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Optimized Support Vector Machine Based Congestion Control in Wireless Sensor Network Based Internet of Things

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Abstract – As the Wireless sensor network (WSN) has significant part in Internet of Things (IoT), it is utilized in various applications such as sensing environment and transmitting data via the internet. Nevertheless, due to the problem of heavy congestion, WSN based IoT obtains longer delay, higher ratio of packet loss and lower throughput. Although machine learning algorithms have been presented by researchers for detecting the congested data in IoT, detection accuracy is further to be improved. So, to control the congestion in WSN based IoT, artificial flora algorithm (AF) based support vector machine (SVM) is presented in this paper. To improve the performance of SVM, penalty parameter and kernel parameter of SVM is optimized using AF algorithm. In this proposed SVM-AF, the performance factors are given as input such as queue size (que), packet loss (pkt loss), cwnd (congestion window size), and throughput (throu). Based on these input factors, the prediction model SVM-AF predicts the congested data and decides whether to offload each device task to the server. Simulation outcomes show that the proposed SVM-AF outperforms the model such as Genetic Algorithm based SVM (SVM-GA) and SVM based on throughput, energy consumption, delivery ratio, and overhead.

Index Terms – WSN, IoT, Congestion Control, Support Vector Machine (SVM), Artificial Flora Algorithm (AF).

1. INTRODUCTION

Wireless Sensor Network (WSN) is one of the ideal models of IoT that comprises an immense number of sensors in a focused zone [1] [2]. It is utilized to give constant services of wireless monitoring, focusing on tasks in dangerous or confined areas where the inclusion of a person could be unsafe. The thought behind this sending is typically to gather significant data concerning the event of a certain occasion for specific applications. WSN conveys a many-to-one information-driven methodology where each node can agreeably connect to forward the sensed information to a destination node [3].

IoT assists various human existence applications, simplifying their reality, more got and more awesome. For e.g, shrewd metropolitan local area, transport and residents are various applications [4] [5]. Due to the assistance of IoT, the metropolitan zone can be upgraded at various levels by upgrading the structures, enhancing public vehicles, diminishing congestion of traffic, and shielding residents who are healthy and continuously busy with the network. In a specific case, a gigantic measure of IoT devices is portrayed by less storage and less operation speed prompting traffic congestion when numerous such devices attempt to connect. The data packets forward by the related device in the IoT system have fewer payloads and afterward, because of congestion, the misfortune of packet brings about costly retransmissions prompting extra delays and tremendous overheads [6-8].

A few components have been coordinated and overseen by the same token proficiently or inertly utilizing an alternate section of the network to manage congestion. Packet loss is among the most normally utilized congestion indications. At the point when a source forwards a packet, it hangs firmly by keeping a clock at its end for a proper proportion of time for an objective certification. Assuming no certification is acquired inside this length, packet of it will be confirmed lost because of network congestion. The congestion control methods consider expect responsibility for diminishing network congestions at whatever point a packet loss is separated. The instrument that depends on packet losses to separate network congestion demonstrates it is of no utilization in IoT network since (I) these parts expect packet loss to happen because of congestion that isn't legitimate for lower power and loss network, for example, loss of packets might happen because of connection error or weak quality of signal, and (ii) postponing the congestion response until the packet loss happens. So, Packet loss is one of the most normally utilized congestion signals. So, to overcome this congestion control, the following contributions are presented in this paper.

➤ For offload loaded data packets, optimized SVM (OSVM) is presented in this paper. The performance of the SVM is optimized using the AF algorithm is applied.

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➢ By presenting this decision model, the congested data packets are offloaded from the IoT devices.

The remaining sections of the article are sorted as follows. Section 2 surveys some recent literature that presented congestion control in IoT and WSN. Section 3 proposes an optimized support vector machine (OSVM) based congestion control in IoT. Results of the work are depicted in section 4. The conclusion of the work is explained in section 5.

2. RELATED WORKS

In this segment, congestion control in IoT and WSN based works of literature are reviewed. P. V. Venkateswara Rao, Kalpana. R and P. Kuppusamy [9] had the objective to reduce the operation time of traffic signals in IoT. To obtain their aim, they had presented an innovative smart system for traffic control with wireless traffic smart server. Using this system, the transition of the vehicle was captured. Then, the high-speed vehicles were tracked with this captured information. By presenting an optimized regression algorithm, the authors had collected multi-path data as well as they had estimated single-point nifty decisions with the density of vehicles. Because of the proposed scheme, the authors had reduced the operation time of the traffic signal. However, delivery ratio is to be improved.

Zhili Xiong, Shaocheng Qu, and Liang Zhao [10] had aimed to enhance the throughput of the WSN network by reducing the problem of congestion. To attain this aim, the authors had proposed a fuzzy sliding mode congestion control algorithm which was abbreviated as FSMC. Initially, they had presented a novel cross-layer congestion control structure between MAC and transmission layers. Besides, they had combined sliding mode control and fuzzy control and were named fuzzy sliding mode controller. Using this algorithm, the buffer queue length of congested nodes was controlled. Because of the proposed scheme, they had achieved better throughput. Nevertheless, accuracy of the proposed model is further to be increased.

