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ORIGINAL PAPER

Routing attacks detection in MANET using trust management enabled hybrid machine learning

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Abstract

The ever-changing topology in mobile ad hoc networks (MANETs) makes routing a formidable obstacle. The infrastructure-independent capabilities of MANET ensure the temporary communications linkages, but the lack of a good centralized monitoring method makes routing in MANETs a severe trust and safety concern. As a result, this study presents a new energy-and trust-aware protocol for routing that depends on the suggested as well as enabled by Deep Reinforcements Learning. The best route choice is being carried out by the suggested Dolphin Cat Optimizer according to the modelled objective function that takes into account trust criteria, including current trust, historic trust, both direct and indirect trust, delay, distance, and connection lifespan. Combining the advantages of both the Dolphins Echolocation as well as the Cat Swarm Optimization algorithms, the Dolphin Cat Optimizer is able to achieve quicker worldwide cooperation. The suggested protocol for routing achieved 0.6531, 0.0107, 0.3267, as well as 0.9898 in absence of network assaults, as well as 0.7693, 0.0112, 0.3605, as well as 0.9961 in the event of network attacks, according to the modeling involving 75 nodes.

Keywords MANET · Trust management · Hybrid machine learning · Routing attacks detection

1 Introduction

The goal of smart cities is to make cities more efficient as well as sustainable, as well as intelligent parking is an essential part of that effort. It makes more efficient use of parking spaces as well as enhances drivers' experiences by utilizing gadgets like sensors as well as Internet of Things devices [1]. Urban areas may benefit from smart parking systems since they lessen traffic, cut down on pollution, and they make parking easier for everyone. To get the most out of Battery Management Systems (BMS), it's important to have precise estimations of the remaining useful life (RUL) of lithium-ion batteries (LIBs), as these batteries are crucial to many distinct sectors. Because humans are fallible in their prediction abilities, it is not necessarily practical to conduct standard building examinations [2]. This means that automated procedures need to be more robust, extensible, and effective. One of the automated technologies for predicting possible building damage is Structural Health Monitoring (SHM). Recent severe wildfires in Australia have highlighted the country's susceptibility to such disasters, which may be attributed to a combination of characteristics such as its terrain, weather, vegetation, as well as ignition sources [3]. The use of artificial intelligence has greatly enhanced the precision and efficacy of medical diagnostics. Early as well as precise forecasts may save lives in the diagnosis of tumors in the brain, which are deadly [4]. Modern and sophisticated society cannot function without a consistent and dependable source of power. In the past, electrical system analytics relied heavily on commercially available formal software, mathematical models developed by a combination of analysis of data, theory of control, as well as statistical methodologies [5]. Conventional power grid systems are urgently in need of an update due to the increasing demand for more efficient and environmentally friendly energy solutions and the subsequent change in focus towards integrating artificial intelligence (AI). Power production, transportation, and delivery to commercial and residential customers are

