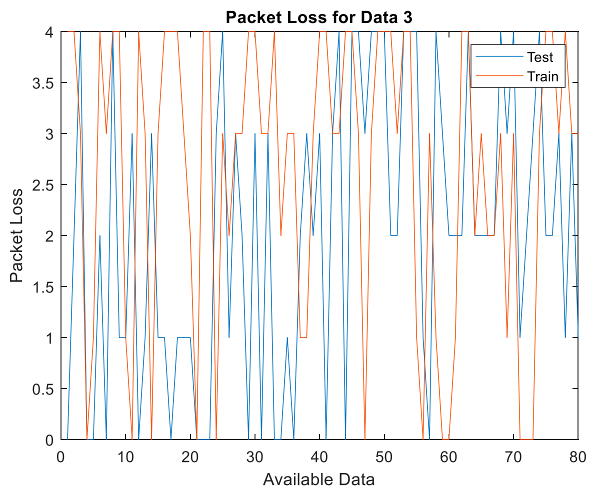

Figure 6. Data compliance in HSA-SVM.

3.2. *Comparison of other classifiers with SVM*

Different error rates are calculated for the static environment with other classification methodologies like k-Nearest Neighbor (KNN), Naive Bayes (NB), Random Forest (RF) and GSVM to assess the quality of

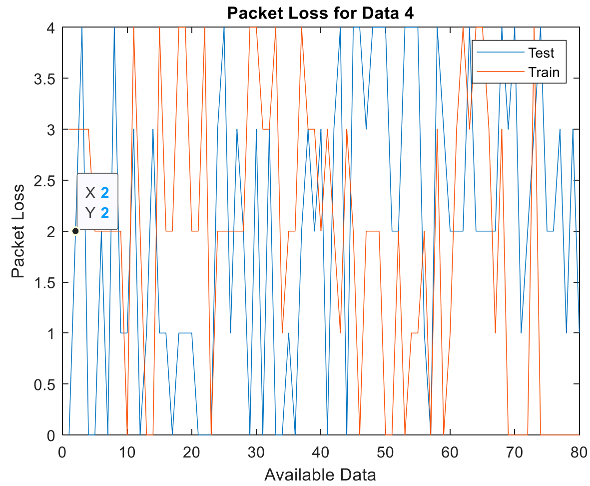

Figure 7. Data compliance in HSA-SVM.

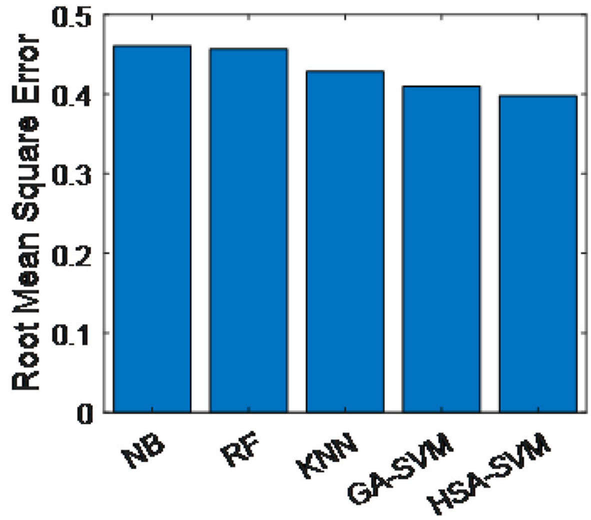

Figure 8. Root mean square erro.

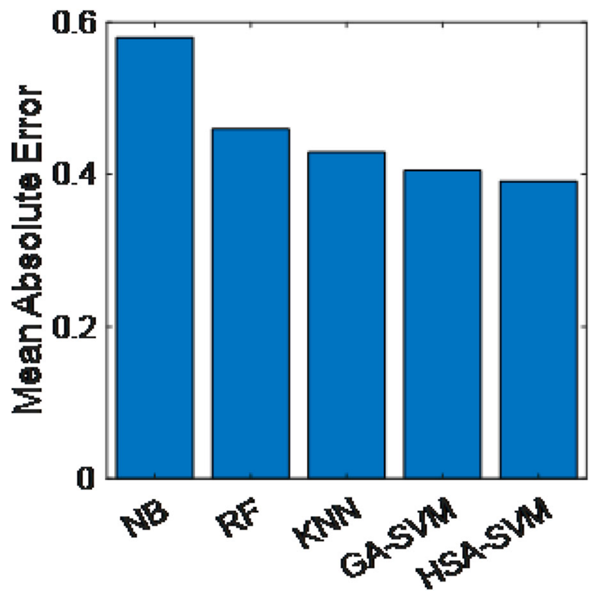

Figure 9. Mean absolute erro.

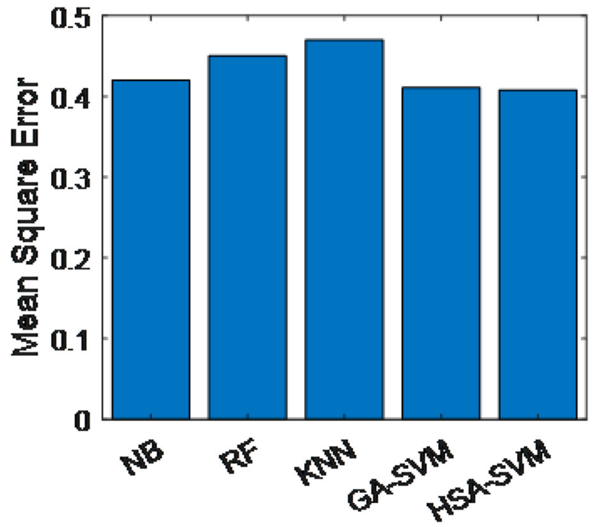

Figure 10. Mean square error.

