Boolean Spider Monkey Optimization Assisted Routing Integrated with Wireless Sensor Network

Ashwini[a], and Dr. N. Guruprasad[b]

[a]Research Scholar, Global Academy of Technology, Bangalore, Karnataka
[b]Professor, Global Academy of Technology, Bangalore, Karnataka

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 20 April 2021

Abstract: The Wireless Sensor Network (WSN) offers greater flexibility in network deployment, especially when powered by batteries. It offers solutions to the sensor nodes' energy consumption as it mainly operates as devices with faster data acquisition. Hence, it is difficult for the sensor nodes to carry such a computational burden from the source nodes to the target base station or the internet gateway. It is essential to maintain the routing paths as well as the balance of the sensor nodes. In this paper, we propose a Boolean Spider Monkey Optimization (BSMO) routing on WSNs is developed to maintain the stable routing path that matches the speed of input data acquisition. The sensor nodes help in data collection and acquisition and WSNs routes the data collected via hops between the source and sink nodes. The BSMO is responsible for controlling the data routing and matches the routing speed with data acquisition speed. Hence, the network is maintained in a stabilized condition. The simulation results are estimated in terms of average delay, throughput, and network energy efficiency. The result shows

Keywords*:* Boolean Spider Monkey Optimization, WSN, Energy efficiency, Networks, ML.

1. Introduction

Since the last decade, several research efforts have investigated emerging applications that allow heterogeneous devices to operate seamlessly in globally integrated communications platforms from smartphones and wireless sensors through to network-enabling physical objects. The new development of intelligent cities, which is conceived as smart, large-scale, and open environments capable of enhancing citizens' daily life, further enhances sensor node technologies research and related standards as an integral foundation for these new scenarios (Bellavista, P., 2013).

For detecting different types of industrial WSN sensor dates in surroundings, a sensor interface device is essential. It allows us to collect data from the sensor. We can therefore better understand the information about the external environment. However, the sheer diversity of WSN applications makes it increasingly difficult to define "typical" requirements for their hardware and software. In fact, the generic WSN components often need to be adapted to specific application requirements and environmental conditions (Kousik, N., 2021).

However, the acquisition interface can simultaneously collect multiple sensor data to comply meet the requirements of a long-term industrial environmental data collection so that more accurate and diverse data can be obtained from the industrial WSN (Bera, S., 2016; Elappila, M., 2018; Yuvaraj N, 2020; Capella, J. V., 2016; Fantacci, R., 2014). These ad hoc modifications have a negative impact on the overall reliability and maintenance, which in turn effectively reduce the use of WSN (Lazarescu, M. T. 2013). This requires a scalable and effective algorithm to handle such a number of nodes. Furthermore, the WSN can alter dynamically due to external causes or device designers. It can affect network routing, location, delay, cross-cutting design, coverage, QoS, quality of the link, detection of failures, and so on. Due to its highly dynamic nature, it may be appropriate to depreciate the excessive network reorientation, while conventional methods resulting in a dynamic network environment are specifically programmed for WSNs.

Machine Learning (ML) (Shanthamallu, U. S., 2017; Gowrishankar, J., 2020; Langley, P., 1995) is an automated method of enhancement or learning that is not specific. ML improved the performance, reliability, and economy of our computing processes. ML creates models automatically, easily, and reliably by processing even more complex data. This is primarily known as supervised, unregulated, semi-controlled teaching. ML is able to deliver detailed solutions through a performance enhancement architecture. It plays an important role in various areas such as engineering, medicine, etc. because of its interdisciplinary nature. ML has made recent strides in solving many WSN problems. Not only does the use of ML enhance WSN performance and restrict human interference or reprogramming. Without ML, it is not easy to access vast amounts of collected sensor data to collect useful data. Hence, in this paper, an ML assisted routing (Veerappan Kousik, N. G., 2020; Na, Z., 2018; Manikandan, R 2017; Kousik, N. V., 2020; Repoussis, P. P., 2010; Zhang, X., 2009; Jiang, B. B., 2011; Wang, X. M., 2010; Jiang, C., 2016; Russell, B., 2011; Prasad A.Y 2019; Prasad A.Y 2019) is enabled to overcome the issues related to WSN.

The main contribution of the work involves the following: Artificial Neural Network (BSMO) [9] is used for routing of high-speed data packets on WSN nodes and finally transmitting it to the cloud. The simulation results are conducted in terms of estimated terms of throughput and network energy efficiency.

The outline of the paper is given below: Section 2 compiles the proposed method. Section 3 evaluates the entire work and section 4concludes the work with possible directions for future scope.