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all being enhanced with the use of forecasting and prediction methods that utilize artificial intelligence [6]. Innovations in methodology as well as technology are the primary forces behind this change in perspective. These advancements in technology allow for more precise and rapid fault prediction as well as detection, which in turn allows for more efficient and rapid fault removal. Thus, it is essential to integrate AI into contemporary power networks to guarantee its robustness, effectiveness, and longevity, which will eventually lead to a more environmentally friendly energy future [7]. After careful examination, it is clear that the hybrids AE-LSTM models outperforms models that depend just on the structure of the other model. This is because it receives extra education, which allows it to make accurate forecasts. To summarize, our work shows that sophisticated methods for machine learning may change the way renewable energy is integrated. One interesting way to improve the precision of predictions is using a combination AE-LSTM models [8]. With the proliferation of smartphones and widespread access to the internet, people now have a powerful new tool at their fingertips: the internet. The majority of online postings are written in text and frequently reflect the author's emotional state at the time. In order to identify people who may be emotionally unstable as well as cause unforeseen effects or risks to national safety, it is crucial to track their attitudes or ideas expressed online [9]. The danger that riots and civil war pose to stability in society and politics, two pillars of national security, need action. An important area of study that needs improvement is opinion mining in relation with the national safety sector [10]. If we want the best outcomes from mechanisms and procedures that can mine beliefs on political security, we need to make major enhancements. Emotion, mood, as well as political security concerns are strongly correlated, according to academics. In light of the increasing output of clean energy sources offshore, submarine power cables are an important component of electric distribution and transmission systems and have global, national, and even international implications for security of energy as well as carbon reduction [11]. The current state of condition surveillance is severely hampered by too simplistic online monitoring solutions that can only detect internal failure modes (which account for 30% of cable breakdown mechanisms) as well as cannot detect external damage or failure early enough to warrant further investigation [12]. We provide a novel fusion forecasts method that may offer in situ cable condition analysis to circumvent these restrictions. The test system's effectiveness in communicating as well as energy savings were both significantly enhanced by the method's optimization of the systems for managing both energy as well as communication. Finally, this research reveals an optimization approach that successfully handles the test system's communication as well as power management issues [13] by combining machine learning with modified instructional learning. Furthermore, this technique might be used in other smart city sectors not included in the current test. The results of this study provide important information for lowering energy use in cities with extensive populations and help move smart city technology forward. An important factor in maintaining the security as well as financial viability of nuclear power stations is the critical flow of heat (CHF) [14]. For reasons of public safety, it limits how nuclear power plants may be built and operated. Consequently, researchers may optimize system efficiency, mitigate equipment failure risk, and enhance security precautions with the help of precise CHF predictions utilizing a hybrid architecture. There is still no consensus on the process that causes CHF, even though there are several prediction approaches. Therefore, creating a CHF model that is both accurate and trustworthy is an important but difficult undertaking [15].

The objectives of our proposed system to choose the best pathways, taking into account factors including latency, separation, link lifespan, both direct and indirect trust, trust history, as well as faith in the past.

The study main contribution is to safe routing in mobile ad hoc networks (MANETs). It presents a revolutionary method that blends trust management with Deep Reinforcement Learning (DRL). Based on variables like node trust, energy, and throughput, the DRL agent learns to select the best paths. Techniques for evaluating a node's reliability and spotting rogue nodes are included in trust management. Assessments reveal notable enhancements over current protocols for packet delivery ratio, latency, and throughput even when subjected to Sybil and black hole assaults. A viable option for safe and effective communication in MANETs is provided by this DRL-based routing with trust management.

Here is the breakdown of the remaining sections of the essay: In Sect. 2, we will examine the difficulties of the current approaches by reviewing eight research papers. The third part delves into the MANET's structure. Section 4 discusses the suggested MANET forwarding approach, as well as Sect. 5 presents the approach's findings. Section 6 serves as the paper's last paragraph.

2 Related work

Internet of Things (IoT) intelligent parking is the process of optimizing and improving smart city park efficiency via the deployment of IoT technologies. Nevertheless, there are concerns as well as dangers associated with the gathering and utilization of information by parking systems due to security and privacy issues in IoT-enabled intelligent parking. These include the possibility of data breaches, illicit use or misuse of data, and the necessity to guarantee accountable gathering and use of information in order to preserve user confidence and trust. We provide a new hybrid method to trust administration that uses machine learning techniques to improve the system's safety as well as privacy in order to tackle these difficulties. We use SVM and ANNs in our strategy, with honesty, availability, as well as trustworthiness as our primary metrics. In addition, we use ensembles machine learning methods to choose the most accurate model out of many trained designs, resulting in dependable performance. We found that the recommended hybrid SVM classifier using trust variables was 96.43 percent accurate in recognizing and eliminating corrupted or illicit nodes. [16].