Azham Hussain *et al* [11] had aimed to achieve efficient delay less service and traffic handling among the number of IoT devices. To achieve this objective, they had proposed an adaptive off-loading depend on the genetic algorithm which was denoted as GA-OA. Using this offloading design, the authors had avoided delays in the process of requests. Also, it had improved the rate of success of the requests of IoT. The performance of the fitness of GA was distributed between the gateways. Besides, it satisfied the various communication metrics. The GA had improved the request-response rate by balancing the solutions of optimal and sub-optimal. Because of this proposed method, they had attained a better ratio of request success. However, the authors have to focus to increase the network lifetime.

M. Swarna and T. Godhavari [12] had the objective that to manage the congestion of WSN based IoT networks. As CoAP is the effective data protocol for controlling congestion in IoT, the authors had used it in their work. They had reduced the consumption of memory utilization and had reduced the energy consumption of the network with the squat overhead of CoAP. Using the efficient technique, the authors had predicted the congestion control. The congestion control scheme had used different margins actualized utilizing CoAP. Due to this proposed method, they had decreased power consumption and latency. However, delivery ratio of the network is further to increased.

Soulmaz Gheisari and Ehsan Tahavori [13] had aimed to increase the high-level intelligence of IoT for congestion control. So, the authors had a cognition technique in IoT. Using cognitive systems depend on learning automata, cognition was added to IoT. Then, the authors had proposed an innovative cognitive method named Cognitive Congestion Control with a game of Learning Automata. To all controllable parameters, Learning Automata was applied. Among the possible values of every automaton, the best one was learned to increase the network performance. Results of the article showed that the proposed scheme achieved better throughput and reliability. Nevertheless, delay of packet delivery is to be decreased.

Faisal Naeem, Gautam Srivastava, and Muhammad Tariq [14] had aimed to improve the execution of the Multipath Transmission Control Protocol abbreviated as MPTCP based congestion control. So, to obtain the aim, the authors had proposed a new fuzzy normalized neural network that depends on adaptive actor-critic deep reinforcement learning network depends on model-free SDN. Due to the proposed method, the authors had achieved better throughput. However, the authors have to focus to increase the accuracy as well as to decrease the delay of packet delivery.

Although above research works attained better results, detection accuracy is further to be enhanced. So, to enhance the performance of congestion control in IoT, an optimized or improved machine learning algorithm is to be presented. Thus, an optimized SVM algorithm is presented in this work. To enhance the detection accuracy of SVM, the tuning parameters of it are optimized using AF algorithm.

3. OPTIMIZED SUPPORT VECTOR MACHINE BASED CONGESTION CONTROL IN IOT

3.1. Overview

To overcome the problem of heavy congestion in IoT networks, an efficient method is to be presented in our research work. To reduce the data congestion in the WSN based IoT network, an optimized support vector machine (OSVM) is proposed in this research work. The number of tasks or data from the IoT devices is taken as input for the