2. Literature Review

This section performs a short survey of different ML and deep learning (DL) based BT diagnosis models available in the literature. In (Sharif M, 2020), feature extraction was applied where brain system interface which undergoes classification using support vector machine (SVM) and Linear Discriminant Analysis (LDA). In recent times, CNN is one of the popular mechanisms with respect to feature extraction under various studies like clinical images, video examination, and natural language processing (NLP). The key objective of CNN is to forecast the chief patterns and data from training images. For example, VGG Net, Google Net, and Alex Net are some of the effectual structures applied in image classification which is also employed for BT prediction.

In (Ezhilarasi, T. P.,2020), pre-processing as well as data preparation using 3D-filters and CNN with multipath and cascaded structures has been presented. In pixel, CNN structure was utilized for generating diverse portraits of same person with distinct poses. In (Seetha J, 2018), a pretrained CNN was employed for BT classification with DNN and SVM. Then, in (Ranjeeth, S., 2020), cascade CNN produced a room decoration. As CNN is expensive, developers concentrated in developing cost-effective methods with exact tumor classification. The common technique is to apply ensemble of tiny collaborative learners rather than using a hectic system, in order to deal with robust trainingexecution as well as convergence. Therefore, learning process of peer networks could be autonomous.

In (Zhang Y, 2018), a Kullback Leibler divergence has been applied for matching the probability estimates of peers in supervised learning. Besides, in (Kushibar K, 2018), multipath learners are involved in the outputs of shared layers. The main aim of this model is detecting the disorder robustly and maintains tumor development within a limited extent. A major challenge in ML model is to evaluate the data distribution. For instance, hardcoded associations between every image pixel and the neighbours are complicated to identify with no advanced knowledge. Additionally, autoregressive approaches are data-driven estimators used to identify these associations with typical information. Next, the produced results have enhanced images with limited noise and outlier. The density estimator tries to resolve various classifications, regression, missing data, and issues. In (Loganathan, J., 2016), a quantum variation Auto Encoder (AE) was presented where the latent generative computation which acts as a quantum Boltzmann machine. By the estimation of BT from MRI, tiny training inputs, various shapes of tumors, and irregular information could be identified for every class. Neural Autoregressive Distribution Estimation is one of the density estimators evolved from Restricted Boltzmann machines (RBM). It is used in estimating the density of binary, real-value data, and alternate network structures like CNN. Afterward, DNN is capable of handling nonlinear conversion, sequence modelling, representation learning and it is also stretchy for learning data from real-time classification as well as recommender systems.

3 Description of research work

In areas that require urgent data transmission, WSN uses opportunity-formed WSN clusters. It is simple, robust, and depends on a single hop and low-speed broadcast. The cluster formation protocol is reactively initiated by any WSN Node called CH which snoops on a route. The protocol in Figure 1 contains three phases.

The study uses three-phased models:

- Sensing plane,
- Control plane and
- Data plane.

The *sensing plane model* is the collection of multiple sensor node clusters that collects data from different physical environments.

The *control plane model* consists of a BSMO model that maintains the routing path by matching the data speeds of input Sensor nodes.

The *data plane model* helps in routing the packets from the collected Sensor node nodes for faster transmission of packets to the destination node.

