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T-Maxoutnet: Taylor Series-Based Deep Maxout Network For Intrusion Detection In Wsn

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Abstract

Wireless sensor networks (WSNs) are susceptible to various types of attacks, which are degraded the performance of entire network. Hence, the primary purpose of this research is to design and develop intrusion detection system in WSN for detecting the attackers. The series of steps carried out for detecting the intrusions in WSN are network initialization phase, setup phase, routing phase, and the intrusion detection phase. The network initialization phase involves three models, such as energy model, mobility model and trust model, which are employed for detecting the shortest path in network. The cluster head selection is carried out in setup phase through O-SEED method, which is optimized through Rider Cat Swarm Optimization (RCSO). RCSO model is intended by the integration of Rider optimization algorithm (ROA) and Cat Swarm Optimization algorithm (CSO). In the routing phase, the multipath transmission is done using Rider Atom Search Optimization (RASO). RASO algorithm is designed by incorporating the ROA and Atom Search Optimization (ASO). In the intrusion detection phase, the packet log data is recorded, and the important attributes, like BOT-IOT data is taken for further processing. Then, the feature selection is performed through Kendall tau distance (KTD) to select the appropriate features for detecting the intrusions. After that, the selected attributes are given to the Deep Maxout Network for intrusion detection. The Deep Maxout Network is trained using the developed optimization algorithm, termed as Taylor Rider Atom Search Optimization (Taylor RASO). Here, the proposed Taylor RASO is designed through integrating Taylor series, ASO, and ROA. The performance of the proposed scheme is evaluated through three metrics, namely accuracy, energy, and throughput, and is compared with that of the existing approaches in order to reveal the efficiency of developed technique. The developed Taylor-RASO outperformed other methods with maximum accuracy of 0.935, maximal average residual energy 0.087J, maximal throughput of 87.91%, correspondingly.

Keywords: Wireless Sensor Network, Rider Optimization Algorithm, Atom Search Optimization, energy, Taylor series, intrusion detection.

Introduction

WSN composed of multiple sensor nodes, which are interconnected in ad-hoc model for sensing and forwarding the gathered information to a base station (BS) or central node. On contrast with other conventional network models was presented by Duan et al., [2018], WSN has numerous quantities of parameters corresponding to the sensor nodes, which are mainly relies on power, memory, energy and storage capacity. Normally, the primary goal of WSN is to place the sensor nodes randomly in various locations and distributers the connection among the nodes in wireless manner. Generally, various routing algorithms are adapted to augment the performance of system based on the ratio of delivered packets and latency. The structural design of Internet of Things (IoT) is dynamic and more complex due to improper arrangement of nodes in WSN. Hence, the simple traditional approaches are not suitable for solving the issues in WSN-based applications. Owing to the tremendous growth in networks, a huge quantity of information and network issues are arises, which effectively destruct the growth. Normally, data aggregation and data broadcasting schemes are partitioned into two major categories. The first one based on random arrangement of nodes called structureless approach, which gathers the information without any proper shape, and performs the aggregation of data, which relies on partial information. The second one is based on the structure-based approach, which partitions the network field into various areas identified as clusters. Afterwards, it broadcasts the aggregated data to BS through the recognized transmission link. Majority of WSN applications poses numerous security attacks on sensor nodes described by Fu X et al., [2020].

An intrusion detection approach is relies on the estimation of trust of nearest node through the remaining nodes, and this model monitors the trust level of its surrounding nodes. The trust aware secure routing approach is employed to regulate the secure multi-hop routing in active WSN besides malicious attackers for the retransmission of path information. The privacy and energy-based disjoint path described by Kominami et al.,[2013] through the secret-communication approach arbitrarily and depressively broadcasts the data to initial two phases of network, and then broadcasts the data to sink knob. The pairing of key establishment scheme relies on pre-distribution of key in first time using combinatorial model. The pairing of key model is based on security and bandwidth necessity, which is applicable for both mobile and static networks. The security-aware effective routing mechanism through Signal to Noise Ratio (SNR)-dependent effective clustering approach derived by Kumar et al.,[2010] is to divide the nodes into various clusters, and then select the cluster head (CH) among the nodes relies on energy, as well as CH free nodes links with a specified CH dependent on the SNR values. An effective load maintaining multipath protocol operates through load balancing, congestion control as well as preventive delivery approach for addressing the impacts of multipath routing models. A biological motivated self-formed preventive self-governing routing protocol augments with a self-governing routing system relies on optimal broadcasting decision achieved through enhanced ant colony optimization. In the face of position-dependent attacks in geographic routing, both the popular selection and prediction scheme utilized to consider the benefit of gathered signal strength values at physical layer developed by Jha et al.,[2018]. The GWO with SVM (GWOSVM-IDS) for recognizing the intrusions in network was developed by Safaldin et al., [2021]. This method was achieved better performance based on efficacy, the count of attributes, implementation time, false alarm rate, as well as detection rate. This method was designed by integrating modified GWO algorithm with SVM algorithm.

The meta-heuristic algorithms, such as Particle Swarm Optimization (PSO), and Cuckoo Search which aims at global exploration, and other algorithms, such as Simulated Annealing (SA) as well as Harmony search algorithm (HSA), which gets restricted to the local exploitation derived by Dong et al., [2020]. For enhanced solution, there might be a balance among the exploitation and exploration. These heuristic characteristics motivate the researchers for joining the common meta-heuristic algorithms, like HSA and PSO. Using various detection approaches, the intrusion detection (ID) for WSN is categorized into two phases, such as anomaly detection as well as misuse detection. The former anomaly detection method relies on the mathematical modelling since the benchmark detection network model is established with the behaviour profile of normal network proposed by Neenavath Veeraiah et al., [2018].In case, the threshold value exceeds, then it is declared that an intrusion has happened. Anomaly detection approaches includes anomaly detection dependent data mining, anomaly detection dependent machine learning and anomaly detection dependent clustering. The latter model is the intrusion detection approach relies on information base, since it creates a data state transition for network behaviour of recognized attack and establishes more than one matching patterns for every intrusion developed by Sesham Anand et al., [2020]. On comparing with user behaviour, the matching pattern exists in the information base, and then the affected intrusion pattern can be easily detected. The neural networks has numerous advantages, like auto learning ability, better robustness, and classification capacity, and have fascinated a large quantity of scholars to evaluate the intrusion detection approach relies on neural network with enormously better results proposed by Zhang et al., [2020].

The purpose of this research is to model and develop an intrusion detection model for recognizing the intrusions exists in the network using Taylor-DASO-based Deep Maxout Network. The intrusions present in the network may cause the data transmissions, which can be detected the performance model. This can be overcome by developing a model, named Taylor-DASO-based Deep Maxout Network. Initially, the BoT-IoT data is to be transmitted from CH to BS through multipath routing using RASO algorithm, which is relied on delay, energy, distance and trust. In addition, CH is selected for data transmission from CH nodes to the BS based on O-SEED clustering. After data transmission, the intrusion exist in the network is detected using Deep Maxout network model, which can be trained using developed Taylor-RASO algorithm. The developed Taylor-RASO algorithm is designed through the incorporation of Taylor series, ROA and ASO algorithm. Finally, the Deep Maxout network model provides the classified output as whether the intrusions are exists in the network or not.

The contribution of the research paper is demonstrated as below

- **Proposed Taylor-RASO for intrusion detection in WSN:** The Taylor-RASO is newly introduced for detecting the intrusions exists in the network. The Taylor-RASO is the combination of Taylor series, ROA and ASO that aims in formulating the optimal path and detecting intrusion in network with secure manner.