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machine learning algorithm. Depend on the input data, the proposed machine learning algorithm decides whether to offload each device task to the server. To enhance the operation of the proposed OSVM in terms of accuracy, an AF algorithm is presented. Using the algorithm, the penalty parameter and kernel parameter of the SVM is optimized. The proposed decision structure is trained as well as tested depend on the input features such as cwnd (congestion window size), packet loss (pkt loss), queue size (que), and throughput (throu). Figure 1 shows the architecture of the presented scheme.
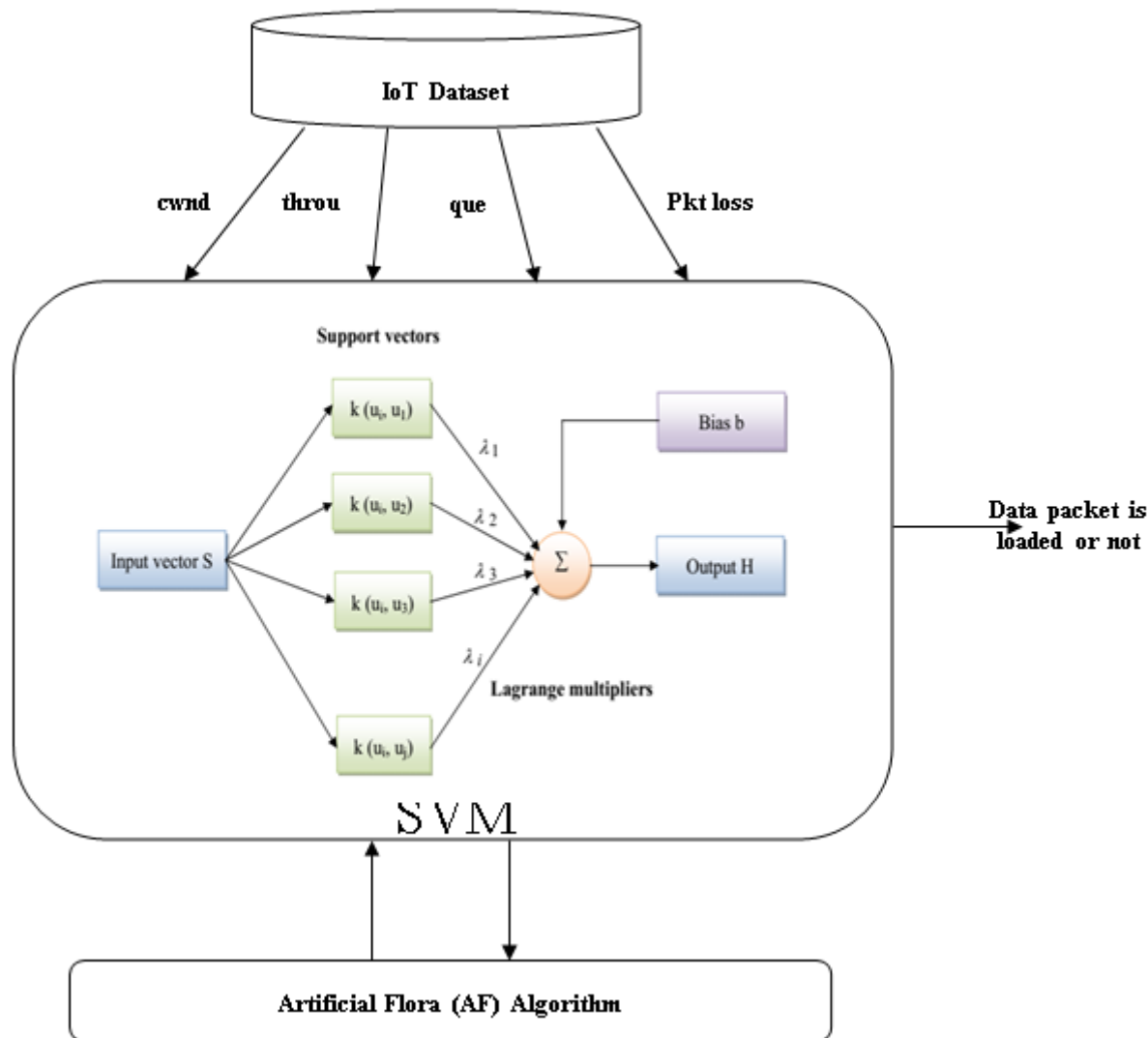

Figure 1 Architecture of the Proposed Scheme

3.2. AF Based SVM for Congestion Control

SVM: SVM is designed for the analysis of the linear two-class with an optimal splitting hyperplane. The margin of the hyperplane is maximal. The ability of the SVM is enhanced using the kernel trick which is utilized to map the input features into a high dimensional space of feature when the classifier couldn't separate the training data linearly. In this work, SVM is used for offloading the task of each device to reduce congestion in IoT.

The collected and measured features are given as input to the SVM. These features are represented in equation (1),

$$S_t = \{(u_1, v_1), (u_2, v_2), \ldots, (u_n, v_n)\} \tag{1}$$

Where, u_i denotes the training samples which has a class labeled by $v_i \in \{+1, -1\}$ and is represented in equation (2),

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$$u_i = \{ \; cwnd, throu, que, pktloss \}_i \tag{2}$$

The input features of SVM are mapped into a high dimensional space of feature using kernel function for the training data which are not separable linearly. The definitions of the kernel functions which are currently used in the SVM are given as follows,

The radial basis kernel function is represented using (3),

$$k(u_i, u_j) = \exp\left(-\gamma \|u_i - u_j\|^2\right) \tag{3}$$

The definition of the splitting hyperplane is given in equation (4),

$$H(u) = b + u * w^T \tag{4}$$

Where, b denotes the bias vector and w denotes the m dimension vector.

By minimizing the function defined in equation (4), an optimal hyperplane is obtained using (5).

$$U(b, w, \vartheta) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\vartheta_i \tag{5}$$

Subject to the conditions (6)

$$v_i\left(b + u_i w^T\right) \geq 1 - \vartheta_i \qquad for \; i = 1,.....,n \tag{6}$$

Where, ϑ_i represents the nonnegative slack variables which are used to calculate the misclassification degree of the input samples u_i, C denotes the penalty parameter which is used to estimate the trade-off between the minimum error of training and maximum rate of classification. The attained optimal hyperplane is also known as the soft-margin hyperplane in which w is denoted as the soft-margin.

As equation (5) is a quadratic optimization problem, it is complicated to attain the solution due to $\|w\|$. So, equation (5) can be defined with the Lagrange function for solving the optimization problem defined in section (7)

$$\max_{\lambda, \rho} \min_{w, b, \vartheta}\left\{\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\vartheta_i - \sum_{i=1}^{n}\lambda_i\left[v_i\left(u_i*w - b\right) - 1 + \vartheta_i\right] - \sum_{i=1}^{n}\rho_i\vartheta_i\right\} \quad \lambda_i, \rho_i \geq 0 \tag{7}$$

Here, λ_i and ρ_i denote the nonnegative Lagrange multipliers.