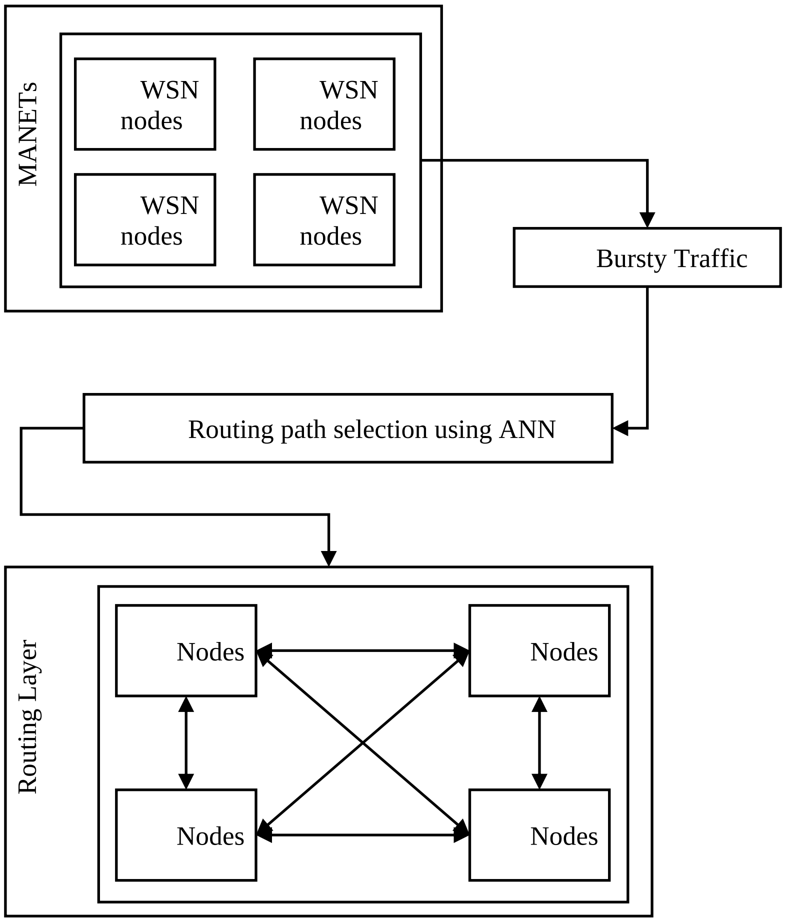

Figure 1. Architecture of the WSN model

In the first stage, the CH removes from the sniffed packet the gradients of the node that routed them and broadcasts a two-hop limitation to request additional nodes by asking them to join the new cluster.

The second stage involves sending a discovery message to nodes to get the best possible gradient between the nodes they can communicate; then compare this to the gradient that is declared on a Join request: in the cluster, only WSN nodes that can communicate better with sensor nodes participate.

The WSN Nodes will receive the application to join in the second phase. In the third and last phases of entering the new cluster, WSN nodes communicate to CH. The CH collects the responses from the cluster nodes and chooses to exit the node. By collecting replies from all the cluster nodes, CH can estimate the number of messages exchanged by WSN: appropriate policies can determine the length and guarantee energy demand for each of them.

4 Clustered Routing using BSMO

At the time of network deployment, the clusters are formed and the cluster formation is not predetermined at the initial stage of operation. The node deployment at the initial stage is performed randomly, with non-fixed nodes in each cluster, and the membership of nodes inside the cluster depends upon its initial location. Each cluster node is aware of its members. The proposed method uses the cluster head selection process by reducing energy consumption and communication delay. Hence, by taking into account the information like residual energy state, sensor node density, and neighborhood distance between the sensor and actuator nodes, the energy efficiency and reduced delay is achieved by computing the sensor node weight $W(i)$. The proposed method considers node beaconing to capture the above information. The cluster messages are exchanged between its cluster members at regular time intervals γ for the establishment and maintenance of cluster head election. The availability of sensor nodes is known to other sensor nodes by broadcasting this beacon message that carries QoS metric information. This message holds each sensor node state and hence the weights are computed using the following expression upon its reception by a cluster head or other sensor nodes.

$$W(i) = \frac{cN_i E_i}{D_i} + \frac{(1-c)k}{\sum_{j=1}^{k} H(i, a_j)}$$

where,

E_i represents the residual energy of sensor node i, and E_i has to be maximized to increase the lifetime of the network by providing priority to the actuator nodes for accessibility.

D_i represents the average values of computed distance between a node (i) and its neighboring nodes, and this should be minimized to reduce the communication delay with the actuator nodes and

N_i represents the total number of neighboring sensor nodes. Here, minimizing D_i and maximizing N_i will give priority to the connection between the packets.

k represents the total number of actuator nodes and

$\sum_{j=1}^{k} H\left(i, a_j\right)$ represents the total sum of distances between all actuator nodes and a sensor node i.

Finally, $c \in [0,1]$ is the coefficient value adjusted based on the application domain and the value should be maintained low to elect the cluster head that lies near to an actuator node. Increasing the value of c gives priority to connectivity and energy efficiency.

Once the weights $W(i)$ are computed, a predefined threshold weighted value (W_t) is used for the purpose of comparison. When the value of $W(i)$ is greater than the W_t, then the beacon message containing the weights of the neighborhood sensor node is broadcasted. The sensor nodes receive the beacon message and store it in local memory. Since it contains the weighted information of all the members in the cluster. The nodes with a higher weight is elected as cluster head, after ordering the sensor node weights. These weights are periodically checked as the sensor nodes are dynamic in nature and the past weight value is replaced by updated weight values in each sensor node to elect its cluster head. Re-election of cluster head is carried out if the weights of cluster head $W_{CH}(n)$ is lesser than its previous weights $W_{CH}(n\text{-}1)$. If $W(i) < W_t$, then the node is removed from the cluster.