The remaining section of the paper is formed as follows: Section 2 depicts the portrayal of intrusion detection in WSN employed in literature and confronts solved, which are selected as the aspiration for constructing the developed technique. The developed approach for intrusion detection is discussed in Section 3. The outcomes of the developed model with former methods are illustrated in section 4, and finally section 5 concludes the paper.

2. Motivation

The wireless sensor networks composed of multiple devices, which are capable of performing evaluation on the sensed data, and then finally processing the information for broadcasting to terrain locations. Providing security to WSN plays an important function in communication since these networks are normally organized in terrain areas through the insecure wireless transmission medium. These motivate the researchers for doing the research in this domain.

2.1 Literature survey

This section demonstrates the distinct existing multipath routing approaches, and the intrusion detection approaches in WSN. T. Shankar et al. [2016] modelled the energy aware cluster head selection model for achieving the global exploration with quicker convergence. This method was modelled by combining the HSA and PSO algorithm. HSA algorithm was employed for improving the efficiency of search, and PSO algorithm was employed for enhancing the lifetime of nodes. Although, this method improved the throughput, but the time consumption of this method was large. Pawan Singh Mehra et al.[2020] designed the fuzzy dependent improved CH selection model for WSN. This method was engaged for diminishing the energy consumption in WSN. This method assured the load balancing by selecting the optimal CH, and this method was improved the lifetime of network. However, this method did not produce the better result when the distance among the nodes gets increased. Xiuwen Fu et al.[2020] developed the fusion-based multiple path routing protocol for WSN. The route maintenance was achieved through the mechanism of traffic allocation and retreat model. Although, this method regulates the broadcasting of information under worst environments, the retransmission of information through multiple paths was not permitted in this model. Roshni Jha and Shivnath Ghosh [2018] developed the optimization-based energy aware routing model in WSN. This method was relied on the energy-aware shortest path among multipath through the PSO optimization model. The optimal shortest path was selected from the total predicted shortest path through the path selection constraints, which relies on energy as well as distance among the nodes. However, the throughput of this model was high.

Mukaram Safaldin et al. [2020] developed the intrusion detection approach through the combined Support Vector Machine (SVM) and Binary grey wolf optimizer (BGWO) in WSN. This method was developed for improving the accuracy, and detection rate through diminishing the features. However, the classification performance of this model may produce the improper classified outcome. Wenjie Zhang et al. [2020] developed the ID model through Multi Kernel Dependent Extreme Learning Machine (MK-ELM) for detecting the intrusions. The hierarchical ID model was employed for clustering the nodes in WSN. Although, this method improved the detection rate, but the energy consumption of this model was high. Shuaj Jiang et al. [2020] developed the ID model for improving the detection rate in WSN.The size of data dimension in traffic information was reduced with the help of sequence backward selection model. Moreover, the lightGBM model was employed for detecting the various attacks in WSN. Although, this model reduced the computational overhead, but the time consumption of this method was high. Shashank Gavel et al.[2020] developed the ID technique through divergence of Pearson for predicting the density in WSN. This model was employed to detect the network and intrusions in network. Although, this method improved the life time of network, this method was failed to process with high dimensional data.

2.2 Challenges

The challenges overcome while analysing the multipath routing, and the intrusion detection technique in WSN are organized as follows.

- The Environment-fusion multipath routing protocol was developed by Fu et al., [2020] for the WSN. However, the developed approach was not enhanced for composing it suitable for multi-sink WSNs.
- In the energy aware PSO facilitated multipath routing approach was developed for WSN. However, the method was not experimentally validated the effectiveness of the system developed by Jha et al.,[2018].
- The next position of wolves is not predicted in GWO method, which reduced the performance of GWO as well as the detection rate. The SVM classifiers employed in this model cannot produce the accurate result proposed by Safaldin et al., [2020].
- MK-ELM method detects only the specified attacks but not others. Thus, the challenge lies on exploring effective techniques for detecting various kinds of attacks proposed by Zhang et al., [2020].
- Generally, the large volume of data was handled through the distributed processing for diminishing the time consumption. However, LightGBM method was not utilized the distributed processing for diminishing the time consumption. Thus, the challenge lies on exploring the distributed processing in real world applications proposed by Jiang et al., [2020].

3. Developed Taylor-RASO-Based Deep Maxout Method for ID in WSN

This section explains the intrusion detection system in WSN through the developed Taylor-RASO-based Deep Maxout method. The phases employed in the developed model are setup, transmission, routing, BoT-IoT features, feature selection and intrusion detection. Initially, the CH is chosen in setup phase for broadcasting the information from source node (SN) to BS based on O-seed clustering, which is recognized through the best CH and threshold based on RCSO algorithm. The RCSO is modelled by incorporating ROA Binu et al., [2018] and CSO Bahrami et al., [2018]. Once the CH is chosen, the data transmission is completed from CH to BS. Then, the multipath routing is done through RASO algorithm, which is the integration of ROA Binu et al., [2018] and ASO Zhao et al.,[2019]. After the routing phase, the intrusion detection phase is performed for detecting the abnormal behaviour. In this phase, the BoT-IoT features are taken, and the appropriate features are selected for further processing using KTD. The selected features are fed into the Deep Maxout model Sun et al., [2018] for detecting the intrusions, which is trained using developed Taylor-RASO algorithm. The developed Taylor-RASO algorithm is the incorporation of Taylor series AlameluMangai et al., [2014], ASO and ROA. The intrusion detection through the developed Taylor-RASO-based Deep Maxout method is depicted in figure 1.

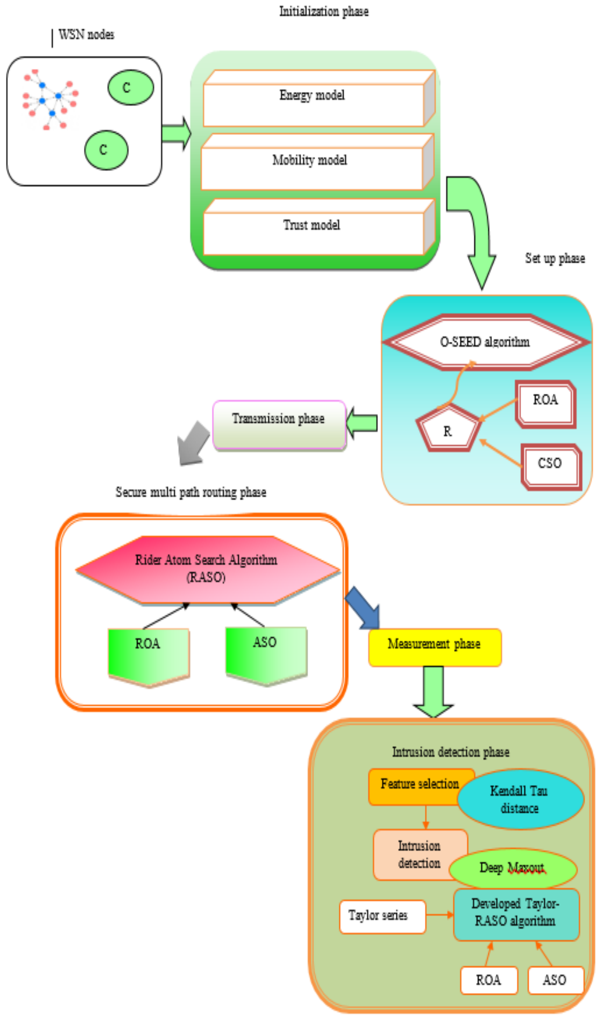


Figure 1. Block diagram of intrusion detection through the developed Taylor-RASO-based Deep Maxout method

3.1 Initialization phase

This section depicts the WSN network with energy model, trust model and mobility model. Here, WSN is segmented into three portions based on three energy levels for solving the energy limitation. The lowest regions have normal node with lowest energy, middle region composed of medium energy with super nodes, and final region contains advance node with maximum energy. In this phase, the clustering algorithm is introduced for choosing the CH based on residual energies. Maheshwari et al., [2021] developed the BOA for picking the best CH from the batch of nodes in network. The since, the CH captures the information from SN nodes, and then forwards the message to BS. Let us select the WSA with l number of nodes where the normal nodes are depicted as p, the CH is denoted as R, and the transmitted input IoT data is depicted as D_{IoT}.