Subject to the conditions (8)

$$\sum_{i=1}^{n}\lambda_i v_i = 0, \qquad C \geq \lambda_i \geq 0 \quad for \; i = 1,....,n \tag{8}$$

At last, an optimal decision hyperplane is attained using equation (9),

$$H(u) = \sum_{i \in U} v_i \lambda_i k(u_i, u_j) + b \tag{9}$$

In this work, the radial basis kernel function $k(u_i, u_j)$ is used. The term U represents a vector related to the nonzero Lagrange multipliers λ_i which are also known as support vectors. Figure 2 depicts the schematic diagram of the SVM.

Using this SVM, data packets from an IoT device are classified as loaded or not to offload the data packets to the server. However, to enhance the classification performance of SVM, the penalty parameter (C) and kernel parameter (γ) are to be optimized. So, to optimize, these parameters, Artificial Flora (AF) algorithm is used. The explanation of this algorithm is presented as follows.

Artificial Flora (AF): Plants have an assortment of methods for spreading seeds. Dispersal of seed can be separated into 'autochory' and 'allochory'. Autochory alludes to plants that spread without help from anyone else, and allochory implies the plants spread via outside powers. Autochory gives the conditions to plants to relocate to a more reasonable climate self-sufficiently. Then again, allochory gives the conditions to plants to move to farther and strange districts. These methods of propagation broaden the extent of the investigation of flora and decrease the chance of the termination of flora. As flora relocates to a new climate because of the change of environment, every factor in the flora will migrate too. Along these lines, the relocation of flora can change the conveyance region and incite the development, annihilation, and flora rebirth. A plant can't migrate and it doesn't have insight, yet flora can track down the good spot to exist with the support of seeds spread and regenerating. The AF comprises four fundamental components: unique plant, offspring plant, plant area, and distance of propagation. Unique plants allude to the plants which are prepared for spreading seeds. Offspring plants represent the unique plants' seeds, and they can't spread seeds at that time. Plant area represents plant's area.
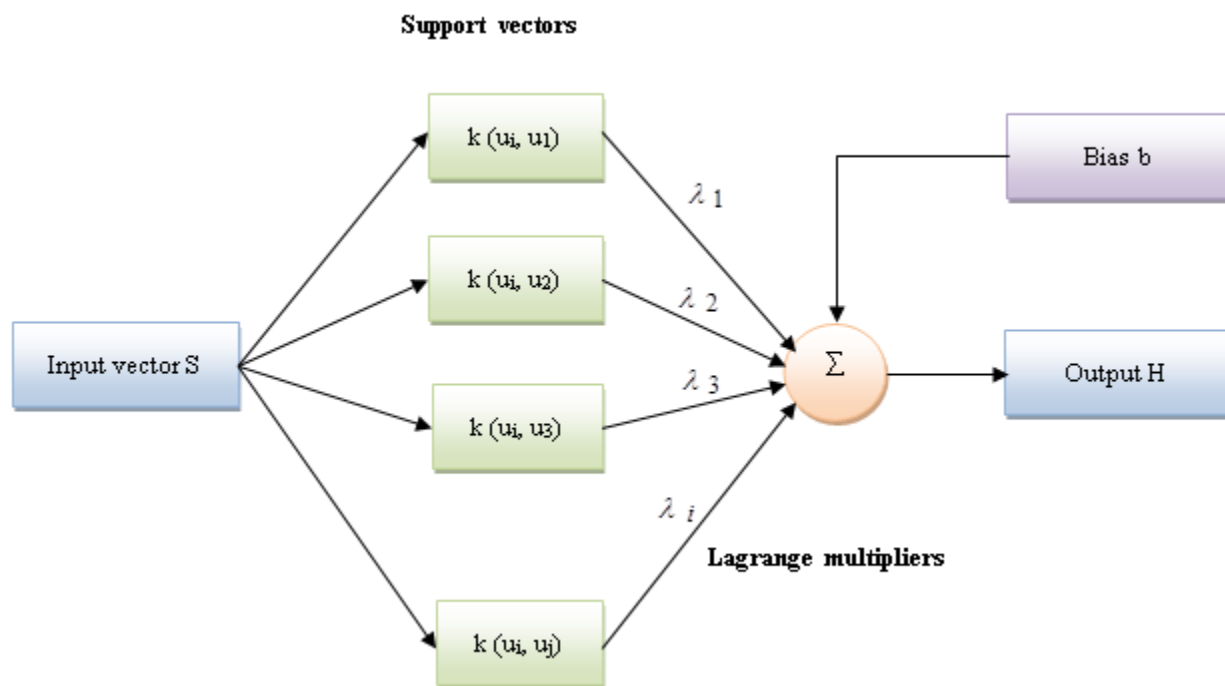
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Figure 2 Schematic Diagram of the SVM

The distance of propagation alludes to total where the spread of seed is possible. AF has 3 significant behavioral standards: behavior of evolution, the behavior of spreading, and behavior of selection.