The DNN model is used to detect and define the mobility patterns of sensor nodes. It analytically uses various QoS metrics like the residual energy (E_r), location information (l), links energy consumption (E), packet reception timestamp (T_R), and packet inter-arrival time (IAI) to authenticate the sensor node for packet forwarding via proper routes. The threshold value of each QoS metric is estimated by setting a predefined value for all metrics that include the reduced value of E_r, high LQI, nearest or lesser l, less E, less T_R, and less IAI. Finally, DNN determines the mobility pattern, and based on the comparison of present state QoS value ($QoS(n)$) and threshold QoS value (QoS_{TH}), the misdirected route is determined. If the value of $QoS(n)$) is lesser than QoS_{TH}, then the sensor node is said to lie in a misdirected path and vice versa inside the sensor network via its mobility pattern estimation.

The QoS metrics provide the indication on the frequency of reliability of packets, strength of the network, and longevity of the network. The performance is further increased by the QoS information in the proposed schema even in the distributed control environment. In this paper, the values of QoS metrics are estimated in the given network and destination area from waypoints distribution.

Moreover, with the knowledge of QoS metric values, the overall performance of the proposed system is improved. In specific, the advantage of QoS metric information is used to improve the packet delivery ratio and reduce the overall delay by avoiding misdirected packets. Further, the consumption of energy and packet delay measurement is evaluated using these QoS metric information in mobile Adhoc networks.

Once the sensor nodes are clustered, the nodes lying inside a cluster is monitored for their mobility pattern. The QoS information of present state QoS(n) is updated through a beacon message to all sensor nodes and this helps to know the state of a sensor node that lies in the secured path or not. If the beacon message QoS(n) sent by a sensor node does not contain its location, then the sensor node is considered to be in a misdirected route. Or if the location value in QoS(n) randomly changes irrespective of the time interval, then the sensor node is said to be in a misdirected route and hence the communication with that node is discarded in the network.

Hence, the node destination is chosen in a uniform way inside a cluster of the radius (R_{max}) from the center of the cluster head. Hence, the cumulative density function of a node for the distance R. The probability density function for a random variable (R) and finally, the expected value of the random variable (R) is thus measured as in (Sharma, D. K., 2016). This helps to determine the patterns by which a sensor node moves using DNN in the network after discarding the misdirected routes in the network.

4. Results and Discussions

The optimization using the BSMO model is verified with various performance metrics that include packet delivery ratio, end-to-end average delay, normalized routing payload, and network lifetime of sensor nodes. To the best of our knowledge, this is the first deep learning technique on MANETs and hence the comparison of BSMO routing is made with conventional machine learning (Veerappan Kousik, N. G., 2020) and reinforcement (Na, Z., 2018) model. The five performance metrics are given below:

Packet delivery ratio (*PDR*): PDR is defined as the ratio of the total number of packets at the base station of MANETs successfully to the total number of packets generated and sent by the source nodes.

End-to-end average delay (*EAD*): The delay is defined as the elapsed time after the successful transmission of packets from the source nodes to the MANET sink nodes and then returning to the source nodes. This delay includes queuing delay at MANET nodes, cache latency at nodes, air propagation delay, retransmission delay at MAC layer of MANETs, and transformation time by the BSMO for route lookup.

Network Lifetime: The network lifetime of MANET is defined as the total time taken to simulate the MANETs from the start of simulation till the last packet transmitted after the death of nodes as the nodes are located in a remote location and that enables failure in getting continuous power supplies.

For the effort to deliver, the PDR and EAD are considered significant that assess the BSMO Routing efficiency with routing loads. MAC payload is a measure of wireless media being used effectively for data streams, where the metrics considered are independent of one another.

4.1 Parametric setting

This section discusses the modeling of a simulation model to evaluate the effectiveness of the DeepSensor DNN model. The simulation of MANET modeling is carried out using NS-2.34 simulation, where the source nodes are programmed to forward a large number of data packets at regular instances. The parameters used for the simulation are given in Table.1.

Table 1. Simulation Parameters

Parameters	Value
MANET sensor nodes	100 (placed in random)
Range	1000 m×1000 m
Simulation time	850 s
Mobility model	Gauss-Markov Model
Routing Protocol	BSMO
Transmission rate	54 Mbps
Pause times	10 – 1000s
ChBSMOel Bandwidth	10 Mbps
MANET Node Velocity	0 – 30km/s
Tx power	20 dBm
Transport protocol	TCP
Beaconing frequency	1 - 4 Hz
Modulation	OFDM
Node failure probability	0.05 - 0.5
Bit rate	5 Mbps

The data packet rate from the sources node is nearly between 45 – 54 Mbps for the generation of the session. This may lead to an increase in the network congestion degree, however, the optimal selection of control and data packet transmission by the BSMO makes the network congestion degree without influencing the communication.