3.1.1 Energy model

This section depicts the energy model of WSN, which is explained as below. The WSN composed of numerous sensor nodes, and each node c consumed energy for proper data transmission. Thus, the expression for transmitter energy is given by,

$$P_e(J,g) = \begin{cases} JL_d + JU_v g^2 & g \le g_u \\ JD_d + JU_o g^4 & g > g_u \end{cases} \quad (1)$$

Where, the term $P_e(J,g)$ depicts the transmitter energy, and L_d depicts the electronic energy, g indicates the distance, J indicates the message, g_u demonstrates the threshold distance, U_v represents the free space amplifier energy, U_o represents the radio amplifier energy. During the reception of information, the expelled energy is derived by,

$$P_o(J) = JL_d \quad (2)$$

where, the term L_d indicates the transmitter energy.

3.1.2 Mobility model

Ahamed G et al., [2016] stated that the mobility model is configured to evaluate the moving location of sensor node using position, acceleration, and speed at particular time instant. Let us assume the node b_f and node b_x are situated at $(h\ ,t\ )$ and (h^*,t^*) at time $a=0$. Here, the nodes b_f and b_x are propagated to the new position with velocities dependent on two angles $\theta_{b,h}$ and $\theta_{b,t}$. Moreover, the node b_h shifts a distance $G_{b,x}$, and node b_x broadcasts through the distance $G_{b,x}$ at time $a=0$. Assume (h_y,t_y) and (h_x,t_x) depicted the renewed positions employed by nodes b_y and b_x at the time $a=1$. At the specific time instant a, the distance is estimated among nodes at b_y location (h_y,t_y) and (h_x,t_x) is denoted by,

$$G(b_y,b_x,a) = \sqrt{|h_y - h_x|^2 + |t_y - t_x|^2} \quad (3)$$

Where, the updated location of nodes b_x and b_y is expressed as (h_y, y_y) and (h_x,t_x).

3.1.3 Trust model

The trust model is organized to communicate securely in WSN for avoiding the miscommunication caused through malicious nodes in the network. Every node is operated based on trust degree value of every neighbouring node where the trust value is estimated using local information. Let us assume W_{rs} be the trust node degree of s^{th} node to its r^{th} neighbour. The trust degree value ranges from 0 *and* 1. The degree of trust-1 depicts the absolute trust and 0 depicts the complete distrust. Here, the trust factor involves in the developed models are direct trust, indirect trust, recent trust, historical trust and expected trust, which is depicted as,

$$W_{rs} = H_{rs} + N_{rs} + M_{rs} + K_{rs} + Y_{rs} \quad (4)$$

Where, H_{rs}, N_{rs}, M_{rs}, K_{rs} and Y_{rs} indicates the direct, indirect, recent, historical and expected trust of s^{th} node to its r^{th} neighbour.

a) Direct trust

Direct trust refers to the direct interactions among nodes. In other words, the forwarding behaviour of packets is termed as direct trust. Here, H_{rs} refers to the direct trust nodes.

b) Indirect trust

This trust is termed as the potential trust relation, which is formed from the recommendation of trust node in the trust path. The degree of indirect trust is computed through the recommendation of neighbour, which enhances the trust evaluation process of nodes. The term N_{rs} depicts the indirect trust.

c) Recent trust

Recent trust model depicts the weighted addition of direct and indirect trust, which is represented as M_{rs}, and is depicted by,

$$M_{rs} = \chi \times H_{rs}(q) + (1-\chi)N_{rs}(q) \quad (5)$$

Where, the term χ denotes the direct trust weight, and the term q depicts the transactions.

d) Historical trust

The historical trust is performed using the interaction of nodes where the trust value is estimated using the records or history. The historical trust is depicted using K_{rs}, which is given by,

$$K_{rs} = \frac{\nu \times K_{rs}(q-1) + M_{rs}(q-1)}{2} \quad (6)$$

where, the term ν depicts the random number varies from 0 *and* 1, q indicates the transactions, and M_{rs} depicts the recent trust.

e) Expected trust

Expected trust depicts the expected presentation of objective agent, which is selected from both historical and recent trust, and is expressed as

$$Y_{rs} = \begin{cases} 0 & ;\textit{if either } M_{rs} \textit{ or } K_{rs} \textit{ are present} \\ \Phi M_{rs} + (1-\Phi)K_{rs} & ;\textit{if neither } M_{rs} \textit{ and / nor } K_{rs} \textit{ is present} \end{cases} \quad (7)$$

3.2 Setup phase

The optimal CH selection is illustrated in setup phase using O-SEED clustering approach [13]. The setup phase is employed for broadcasting the information D_{IoT} from source node (CH) to BS using O-SEED clustering model. The O-SEED clustering model is trained using the integration of ROA and CSO model, named RCSO algorithm. Moreover, O-SEED clustering model achieves the long lifetime of system, high throughput and lower energy consideration. The CSO algorithm is swarm-based algorithm, which relies on the tracing and seeking mode of cats. Moreover, ROA is the optimized algorithm, which is done based on the batch of riders running to pointing towards the target position. The advantage of ROA algorithm is that, this algorithm achieved low processing time and low computational time. Thus, the ROA algorithm and CSO algorithm is combined for achieving the optimal selection of cluster head from total nodes. The final updated equation of RCSO algorithm is given by,

$$E_{mn}(u+1) = E_{mn}(u) + \Phi_{mn}(\mu) - \omega\psi\lfloor E_{\nu}^{*}(u) * \cos(S_{mn} \quad (8)$$

where, the term $E_{\nu}^{*}(u)$ depicts the leading rider location, $S_{mn}(\mu)$ denotes the steering angle of m^{th} rider in μ^{th} coordinate, and the distance traversed by m^{th} rider is depicted as $z_m(\mu)$. The above equation demonstrates the optimal solution for selecting the cluster head E using RCSO algorithm.

3.3 Transmission phase

Once the CH E is selected using RCSO algorithm, the data D_{IoT} is to be broadcasted from CH to BS, and the optimal path for data transmission is based on threshold, energy and distance.