Phases for optimizing the parameters of SVM using AF are depicted as follows:

Initialization: In this algorithm, unique floras are initialized randomly as candidate solutions, which denote N plants in the flora. In the work, the parameters C and γ are considered as solutions. Initialization of these solutions is represented in (10).

$$A = \{A_{i,j}\} \qquad 1 \le i \le Q; 1 \le j \le A \qquad (10)$$

Where, A denotes the count of solutions, Q denotes the dimension of the problem of optimization, and $A_{i,j}$ depicts the matrix of the position of the unique plant in i^{th} dimension and j^{th} quantity of plant and is defined using (11).

$$A_{i,j} = rand(o,1) \times d \times 2 - d \qquad (11)$$

Where, d denotes the maximum limited region and rand (0, 1) represents the array of random numbers within (0, 1).

The behavior of Evolution: The distance of propagation that is developed from the spread distances of the parent plant and grandparent plant. It is estimated using (12),

$$d_j = d_{1j} rand(o,1) \times c_1 + d_{2j} \times rand(0,1) \times c_2 \qquad (12)$$

Here, c_1 and c_2 represent the learning coefficient, d_{2j} denotes the distance of propagation of the parent plant, rand(0,1) depicts the randomly distributed number within (0, 1) and d_{1j} represents the distance of propagation of the grandparent plant.

New grandparent's propagation distance is estimated using (13),

$$d'_{1j} = d_{2j} \qquad (13)$$

A new parent's propagation distance is calculated using the standard deviation of the position of the offspring plant and unique plant as defined in (14)

$$d'_{2j} = \sqrt{\frac{\sum_{i=1}^{N}\left(A_{i,j} - A'_{i,j}\right)^2}{N}} \qquad (14)$$

The Behavior of Spreading: Using the propagation function (15), the offspring plant's position is estimated using (15).

$$A'_{1,j \times m} = D_{i,j \times m} + A_{i,j} \qquad (15)$$
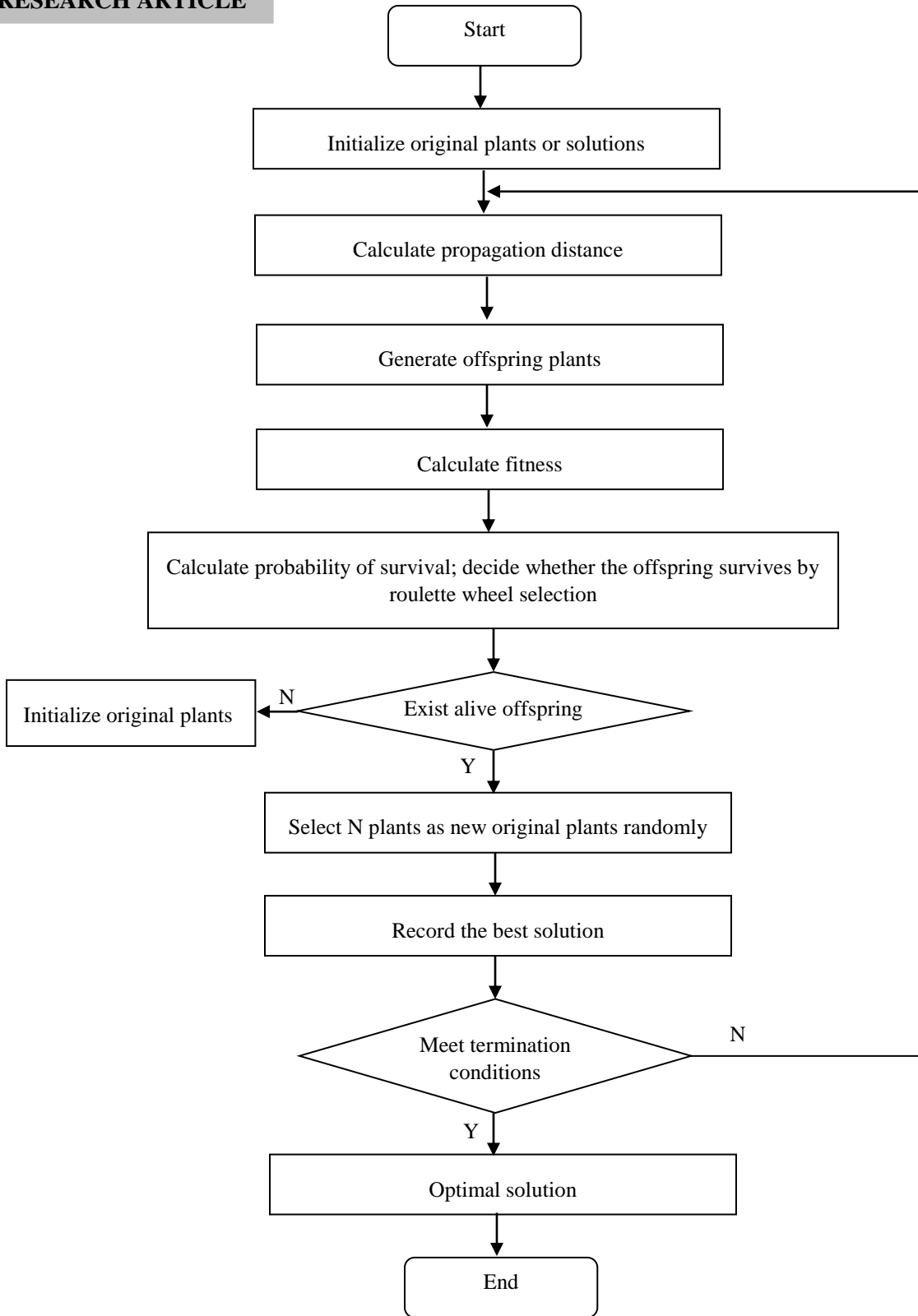
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Figure 3 AF Algorithm's Flowchart