Figure 3 shows the simulation results of PDR for different sessions that include the transmission of packets at source IoT nodes and reception at the sink MANET nodes. The result shows that with reduced nodes, the PDR is relatively lower than the increased nodes. With an increasing number of sessions from 10 to 40, it is noticed that the PDR reduces, however, it is higher than the SVM and DT. The increased performance in the deep learning model is due to the effective computational of paths for the data transmission to the sink nodes. The conventional systems fail in computing the paths, where it fails to match the generated data rates at IoT devices. Hence, the performance of the BSMO model is considered stables and it stabilizes the routing link with higher route stability and minimal link failure.

Figure 4 shows delays for different sessions, where the delay is lowered for the reduced nodes and it increases with the increased nodes. With increasing sessions, the delay increases considerably however, it is lower than SVM and DT. The increased delay is due to the selection of longer routes while computing delay poses serious network congestion in MANETs. Thus it fails in balancing the loads in deep, machine, and DT. However, after certain iterations, the deep learning model increases the potential of computing the routes by minimizing the data transmission rate at that particular instant. On other hand, the consideration of queuing delay at MANET nodes increases the overall delay without compromising the stability of nodes.

Figure 5 and Figure 6 shows energy consumption and network throughput for different sessions, where the energy consumption and network throughput gets lowered for the increased nodes. With increasing sessions, energy consumption and network throughput reduce considerably, which is lower than SVM and DT. The increased computational speed of BSMO handles effectively the address resolution packets, routing and control packets, and overhead packets.