3.4 Secure aware multipath routing through Rider atom search optimization

This section depicts the secure multipath routing using Rider-ASO algorithm, which is designed by the incorporation of ROA and ASO. The purpose of developing the hybrid optimization algorithm is to achieve the global optimal multiple path for data transmission by predicting the appropriate parameters. ROA algorithm is modelled by the behaviour of Riders, whose aim is to depart the optimal target position to become a winner. However, the searching behaviour is not exists in the ROA algorithm. Hence, the ASO algorithm is integrated with ROA for searching the new location. The ASO is developed by taking the advantage of attraction and repulsion behaviour of atoms, and the atom location is measured based on mass. In ASO, the heavier atom is to estimate the best solution in search space, whereas the lighter atomic mass atoms are utilized to estimate the new location in search space. Hence, the hybrid optimization algorithm, named Rider-ASO algorithm is to be obtained for getting the global optimal solution with high convergence rate. Here, once the data is transmitted, then the Rider-ASO algorithm checks the feasibility conditions for transmission. In case, it satisfies the feasibility conditions, then the Rider-ASO algorithm updates the new path and transmits the information via multiple paths. The final updated equation of Rider-ASO algorithm for multipath routing is expressed as follows.

$$f_x(u+1)=\frac{w\alpha}{w\alpha-1}\left[rand_x T_x(u)+Q_x(u)-\frac{f_\delta(u)(1-\alpha)}{\alpha}\right] \quad (9)$$

where, the term w and α depicts the random number whose range is from $0\, to\, 1$, $T_x(u)$ depicts the velocity of x^{th} atom, $Q_x(u)$ indicates the acceleration of x^{th} atom. The integration of parametric features of Rider in ASO provides the efficient multipath routing in WSN.

3.5 Measurement phase

In the measurement phase, the residual energies exists in the nodes are renewed in measurement phase. Once the data is transmitted through multipath, then the process is to be sustained until the data is to be finishes the CH node. The transmitted information is depicted as S.

3.6 Intrusion detection phase using developed Taylor RASO-based Deep Maxout Network

Once the data S is to be transmitted using secure multipath routing, then the intrusion exists in the network is determined using developed Taylor-RASO-based Deep Maxout network. In the intrusion detection phase, the intrusion exist in the network is classified using Deep Maxout network, which is trained using developed Taylor-RASO algorithm. The developed Taylor-RASO-based Deep Maxout network stated by Weichen Sun et al. [2018] is developed by integrating the Taylor series AlameluMangai et al.,[2014], ROA and ASO algorithm. The intrusion detection process involves two phases, such as feature selection and intrusion detection. In this phase, the log file is generated based on the transmitted information S, which records the unusual activities occurred in the operating system, and the log file is depicted as L_1.

3.6.1 Feature extraction

After the log file creation L_1, the BoT-IoT features are extracted in the feature extraction phase, which is represented as B_f. Since, the input transmitted information utilized in the multipath transmission is the BoT-IoT dataset, which contains the BoT-IoT features stated by Koroniotis N et al.,[2019]. Some of the BoT-IoT features and their explanations are explained in table.1.

Table 1. BoT-IoT features and their descriptions

Feature	Explanation
pkSeqID	Row identifier
Stime	Record initial tome
sport	Source port number
attack	0 for normal traffic, 1 for attack with traffic
dur	Record total time
sum	Time consumption of aggregated records
spkts	Packet count of source to destination

3.6.1 Feature selection using KTD

After the features B_f are extracted, the feature selection is executed to chosen the appropriate features using KTD. The KTD is mainly relies on the correlation coefficient of kendall tau rank. The expression for KTD [15] is given by as follows.

$$K_D(O_1,O_2)=|c| \quad (10)$$

$$K_D(O_1,O_2)=\frac{2|c|}{s*(s-1)} \quad (11)$$

where, c is the set of discordant pairs, n be the interval parameter. The output of feature selection is depicted as f_l.

3.6.2 Deep Maxout network

The selected feature f_l is fed into the input of Deep Maxout network stated byWeichen Sun et al.,[2018]. The purpose of Deep maxout network is to monitor and classify the unauthorized user enter into the network. Once the data transmission is completed, the Deep Maxout network is to classify whether the intrusions exists or not.

3.6.2.1Structural design of Deep Maxout network

Here, the Deep Maxout network is adapted to classify whether the intrusions exist in the network or not with the aid of selected feature f_l. The performance of Deep Maxout Network stated by Fortino G et al.,[2017]. mainly relies on the trainable activation function together with multilayer arrangement. The primary purpose of adapting this classifier is that, the training speed of this classifier is maximum due to the activation function. The selected feature f_l is fed into the input of classifier for generating the hidden activation unit, which is represented as,

$$B^1_{u,v} = \max_{b\in[1,s_1]} J^T M_{uv} + N_{uv} \quad (12)$$

$$B^2_{u,v} = \max_{b\in[1,s_2]} B^{1\,T}_{u,v} M_{uv} + N_{uv} \quad (13)$$

$$B^s_{u,v} = \max_{b\in[1,s_k]} G^{k-1\,T}_{u,v} M_{uv} + N_{uv} \quad (14)$$

$$B^\phi_{u,v} = \max_{b\in[1,k_\phi]} B^{\phi-1\,T}_{u,v} M_{uv} + N_{uv} \quad (15)$$

$$\Delta_i = \max_{b\in[1,s_\phi]} B^\phi_{u,v} \quad (16)$$

where, s_k depicts the number of functions in k^{th} layer, Δ_i denotes the classified output, and ϕ depicts the count of layers present in Deep Maxout network. Though, activation function of classifier is more powerful to approximate the continuous activation function. The training process of Deep Maxout network is done by the developed Taylor-RASO algorithm, which is explained in the below section. Figure 2 specifies the structure of Deep Maxout network.

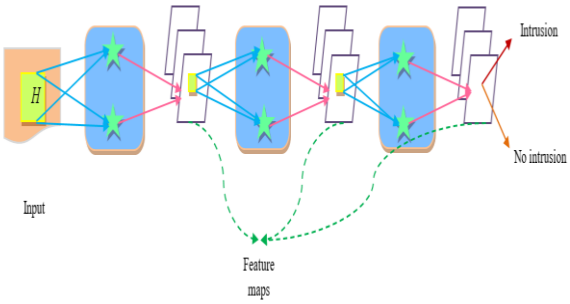


Figure 2. Structure of Deep Maxout network

3.6.2.2 Developed Taylor-RASO algorithm for training the Deep Maxout Network

The classified output of Deep Maxout network is Δ_i, and the deep maxout network is trained using developed Taylor RASO algorithm, which is modelled by the combination of Taylor series, ROA and ASO algorithm. ROA algorithm is modelled by the behaviour of Riders, whose aim is to depart the optimal target position to become a winner. The ASO is developed by taking the advantage of attraction and repulsion behaviour of atoms, and the atom location is measured based on mass. In ASO, the heavier atom is to estimate the optimal solution in search space, whereas the lighter atomic mass atoms are utilized to estimate the new location in search space. However, the RASO algorithm did not produce the accurate result and the time consumption of this method was high. Hence, the Taylor series is introduced to overcome these issues. Thus, the function of Taylor series is that, it produced the accurate result, and it is able to calculate the entire function at any point. Thus, these three algorithms are adapted to integrate, and then produced a new algorithm, named Taylor-RASO algorithm. The working principle of new developed Taylor-RASO algorithm is organized as follows.

a) Solution encoding

The solution encoding expresses the depiction of solution, which is predicted with the aid of developed model. Let us assume q quantity of nodes in WSN from which k optimal cluster head is selected from the developed model, where, k value is ranging from $1 \le k \le q$, correspondingly. The solution needs nodes q and best cluster head k is selected in the optimal path relies on objective function of developed model.