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Here, m denotes the count of seeds, $A_{i,j}$ represens the position of the unique plant, $A'_{i,j \times m}$ denotes the offspring plant's position and $D_{i,j \times m}$ represents the Gaussian distribution.

Fitness: The optimal parameters of SVM are chosen by calculating the fitness of every solution. The calculation fitness is defined using (16),

$$Fit = Max(CR_S(t)) \qquad (16)$$

Where, CR_S defines the classification rate of the Sth set of training samples.

The obtained solutions are sorted based on the worst and best fitness. The solution is selected as the optimal solution if it has a maximum value of fitness. Using these selected parameters, SVM is updated. The solutions get updated it not satisfy the objective function of the algorithm.

The Behavior of Selection: Using the probability of survival, the presence of an offspring plant is estimated. It is defined using (17),

$$p = \left| \sqrt{\frac{F(A'_{i,j \times m})}{F_{max}}} \right| \times P_x^{(j \times m - 1)} \qquad (17)$$

Here, $P_x^{(j \times m-1)}$ represents the probability of selection. For attaining the best local solution, the P_x value must be higher. F_{max} represents maximum fitness and $F(A'_{i,j \times m})$ represents j^{th} solution's fitness.

A roulette wheel determination strategy is utilized to find the presence of offspring plants. It is likewise called the proportion select technique [15]. Its essential reason for existing is to "acknowledge agreeing on probability"; in other words, there are a few other options and each has its possible score. Notwithstanding, selection doesn't depend on the estimation of the score. Depend on the accepting probability, the selection is done. The more noteworthy the tolerant likelihood is the higher the score.

Termination: The algorithm is continued until finding the optimal solution. Else it will be terminated.

The overall steps of the proposed algorithm are described in Algorithm 1.

Input: Penalty parameter (C) and kernel parameter (γ)

Output: Optimal C and γ

1. Initialize N count of unique Flora or SVM parameters.

2. Calculate the distance of propagation using (14)

3. Calculate the offspring of the plant using (15)

4. Estimate fitness to each unique plant using (16).

5. If rand (0,1) > p

    Consider the Offspring plant is alive

6. Else

    Consider the Offspring plant has died

7. End if

8. Make new solutions randomly.

9. Consider the new solution as the optimal solution if it has the maximum fitness value.

10. Terminate the algorithm if the optimal solution is attained.

Algorithm 1 Optimization of Parameters of SVM Using AF Algorithm

Testing Phase: Finally, the trained or optimized structure of SVM is tested using the testing data samples. Depend on the input data packets, the optimized SVM outputs whether the data packet is loaded or not. If the packet is loaded, then the output is labeled as '-1'. Otherwise, it is labelled as '1'. At last, to the loaded data packet, priority is given and the packet is offloading to the server.

Flowchart of the AF Algorithm is shown in the Figure 3.

4. RESULTS AND DISCUSSIONS

The SVM-AF (AF-based SVM) for congestion control is simulated in NS2. In the search space of 1000m×1000m, 250 IoT nodes are used. Every node runs with a transmit power of 0.66W and also a receive power of 0.395W. The range of transmission of every node is 250 m. For routing, AODV protocol is utilized. Also, the two-radius radio propagation model is utilized. The simulation parameter and its value are shown in Table 1. The entire simulation is completed in 100 seconds.

Parameter	Value
Packet size	512bytes
Area size	1000m×1000m
Antenna	Omni Antenna
Initial receiving power	0.395W
Initial transmitting power	0.660W
Simulation time	100secs
Initial energy	10.3J

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MAC	802_11
Nodes	250
Radio propagation model	Two Ray Ground
Routing protocol	AODV

Table 1 Simulation Parameter and its Value

4.1. Performance Analysis

The proposed approach SVM-AF's performance metrics are appraised for varying nodes 50, 100, 150, and 200 nodes. Figure 4 and table 2 depict the output of the different techniques in terms of throughput. Because of the selection of optimized SVM parameters using AF, the prediction of congested packets is improved accurately. It leads to an increase in the throughput of the network. Also, compared to existing decision models SVM-GA and SVM, the throughput of the SVM-AF is increased to 5% and 23% respectively.