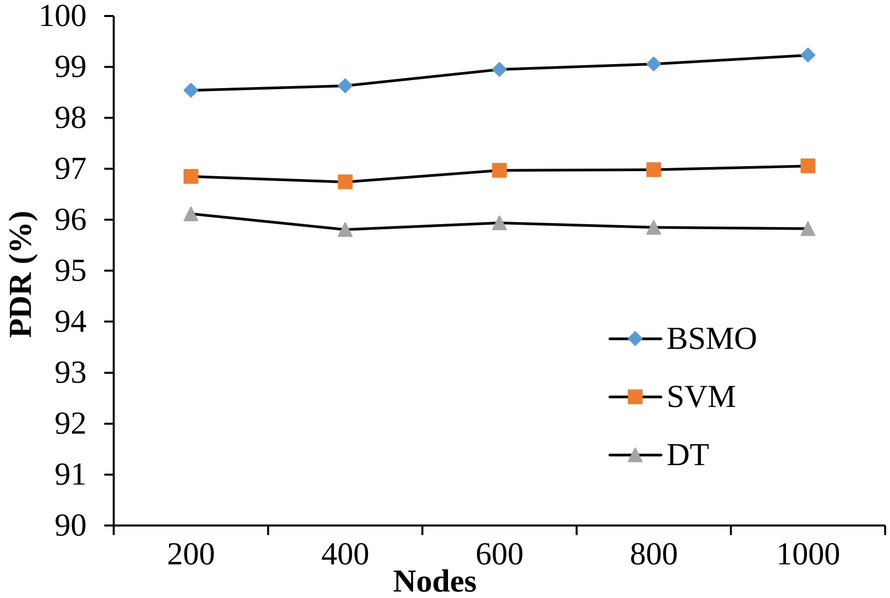

Figure 2. Packet Delivery Rate

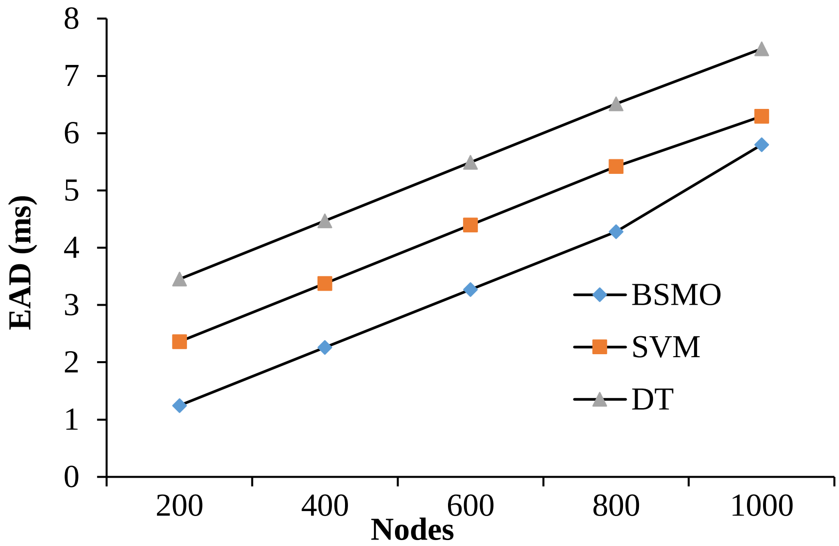

Figure 3 Average end-to-end delay

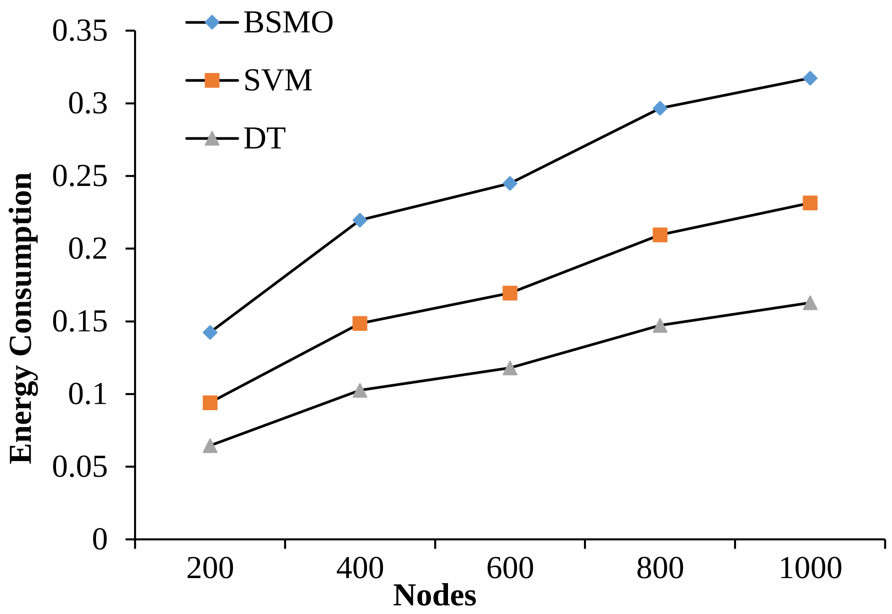

Figure 4. Energy Consumption (J)

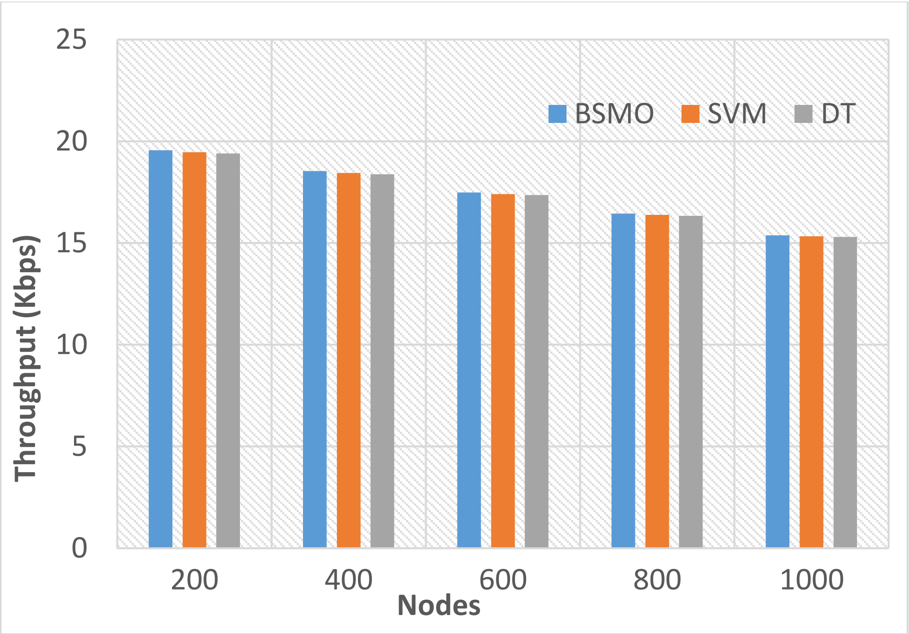

Figure 5. Throughput

5. Conclusions

In this paper, BSMO routing is established on WSNs to maintain the high stabilized routing. The BSMO controls the routing and matches the routing speed with data acquisition speed. The machine learning in the control phase maintains the WSN in a stabilized condition. The study offers greater flexibility while powered with Sensor nodes over WSN network deployment. The solutions on energy consumption between the sensor nodes are maintained effectively using BSMO. The simulation results show that the proposed BSMO module offers an improved balance of network and maintains the scalability of the network.