b) Algorithmic procedure of the developed Taylor-RASO for intrusion detection

The algorithmic procedure involved in developed Rider-ASO is illustrated below.

i) Initialize the population: The initialization step for population of atom is resolved through the optimization of unconstrained problems. Here, M be the quantity of atoms and the position of x^{th} atom is depicted by,

$$f_x = [\rho^1_x, \ldots \rho^M_x]; \quad x = \{1, \ldots, n\}. \quad (17)$$

where, $\rho^b_x \,(b = 1, \ldots M)$ expresses b^{th} position of x^{th} atom in M^{th} dimensional space.

ii) Fitness measure: The fitness function is employed to evaluate the global best solution through attained optimal fitness value for the classification problem. However, the fitness measure is depicted as,

$$\varepsilon = \frac{1}{C}\sum_{t=1}^{C}[X_t - \Delta_t]^2 \quad (18)$$

Here, ε denotes fitness, Δ_t is the output of Deep Maxout network, X_t denotes target value, and C denotes total number of training samples.

iii)Mass computation: The mass of atom is computed with the usage of fitness value at lowest level. Thus, the mass of x^{th} atom at u^{th} iteration is expressed by,.

$$T_x(u)=\frac{\sigma_x(u)}{\sum_{x=1}^{n}\sigma_x(u)} \quad (19)$$

where, the mass is depicted as $T_x(u)$, and $\sigma_x(u)$ is illustrated as,

$$\sigma_x(u)=\frac{H_x-H^{best}}{e^{H^{worst}-H^{best}}} \quad (20)$$

where, H^{best} and H^{worst} are demonstrated as, $H^{best}=\min_{x=1,\ldots n} H_x$, and $H^{worst}=\max_{x=1,\ldots n} H_x$, correspondingly.

iv)Identification of M neighbours: All the atoms interact relies on the optimal fitness value with other atoms and M neighbours. Hence, X is slowly diminished through changing the lapse of iterations at specific time. Hence, the value of X is estimated through the following equation,

$$M(u)=n-(n-2)\times\sqrt{\frac{u}{\nu_x}} \quad (21)$$

v) Constraint and total force estimation: The random weight is included with entire elements that is proceeded on atom b from remaining atoms is chosen as the total force, and is expressed as,

$$C_x(u)=\sum_{T\in R^{best}} rand_T w_{jT}(u) \quad (22)$$

where, $C_x(u)$ depicts the total force, and $rand_T$ illustrates the random number varying from 0 and1, correspondingly. Every atom in population space proceed relies on constraint force from the optimal atom, hence constraint force of x^{th} atom is depicted by,

$$w_x(u)=N_x(u)\left(f^b_{best}(u)-f_x(u)\right) \quad (23)$$

where, $N_x(u)$ denotes the lagrangian multiplier, $f^b_{best}(u)$ indicates the position of optimal atom at u^{th} iteration, and $f_x(u)$ represents constraint force. Here, the lagrangian multiplier is depicted as,

$$N_x(u)=\zeta_x e^{\frac{20u}{\nu_x}} \quad (24)$$

where, the multiplier weight is termed as ζ_x .

vi)Acceleration evaluation: The acceleration of x^{th} atom at u^{th} time is estimated with the help of total force as well as the geometric constraint, and is illustrated by,

$$Q_x(u)=\frac{C_x(u)}{T_x(u)}+\frac{w_x(u)}{T_x(u)} \quad (25)$$

where, the constraint force is depicted as $w_x(u)$, the mass is demonstrated as $T_x(u)$, and $C_x(u)$ is the total force.

vii) Update the velocity: The velocity of x^{th} atom is renewed through the basis of iteration $(u+1)$, and is depicted by,

$$T_x(u+1)=rand_x\, T_x(u)+Q_x(u) \quad (26)$$

where, the random number is depicted as $rand_x$, and $Q_x(u)$ refer to acceleration.

viii) Update the atom location: The update steps of the proposed Taylor RASO are done through modifying the position of x^{th} atom of ASO with the x^{th} riders position. The Deep maxout algorithm is trained using developed Taylor RASO algorithm, which is the incorporation of Taylor series, Rider algorithm and Atom search algorithm, named Taylor-RSO algorithm. The final updated equation of Rider-ASO algorithm for multipath routing is depicted as follows.

$$f_x(u+1)=\frac{w\alpha}{w\alpha-1}\left[rand_x T_x(u)+Q_x(u)-\frac{f_\delta(u)(1-\alpha)}{\alpha}\right] \quad (27)$$

Subtracting $f_x(u)$ on both sides

$$f_x(u+1)-f_x(u)=\frac{w\alpha}{w\alpha-1}\left[rand_x T_x(u)+Q_x(u)-\frac{f_\delta(u)(1-\alpha)}{\alpha}\right]-f_x(u) \quad (28)$$

From Taylor series prediction: A cache replacement policy based on second order trend analysis [14] is given by,

$$f_x(u+1)=f_x(u)+\frac{f'_x(u)}{1!}+\frac{f''_x(u)}{2!} \quad (29)$$

$$f_x(u+1)-f_x(u)+\frac{f_x(u)-f_x(u-v)}{v!}+\frac{f_x(u)-2f_x(u-v)+f_x(u-2v)}{2!v^2} \quad (30)$$

Assuming that $v=1$, then the equation becomes,

$$f_x(u+1)=f_x(u)+f_x(u)-f_x(u-1)+\frac{f_x(u)}{2}-\frac{2f_x(u-1)}{2}+\frac{f_x(u-2)}{2} \quad (31)$$

$$f_x(u+1)=\frac{5}{2}f_x(u)-2f_x(u-1)+\frac{f_x(u-2)}{2} \quad (32)$$

$$f_x(u)=\frac{2}{5}\left[f_x(u+1)+2f_x(u-1)-\frac{f_x(u-2)}{2}\right] \quad (33)$$

Substitute in RHS of equation (29)

$$f_x(u+1) - f_x(u) = \frac{w\alpha}{w\alpha - 1}\left[rand_x T_x(u) + Q_x(u) - \frac{f_\delta(u)(1-\alpha)}{\alpha}\right] - f_x(u) \quad (34)$$

$$f_x(u+1) - f_x(u) = \frac{w\alpha}{w\alpha - 1}\left[rand_x T_x(u) + Q_x(u) - \frac{f_\delta(u)(1-\alpha)}{\alpha}\right] - \frac{2}{5} f_x(u+1) - \frac{2}{5}\left[f_x(u-1) - \frac{f_x(u-2)}{2}\right] \quad (35)$$

$$f_x(u+1) + \frac{2}{5} f_x(u+1) = f_x(u) + \frac{w\alpha}{w\alpha - 1}\left[rand_x T_x(u) + Q_x(u) - \frac{f_\delta(u)(1-\alpha)}{\alpha}\right] - \frac{2}{5}\left[f_x(u-1) - \frac{f_x(u-2)}{2}\right] \quad (36)$$

$$f_x(u+1)\left[1 + \frac{2}{5}\right] = f_x(u) + \frac{w\alpha}{w\alpha - 1}\left[rand_x T_x(u) + Q_x(u) - \frac{f_\delta(u)(1-\alpha)}{\alpha}\right] - \frac{2}{5}\left[f_x(u-1) - \frac{f_x(u-2)}{2}\right] \quad (37)$$

$$f_x(u+1)\left[\frac{7}{5}\right] = f_x(u) + \frac{w\alpha}{w\alpha - 1}\left[rand_x T_x(u) + Q_x(u) - \frac{f_\delta(u)(1-\alpha)}{\alpha}\right] - \frac{2}{5}\left[f_x(u-1) - \frac{f_x(u-2)}{2}\right] \quad (38)$$

$$f_x(u+1) = \frac{5}{7}\left[f_x(u) + \frac{w\alpha}{w\alpha - 1}\left[rand_x T_x(u) + Q_x(u) - \frac{f_\delta(u)(1-\alpha)}{\alpha}\right] - \frac{2}{5}\left[f_x(u-1) - \frac{f_x(u-2)}{2}\right]\right] \quad (39)$$

where, $w, \alpha = [0,1]$, $Q_x(u)$ denotes the acceleration, $T_x(u)$ depicts the velocity, $f_x(u-1)$ denotes the solution at iteration $u-1$, and $f_x(u-2)$ specifies the solution at $u-2$.