Figure 5 and table 2 depicts the comparison of the different techniques in terms of delivery ratio for the varying count of IoT devices. As shown in the figure, when the count of IoT devices increases, the delivery ratio of the network gets decreases. However, the delivery ratio of SVM-AF is increased to 10% and 18% than that of SVM-GA and SVM respectively. By detecting the congestion in the network using the proposed SVM-AF, the congested packets are offloaded, because of that, the source node sends the sensed data to the server with fewer amount of drops. So, the delivery ratio of the SVM-AF is maximized than the SVM-GA and SVM.

The comparison of the energy consumption of the different decision models for the varying count of IoT devices is depicted in figure 6 and table 2. Energy consumption is maximized when the count of IoT devices increases as shown in the figure. Nevertheless, compared to existing decision models SVM-GA and SVM, the energy consumption of SVM-AF is decreased to 79% and 86% respectively. As the congestion in the network is reduced by offloading the data packets, retransmission of failed packets is also decreased. So, the energy consumption of th network is decreased.

The comparison of the delay of various decision models for changing the number of IoT devices is displayed in Figure 7 and table 2. By avoiding the congested packets, the delay of data transmission is decreased. So, the delay of the proposed SVM-AF is 62% and 67% than that of SVM-GA and SVM individually. In Figure 8 and table 2, the comparison of the overhead of the various decision models for the varying count of IoT devices is shown. As depicted in the figure, overhead is maximized when the number of IoT devices increases. However, the overhead of SVM-AF is reduced to 39% and 46% respectively. The accuracy of the different prediction

models is depicted in figure 9. As depicted in the figure, the proposed decision model SVM-AF obtains 92% of accuracy while conventional decision models SVM-GA and SVM attain 89% and 85% of accuracy respectively.
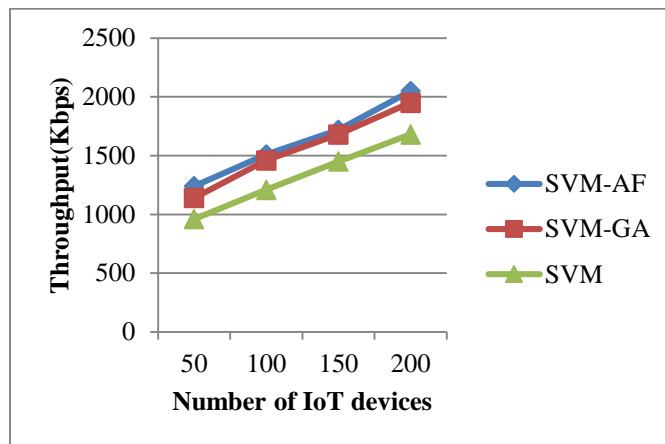

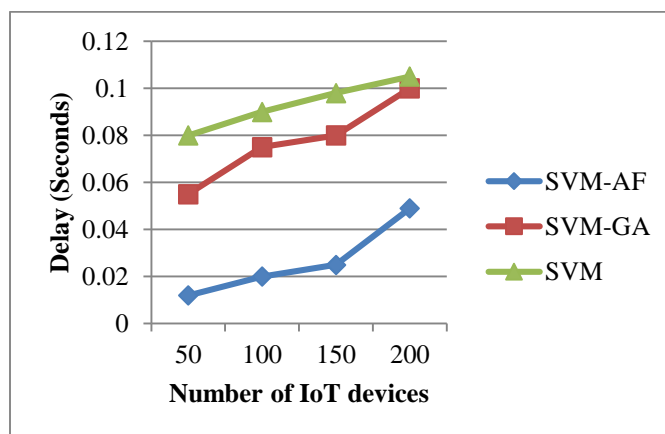Figure 4 Number of IoT Devices Vs Throughput
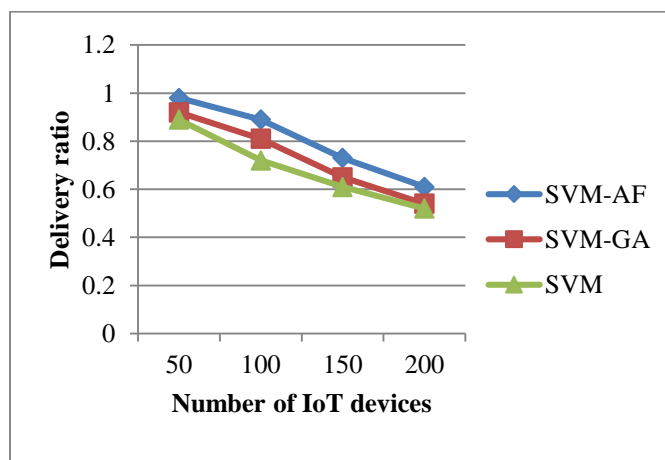