References

1. Arunkarthikeyan, K. and Balamurugan, K., 2020, July. Performance improvement of Cryo treated insert on turning studies of AISI 1018 steel using Multi objective optimization. In 2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE) (pp. 1-4). IEEE.
2. Aroulanandam, V.V., Latchoumi, T.P., Bhavya, B., Sultana, S.S. (2019). Object detection in convolution neural networks using iterative refinements. Revue d'Intelligence Artificielle, Vol. 33, No. 5, pp. 367-372. https://doi.org/10.18280/ria.330506
3. Bellavista, P., Cardone, G., Corradi, A., & Foschini, L. (2013). *Convergence of MANET and WSN in IoT urban scenarios. IEEE Sensors Journal, 13(10), 3558-3567.*
4. Bera, S., Misra, S., Roy, S. K., &Obaidat, M. S. (2016). *Soft-WSN: Software-defined WSN management system for IoT applications. IEEE Systems Journal, 12(3), 2074-2081.*
5. Bhasha, A.C. and Balamurugan, K., 2020, July. Multi-objective optimization of high-speed end milling on Al6061/3% RHA/6% TiC reinforced hybrid composite using Taguchi coupled GRA. In 2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE) (pp. 1-6). IEEE.
6. Capella, J. V., Campelo, J. C., Bonastre, A., &Ors, R. (2016). *A reference model for monitoring IoT WSN-based applications. Sensors, 16(11), 1816.*
7. Chinnamahammad Bhasha, A., Balamurugan, K. Fabrication and property evaluation of Al 6061 + x% (RHA + TiC) hybrid metal matrix composite. SN Appl. Sci. **1,** 977 (2019). https://doi.org/10.1007/s42452-019-1016-0
8. Deepthi, T. and Balamurugan, K., 2019. Effect of Yttrium (20%) doping on mechanical properties of rare earth nano lanthanum phosphate (LaPO4) synthesized by aqueous sol-gel process. Ceramics International, 45(15), pp.18229-18235.
9. Elappila, M., Chinara, S., &Parhi, D. R. (2018). *Survivable path routing in WSN for IoT applications. Pervasive and Mobile Computing, 43, 49-63.*
10. Garikipati P., Balamurugan K. (2021) Abrasive Water Jet Machining Studies on $AlSi_7$+63%SiC Hybrid Composite. In: Arockiarajan A., Duraiselvam M., Raju R. (eds) Advances in Industrial Automation and Smart Manufacturing. Lecture Notes in Mechanical Engineering. Springer, Singapore. https://doi.org/10.1007/978-981-15-4739-3_66
11. Gowrishankar, J., Kumar, P. S., Narmadha, T., *A Trust Based Protocol For Manets In Iot Environment., International Journal of Advanced Science and Technology, Vol. 29, No. 7, pp. 2770-2775, 2020.*
12. Gowthaman, S., Balamurugan, K., Kumar, P.M., Ali, S.A., Kumar, K.M. and Gopal, N.V.R., 2018. Electrical discharge machining studies on monel-super alloy. Procedia Manufacturing, 20, pp.386-391.
13. Jiang, C., Zhang, H., Ren, Y., Han, Z., Chen, K. C., &Hanzo, L. (2016). *Machine learning paradigms for next-generation wireless networks. IEEE Wireless Communications, 24(2), 98-105.*
14. Jiang, B. B., Chen, H. M., Ma, L. N., & Deng, L. (2011). *Time-dependent pheromones and electric-field model: a new ACO algorithm for dynamic traffic routing. International Journal of Modelling, Identification and Control, 12(1-2), 29-35.*
15. Kousik, N. V., Raja, R. A., & Saravanan, M. (2020). *Automatic skull-face overlay and mandible articulation in data science by AIRS-Genetic algorithm. International Journal of Intelligent Networks, Elsevier Publisher, Vol. 1, 9-16*
16. Kousik, N., Natarajan, Y., Raja, R. A., Kallam, S., Patan, R., &Gandomi, A. H. (2020). *Improved Salient Object Detection Using Hybrid Convolution Recurrent Neural Network, Expert Systems with Applications, Vol 166, 114064, 2021.*
17. Lazarescu, M. T. (2013). *Design of a WSN platform for long-term environmental monitoring for IoT applications. IEEE Journal on emerging and selected topics in circuits and systems, 3(1), 45-54.*
18. Langley, P., & Simon, H. A. (1995). *Applications of machine learning and rule induction. Communications of the ACM, 38(11), 54-64.*
19. Loganathan, J., Latchoumi, T.P., Janakiraman, S. and parthiban, L., 2016, August. A novel multi-criteria channel decision in co-operative cognitive radio network using E-TOPSIS. In *Proceedings of the International Conference on Informatics and Analytics* (pp. 1-6). https://doi.org/10.1145/2980258.2982107
20. M. Sivaram, A. S. Mohammed, V. Manikandan, V. Porkodi et al., *"Improved enhanced dbtma with contention-aware admission control to improve the network performance in manets," Computers, Materials & Continua, vol. 60, no.2, pp. 435–454, 2019.*
21. M. Sivaram, V. Porkodi, A. S. Mohammed, V. Manikandan, *"Retransmission DBTMA Protocol with Fast Retransmission Strategy to Improve the Performance of MANETs," in IEEE Access, vol. 7, pp. 85098-85109, 2019, doi: 10.1109/ACCESS.2019.2918723.*