ix)Estimate the feasibility of solution: The fitness value of every search agent is estimated through equation (18) such that the lowest value produces optimal fitness evaluation and the function with optimal outcome is chosen as optimal solution.

x) Termination: The steps ii) to ix) are continued till the particular iteration met or the best solution is achieved. Algorithm 1 specifies the pseudo code of developed Taylor-RASO.

Algorithm 1. Pseudo code of the developed model

Input: Random population $f_x = \{\rho_x^1, \ldots \rho_x^M\}$; $x = \{1, \ldots, n\}$
Output: Best position
Initialize the set of atoms and velocity
While termination criteria is not fulfilled
Do
Estimation of objective function
Mass computation through equation (20)
M neighbors are predicted through equation (22)
Total and the constraint force are evaluated through equation (23) and (25)
Estimate acceleration through equation (26)
Renew the velocity through equation (27)
Update the location of atom through Taylor series prediction in (40)
End for
End while
Best solution is attained

4. Results and discussion

This section depicts the results and discussion of the developed Taylor RASO-based Deep Maxout using evaluation metrics, like accuracy, energy, and throughput based on 50, 100 and 150 nodes.

4.1 Experimental setup

The implementation of developed model is performed in MATLAB tool with the windows 10OS, 4GB RAM, and Intel I3 core processor. The dataset employed for transmitting the information is BoT-IoT dataset.

4.2 Evaluation metrics

The performance of developed Rider-ASO+Taylor RASO-based Deep Maxout is employed for analyzing network parameters, such as accuracy, throughput and energy, which are given below.

a) Accuracy: Accuracy measures that how the predicted value closed to the actual value, which is expressed as, $A = \frac{x_p + x_n}{x_p + x_n + y_p + y_n}$ (40)

where, x_p depicts the true positive, x_n depicts the true negative, y_p specifies the false positive, and y_n specifies the false negative.

b)Throughput: Throughput is defined as the number of packets successfully transported to the destination at a certain interval of time, and is expressed as,

$$Throughput = \frac{N}{t} \quad (41)$$

where, the term N depicts the number of nodes arrived at the execution time t.

c) Energy: It calculates the energy residues in the nodes at highest iteration and energy remains in nodes at effective approach.

4.3 Experimental Results

This section demonstrates the experimental set-up of developed approach. Figure 3 illustrates the sample outcome of developed model. Figure 3 a), b) and c) depicts the experimental outcome of the developed model with varying numbers of nodes, such as 50, 100 and 150, respectively. During transmission, if the nodes are placed within the communication range, then the data transmission occurs in effective manner. If the nodes are placed far away from the range, then the data communication does not entailed in effective manner, which is marked with red colour is shown in figure 1. The red colour circle depicts the sink node and green circle indicates the source node, and then the triangle depicts the cluster head.

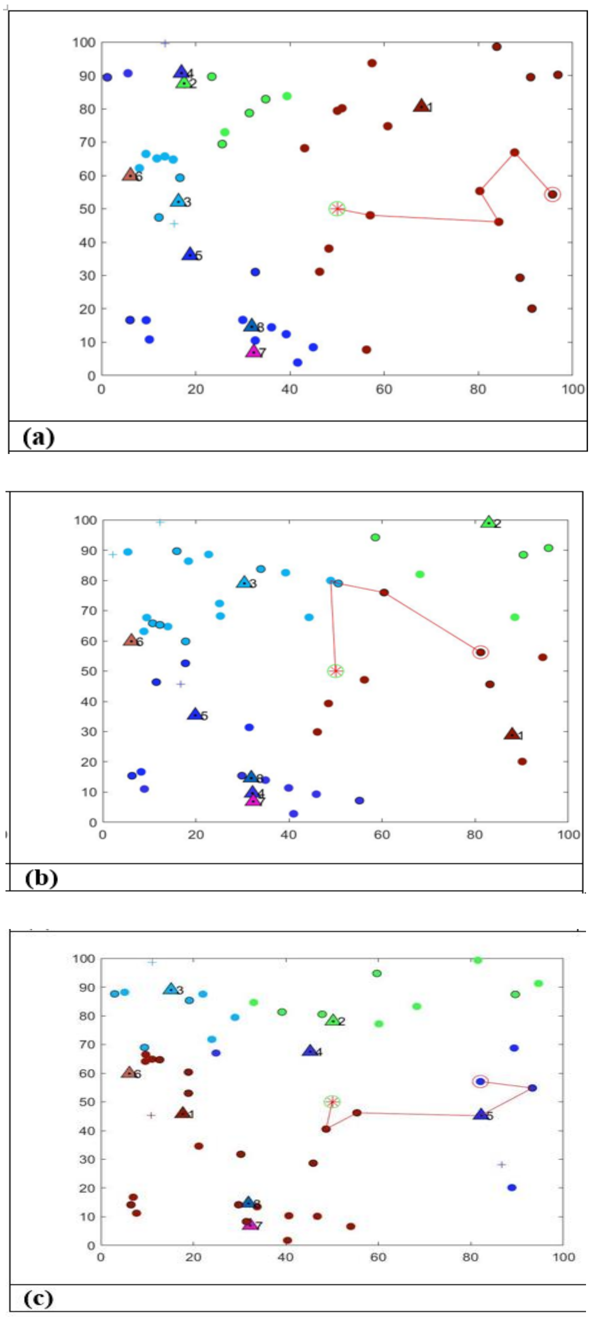


Figure 3. Sample results based on different nodes, a) 50 nodes, b) 100 nodes, c) 150 nodes

4.4. Comparative methods

The performance of the developed Taylor RASO-based Deep Maxout method is analyzed by comparing the existing techniques, such as Fractional Artificial Bee colony (FABC)+ Exponential Ant Colony Optimization (EACO) stated by Rajeev Kumar et al.,[2017]_ Maxout Weichen Sun et al.,[2018], Artificial Bee colony (ABC)+ Ant Colony Optimization (ACO) Dervis Karaboga et al.,[2012]+Long Short Term Memory (LSTM) Zhu,W et al.,[2016] and Threshold+ACO Jing Yang et al.,[2010]+ Neural Network (NN) Vohradsky et al.,[2001].

4.5 Comparative analysis

The comparative analysis of the developed Taylor RASO-based Deep Maxout method is done by comparing the performance of existing methods, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN based on accuracy, throughput and energy.