Figure 5 Number of Nodes Vs Throughput

Figure 6 Number of IoT Devices Vs Delivery Ratio

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No. of IoT Devices	Throughput			Delay			Delivery ratio			Energy consumption			Overhead		
	SVM-AF	SVM-GA	SVM	SVM-AF	SVM-GA	SVM	SVM-AF	SVM-GA	SVM	SVM-AF	SVM-GA	SVM	SVM-AF	SVM-GA	SVM
50	1240	1140	960	0.012	0.055	0.08	0.98	0.92	0.89	10	30	50	5	18	19
100	1510	1460	1210	0.02	0.075	0.09	0.89	0.81	0.72	10	48	70	10	19	20
150	1720	1680	1450	0.025	0.08	0.098	0.73	0.65	0.61	11	50	80	12	20	25
200	2050	1950	1680	0.049	0.1	0.105	0.61	0.54	0.52	12	78	100	20	25	28

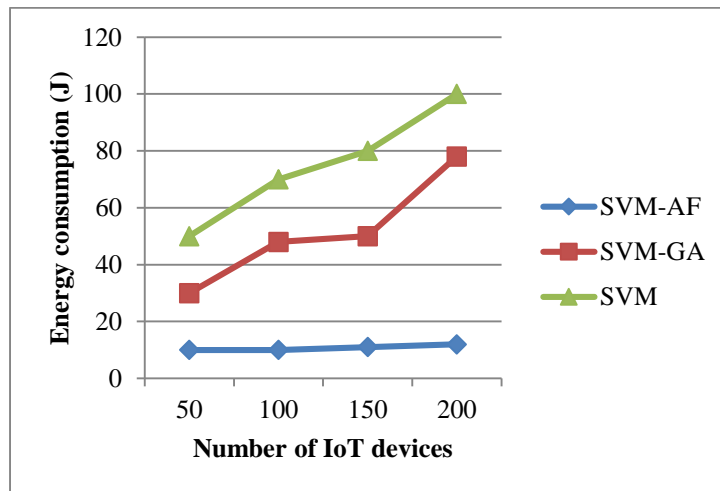Table 2 Performance Analysis of Different Models

Figure 7 Number of IoT Devices Vs Energy Consumption
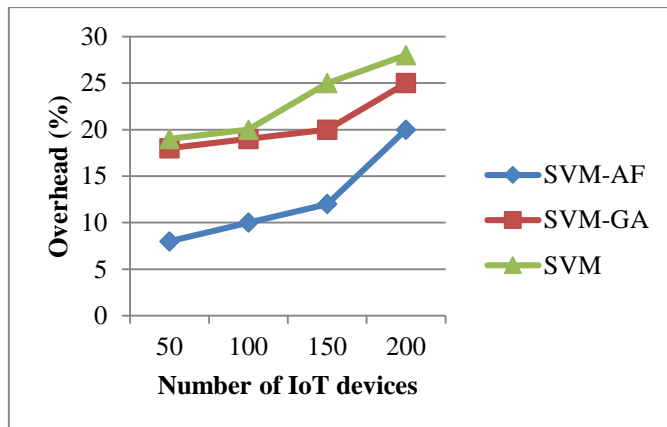
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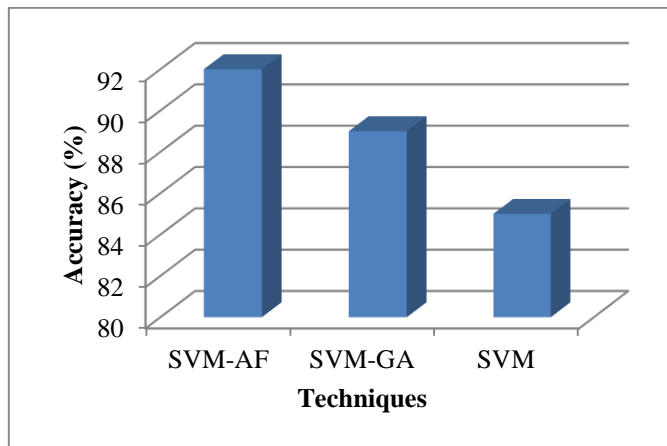

Figure 8 Number of IoT Devices Vs Overhead

Figure 9 Accuracy of Different Techniques

5. CONCLUSION

To control the congestion of data packets in WSN based IoT, artificial flora (AF) algorithm-based support vector machine (SVM) has been presented. The performance of the SVM has been improved by optimally selecting the parameters penalty parameter and kernel parameter of SVM using the AF algorithm. To this optimized SVM, the measured features such as queue size (que), packet loss (pkt loss), cwnd (congestion window size), and throughput (throu) have been given as input for both training and testing phases. By utilizing these input factors, congested packets from the sensor nodes have been predicted. The performance of the SVM-AF has been compared with that of the SVM-GA and conventional SVM. As shown in the results, the detection accuracy of the SVM-AF has been increased to 92% than that of the SVM-GA and SVM.

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