22. Na, Z., Pan, Z., Liu, X., Deng, Z., Gao, Z., & Guo, Q. (2018). *Distributed Routing Strategy Based on Machine Learning for LEO Satellite Network. Wireless Communications and Mobile Computing, 2018.*
23. Na, Z., Pan, Z., Liu, X., Deng, Z., Gao, Z., & Guo, Q. (2018). *Distributed Routing Strategy Based on Machine Learning for LEO Satellite Network. Wireless Communications and Mobile Computing, 2018.*
24. Prasad A.Y & DR R. Balakrishna , I*mplementation of optimal solution for network lifetime and energy consumption metrics using improved energy efficient LEACH protocol in MANET, International Journal of Telecommunication, Computing, Electronics and Control, ISSN: 1693-6930' at Vol.17, No.4, August 2019.*
25. Prasad A.Y & Dr R. Balakrishna , *"A generic algorithmic protocol approaches to improve network life time and energy efficient using combined genetic algorithm with simulated annealing in MANET" International Journal of Intelligent Unmanned Systems, July 2019, Vol. 8 No. 1, pp. 23-42, ISSN: 2049-6427.*
26. Ranjeeth, S., Latchoumi, T.P., Sivaram, M., Jayanthiladevi, A. and Kumar, T.S., 2019, December. Predicting Student Performance with ANNQ3H: A Case Study in Secondary Education. In 2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE) (pp. 603-607). IEEE.
27. Russell, B., Littman, M. L., & Trappe, W. (2011). *Integrating machine learning in ad hoc routing: A wireless adaptive routing protocol. International Journal of Communication Systems, 24(7), 950-966.*
28. Repoussis, P. P., Tarantilis, C. D., Bräysy, O., &IoBSMOou, G. (2010). *A hybrid evolution strategy for the open vehicle routing problem. Computers & Operations Research, 37(3), 443-455.*
29. Sharma, D. K., Dhurandher, S. K., Woungang, I., Srivastava, R. K., Mohananey, A., & Rodrigues, J. J. (2016). *A machine learning-based protocol for efficient routing in opportunistic networks. IEEE Systems Journal, 12(3), 2207-2213.*
30. Shanthamallu, U. S., Spanias, A., Tepedelenlioglu, C., & Stanley, M. (2017, August). *A brief survey of machine learning methods and their sensor and IoT applications. In 2017 8th International Conference on Information, Intelligence, Systems & Applications (IISA) (pp. 1-8). IEEE.*
31. Veerappan Kousik, N. G., Natarajan, Y., Suresh, K., Patan, R., &Gandomi, A. H. (2020). *Improving Power and Resource Management in Heterogeneous Downlink OFDMA Networks. Information, 11(4), 203.*
32. Wang, X. M., & An, X. M. (2010). *An energy and location aware ACO based routing algorithm for wireless sensor networks. DianziXuebao(Acta Electronica Sinica), 38(8), 1763-1769.*
33. Yuvaraj N, Pragash and Karthikeyan, *"An Improved Task Allocation Scheme in Serverless Computing using Gray Wolf Optimization (GWO) based Reinforcement Learning (RIL) Approach", Wireless Personal Communication, 2020. https://doi.org/10.1007/s11277-020-07981-0*
34. Zhang, X., Ding, L., & Rao, Y. (2009, December). *Qos routing by genetic algorithm for leo satellite networks. In 2009 Second International Symposium on Computational Intelligence and Design (Vol. 1, pp. 341-344). IEEE.*