4.5.1 Analysis using 50 nodes

The analysis of techniques based on accuracy, average residual energy and throughput using 50 nodes are given in figure 4. Figure 4 a) illustrates the analysis of techniques by changing the training data based on accuracy. When the training data is 90%, then the accuracy achieved by the developed model is 0.9298, whereas the accuracy achieved by the existing techniques, like FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN are 0.89, 0.8897 and 0.9. The performance improvement of the developed method with previous techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN based on accuracy is 4.28%, 4.31% and 3.20%.

Figure 4 b) depicts the investigation of techniques with varying the number of rounds based on average residual energy. When theround = 600, the average residual energy measured by the developed Taylor RASO-Based Deep Maxout method is 0.2138 J, and the existing techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN achieved by the average residual energy is 0.1811 J, 0.1929 J and 0.2029J. The performance improvement of the developed Taylor RASO-Based Deep Maxout method with respect to the existing techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN is 15.27%, 9.75% and 5.08%.

Figure 4 c) illustrates the performance analysis of developed technique on the basis of throughput with respect to the existing techniques. When the round=500, the throughput achieved by the developed method, and the existing approaches, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN are 94.70%, 93.32%, 93.35% and 94.53%. The performance improvement of the developed Taylor RASO-Based Deep Maxout method with respect to the existing techniques such as, FABC+ ESCO_ Maxout, ABC+ACO +LSTM and Threshold+

ACO +NN based on throughput is 1.46%, 1.42% and 0.18%.

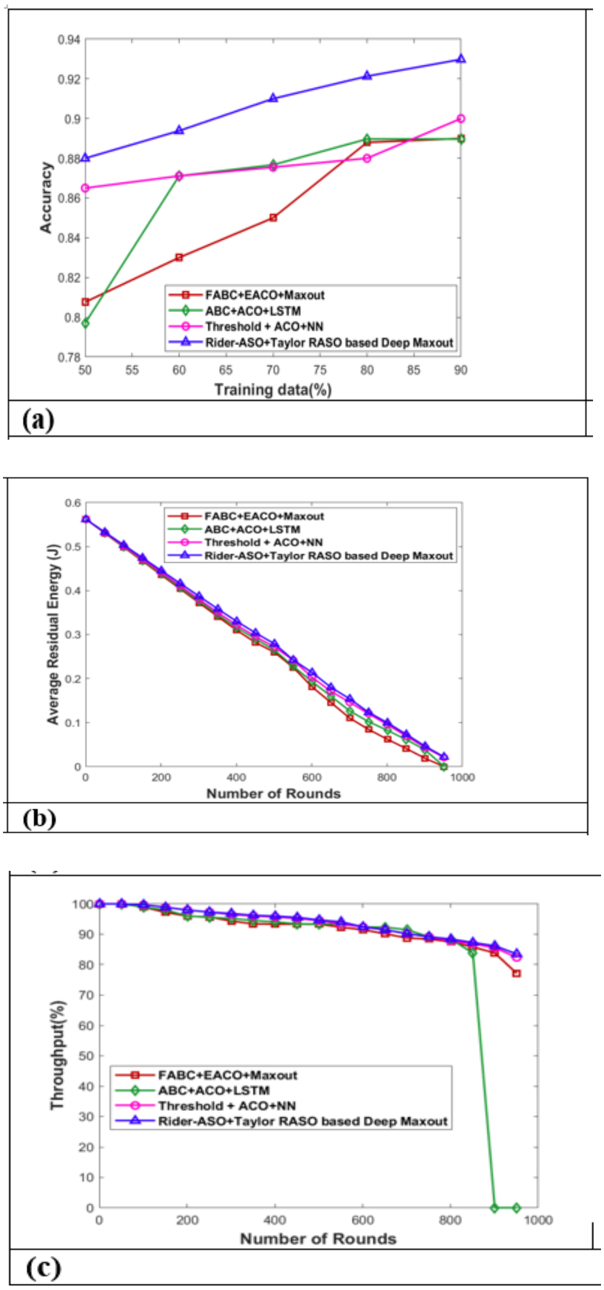


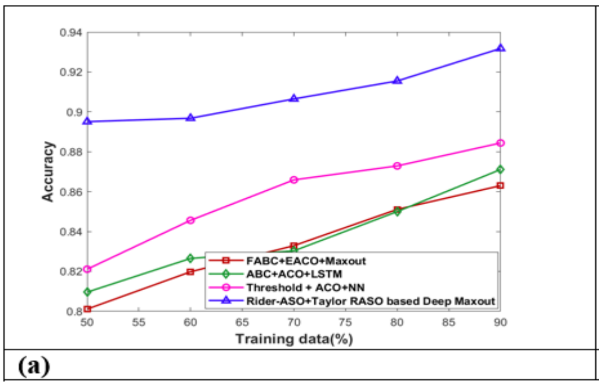
Figure 4. Comparative analysis of evaluation parameters with various training data at 50 nodes, a) Accuracy, b) Average residual energy, c) Throughput

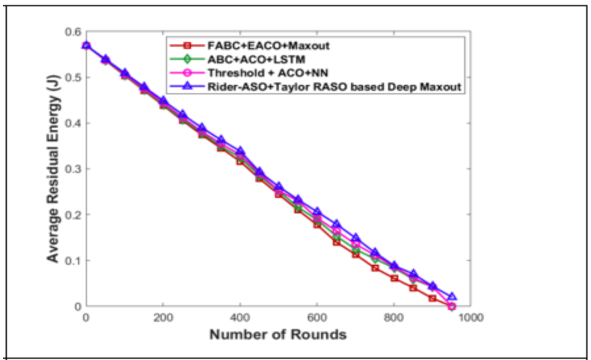
4.5.2 Analysis through 100 nodes

The analysis of developed techniques based on accuracy, average residual energy and throughput using 100 nodes are given in figure 5. Figure 5 a) illustrates the investigation of developed Taylor RASO-based Deep Maxout method based on accuracy by varying the training data. The performance analysis of developed method with respect to the existing techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN based on accuracy is 0.9318, whereas the existing techniques achieved the accuracy of 0.863, 0.871 and 0.884, when the training data is 90%. The performance development of the developed method based on the existing techniques is 7.38%, 6.51% and 5.08%.

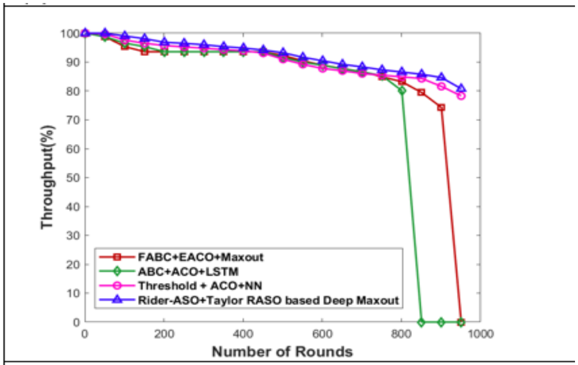
Figure 5 b) illustrates the performance analysis of developed Taylor RASO-based Deep Maxout method based on average residual energy with varying the number of rounds. The average residual energy of the developed method Taylor RASO-based Deep Maxout method is 0.2059 J, whereas the existing techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN achieved the average residual energy of 0.1775 J, 0.1883 J and 0.1922 J, when the round = 600. The performance improvements of the developed method with respect to the existing techniques are 13.81%, 8.55% and 6.63%.