Table 1. Errors of all classification.

	Random Forest	Nave Bayes	k-NN	GA-SVM	HSA-SVM
RMSE	0.457	0.461	0.428	0.410	0.398
MSE	0.452	0.421	0.470	0.411	0.408
MAE	0.468	0.581	0.429	0.405	0.391

the proposed approach. For the evaluation purpose, similar data have been taken for all the methods during the training and testing phases. The bar plots Figures 9, 10, and 11 depicts the performance of KNN, NB,RF,GSVM,HSVM with the given data set.

1. Random Forest: A numerous trees are comprised in Random Forest (RF). The votes of each tree do classification, and the votes are full features oriented. However, RF falls short of producing more accurate results to the proposed techniques.
2. Naive Bayes: NB is an added efficient classification method; the method of delivering a prediction outcome is based on the conditional probabilities strategy. The accuracy is the best feature of NB, which is suitable for a real-world situation. The working principle of NB is the statistical assessment of each feature independently on the given data. This has established a strong correlation among the factors that were made. NB handles the features autonomously and presumes the occurrence of feature is un-associated to the other features.
3. k-Nearest Neighbor (k-NN): The prediction principle of this method is based on the voting of the closest neighbours. Here, the K value impacts its closest neighbours, and the predictions' accuracy helps measure the divergence in relation to a specified distance and assigns a class to the instance according to the neighbours' votes (Figure 8).

Simulation results show performance of HSA-SVM significantly performs better than the other classifiers. The deployment strategy supports the proposed method to achieve the congestion problem. Similar datasets have been considered for a comparative analysis of all the preferred classifiers. However, HSA-SVM proceeded to a more precise classification with fewer errors than any other method HSA efficiently classifies the continuous given data and provides the significant result.

Table 1 shows the overall error rate of Mean Square Error, Mean Absolute Error and Real Mean Square Error displayed for RF, NB, K-NN GA-SVM and HSA-SVM.

The observation from Figure 11(a) and Figure 11(b) shows the minimum hop and minimum latency delay in communication of the proposed method. Furthermore, the simulation result shows that choosing the best communication path significantly impacts packet loss. The packet identification is done and forwarded through uninterrupted path1 and path2 with modified data.

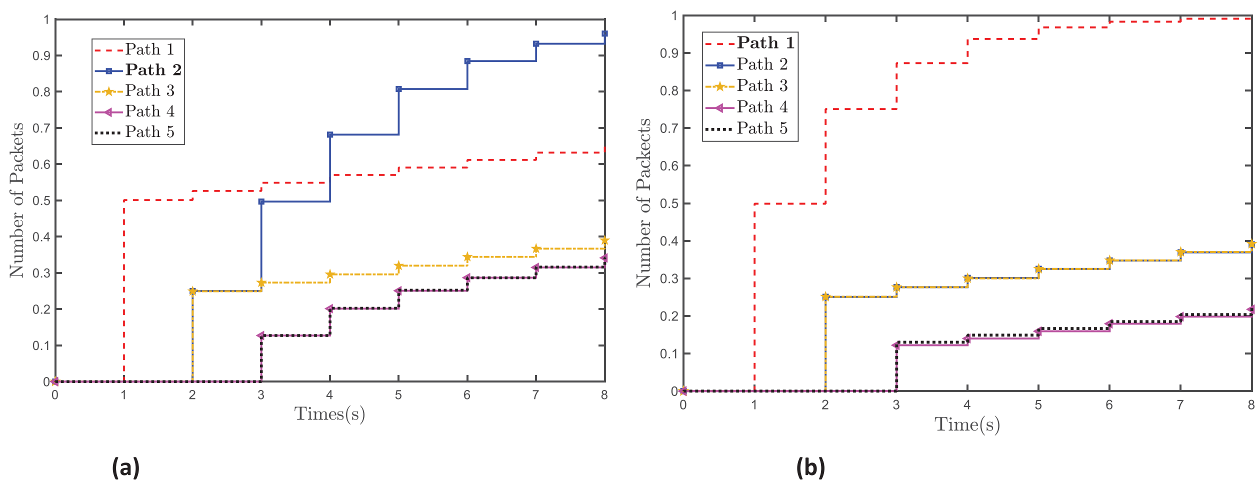

Figure 11. (a) Minimum hop path identification (b) Minimum hop path identification.

4. Conclusion

The proposed method modifies the data transmission rate of each node by considering the traffic in both the current node and the downstream nodes with HSA optimization algorithm. The primary objective is to control high traffic congestion in communication by adjusting the transmission rate in the static WSNs. To achieve this, SVM classification method is used for complex data analysis in a specific environment. HAS algorithm has been used for tuning purposes and may have features to reduce the error of classification by continuously filters the buffer space and always ensures the availability to the next transmission, which supports the network to avoid the overflowed data transmission during the communication. The result of simulations shows the proposed hop-by-hop method effectively addresses the complex data in terms of classification error.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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