Figure 5 c) illustrates the analysis of developed Taylor RASO-Based Deep Maxout method based on throughput by varying the number of rounds. The throughput obtained by the developed method is 86.55%, and the existing techniques, like FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN achieved the throughput of 83.19%, 80.10% and 84.87% when the round =800. The performance improvement of the developed method with respect to the existing techniques, such as FABC+ ESCO_ Maxout, ABC+ACO +LSTM and Threshold+ ACO +NN based on throughput is 3.88%, 7.45% and 1.94%.





(b)



(c)

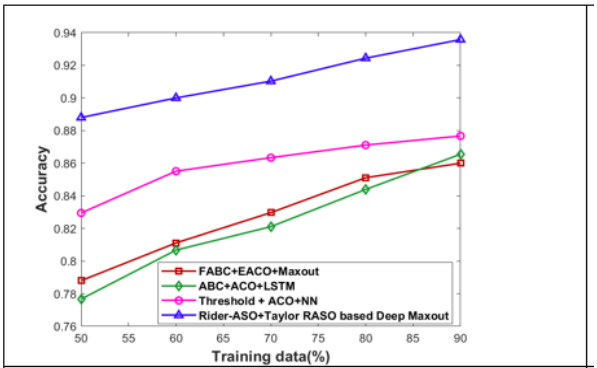
Figure 5. Comparative analysis of evaluation parameters with various rounds at 100 nodes, a) Accuracy, b) Average residual energy, c) Throughput

4.5.3 Analysis through 150 nodes

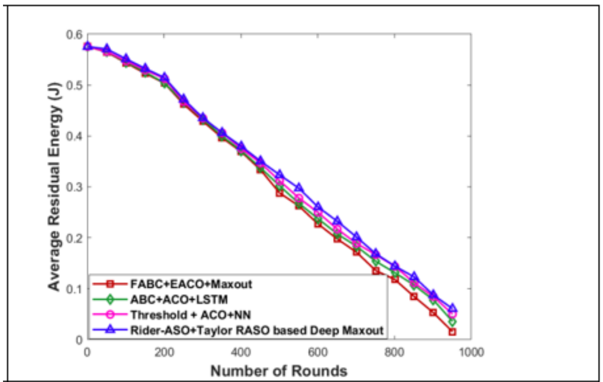
Figure 6 illustrates the analysis of developed model in terms of evaluation parameters, like accuracy, average residual energy and throughput using 150 nodes. Figure 6 a) shows the performance of developed method based on accuracy using 150 nodes. The accuracy obtained by the developed model, and the existing techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN is 0.9244, 0.8511, 0.8439 and 0.8711. The performance improvement of the developed model with respect to the existing techniques is 7.92%, 8.70% and 5.76%.

Figure 6 b) shows the performance analysis of developed Taylor RASO-based Deep Maxout method based on average residual energy with varying rounds. The average residual energy achieved by the developed Taylor RASO-Based Deep Maxout model is 0.2014J, whereas the existing techniques, such as FABC+ESCO_ Maxout, ABC+ACO +LSTM and Threshold+ ACO +NN achieved the average residual energy of 0.1716 J, 0.1833 J and 0.1891 J, when the round= 700. The performance improvement measured while evaluating the performance of developed model with respect to existing techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN based on throughput is 14.78%, 8.99% and 6.11%.

Figure 6 c) illustrates the analysis of developed model based on throughput using 150 nodes. The existing techniques, like FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN achieved the throughput of 79.25%, 75.15% and 77.86%, while the developed method achieved the maximum throughput of 87.91% when the round=800. The performance improvement achieved while evaluating the analysis of developed Taylor RASO-Based Deep Maxout with respect to the existing techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN based on throughput is 9.84%, 14.51% and 11.42%.



(a)



(b)

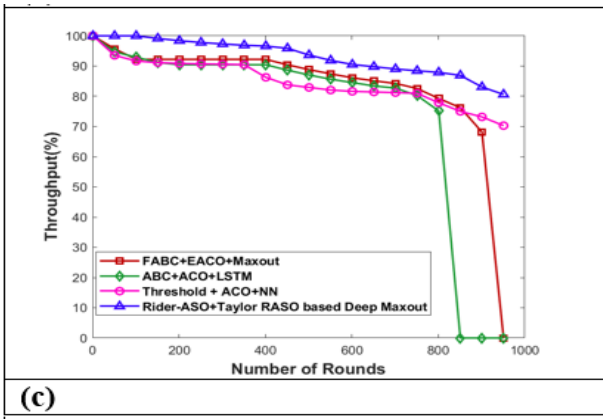


Figure 6. Comparative analysis of evaluation parameters with various rounds at 150 nodes, a) Accuracy, b) Average residual energy, c) Throughput

4.6 Comparative Discussion

Table 2 illustrates the comparative discussion of developed Taylor RASO-Based Deep Maxout method. Based on 50 nodes, the accuracy achieved by the developed model is 0.9358 and the accuracy achieved by the existing techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN method is 0.86, 0.8655 and 0.8767, respectively. The developed method achieved the average residual energy of 0.0876 J, and the existing techniques, such as FABC+ESCO_Maxout, ABC+ACO +LSTM and Threshold+ACO +NN achieved the average residual energy of 0.0530 J, 0.0781 J and 0.0846 J using 150 nodes. The throughput achieved by the developed method is 87.91%, and the existing method, such as FABC+ESCO_ Maxout, ABC+ACO +LSTM and Threshold+ ACO +NN achieved the throughput of 79.25%, 75.15% and 77.86% through 150 nodes.

Table 2. Comparative discussion

Number of Nodes	Metrics	FABC+ESCO_Maxout	ABC+ACO +LSTM	Threshold+ACO +NN	Developed Taylor RASO-Based Deep Maxout
50	*Accuracy*	0.89	0.8897	0.9	**0.9298**
	Average residual energy	0.018689	0.038037	0.043422	**0.04632**
	Throughput	85.84065	83.83514	86.85574	**87.28014**
100	*Accuracy*	0.863	0.8711	0.8844	**0.9318**
	Average residual energy	0.0171	0.042195	0.042385	**0.043573**
	Throughput	83.19691	80.10517	84.87568	**86.55656**
150	*Accuracy*	0.86	0.8655	0.8767	**0.9358**
	Average residual energy	0.053049	0.078139	0.084627	**0.087668**
	Throughput(bits per second)	79.25748	75.15528	77.86885	**87.91707**

5. Conclusion

This paper presents the intrusion detection system, named Taylor-RASO to detect the intrusions in WSN. The proposed Taylor-RASO is designed by incorporating Taylor series, ROA and ASO algorithm. The method enhanced the energy efficiency and maximized the lifetime of nodes, thereby performance of intrusion detection is improved, along with proposed Taylor-RASO, a fitness function, like delay, trust, distance, and energy is considered. The proposed Taylor-RASO with the fitness function enhanced the overall network performance and regulates secure data transmission for detecting the intrusions in network. The CH is chosen based on O-SEED clustering, where the optimal threshold and the CH are determined using RCSO, which is the combination of ROA, and CSO. The major significance of Taylor-RASO is that the optimal exploration and convergence rate of network and in addition, the importance of the research is on the fitness evaluation for predicting intrusions in network. The developed Taylor-RASO outperformed other methods with maximum accuracy of 0.935, maximal average residual energy 0.087J, maximal throughput of 87.91%, correspondingly. While using 200, 500, 800 nodes are the accuracy, maximal residual energy and maximal throughput increases .In future multi-path routing with intrusion detection performance shall be enhanced by any other hybrid optimization algorithms, and the immune computing algorithms.

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