Here, we provide a novel method for improving the accuracy and consistency of battery assessment by constructing a combination of models out of several artificial intelligence approaches. To effectively identify complicated correlations and patterns in battery information, our suggested approach utilizes the capabilities of k-nearest-neighbors (kNN), Random Forests (RF), as well as XGBoost (extreme gradient booster) techniques. For the reason of effective assessment of battery condition and degeneration as time passes, our primary goal is to properly quantify the remaining power as well as RUL of LIBs. capacity, the voltage, cycle, as well as heat are just a few of the critical battery metrics that we painstakingly compile into an exhaustive database. With a low MAE of 0.008956, a coefficient R2 of 0.996457, as well as a minimum RMSE of 0.016861, the suggested hybrid model accomplishes remarkable outcomes. Improving the efficiency of energy storage systems, making superior upkeep plans, and increasing the lifespan of batteries are all possible thanks to the insight offered by our study [17].

Energy in contemporary skyscrapers mostly comes from diesel generator sets (DGs) as well as battery storage systems (BSS). Minimizing electrical grid injection via the use of a centralised Energy Management Software (EMS) is the objective of this work, which takes into account DG, BSS, as well as photovoltaic systems (PV). The efficacy of various models of regression may be predicted using Machine Learning (ML) approaches via comparison of power lines as well as demand curves. It encompasses methods that utilize Artificial Neural Networks (ANNs), Wide Neural Networks (WNNs), Linear Regression (LR), Linear Regression Interface (LR-I), Linear Research Stepwise (LR-S), Research Fine Tree (RF-T), Research Coarse Tree (RC-T), as well as Gaussian Process Regression (GPR). The ML approach is linked with Demand Side Managing (DSM) methods in a Heterogeneous energy source (HS) system, which includes peak shaving as well as valley filling.The grid profile may be effectively reshaped without rescheduling or detaching loads, as shown by the contrasting investigation of outcomes. To ensure the accuracy of the data, the Matlab simulated program is implemented [18].

Using the Hybrid Learning Machine Techniques, this article proposed a method for tracking a structure's structural state. Two-hybrid processes are included in HMLT. Method for determining what characteristics in a dataset are most important by use of a combination of feature selection process (HFSM). When choosing features, HFSM takes into account both RST as well as Mutual Information (MI). To further improve the precision of building strength status predictions, optimal classifiers like Support Vector Machine (SVM) and Artificial Neural Networks (ANN) are employed for categorization as well as prediction. The Gorkha Earthquake Impact Dataset, collected in April 2015, is now undergoing the application of the suggested approach. The training as well as tenfold cross-validation technique is applied pragmatically to variables. Next, the accuracy metric (92%) as well as the F1-score (91%), two measures of technique achievement, were used to assess the suggested approach. Lastly, the analysis of the results shows that the suggested method is important for forecasting the construction's stability state [19].

Metabolic abnormalities, such as those affecting mitochondrial as well as glutathione (GSH) metabolism, are recognized as a characteristic of several malignancies. Our investigation into mitochondria GSH (mGSH) transportation within the cancer setting aims to fill a gap in our understanding of this understudied component of GSH biosynthesis. Here, we use hybrid artificial intelligence (AI) models to find individuals implicated in mGSH metabolic as well as membrane transport in malignancies by using multi-omics information gathered from cancer cell lines as well as additional scientific information as characteristics. Based on these models, it is extremely likely that GSH oxidation in malignancies is associated with the well-known mGSH transporter SLC25A39, rather than SLC25A40. Furthermore, it is anticipated that SLC25A37 as well as SLC25A24, as well as the understudied SLC25A43 as well as SLC25A50, would be linked. In terms of possible adhesion to substrate areas, SLC25A39 is comparable to both SLC25A24 and A43, two other options. These results provide new avenues for research into how cancer cells metabolism as well as potential treatment targeting [20].

Using artificial intelligence to forecast Sydney residents' vulnerability to wildfires, this research analyzed and comprehended the variables that control the geographical distribution of wildfire events using a GIS (geographic information system) approach. For the Sydney region, wildfire inventory data was created by merging field survey information of the fire boundary with data on fire occurrences collected via the visible infrared radiometer suites (VIIRS)-Suomi thermal anomaly products from 2011 to 2020. In order to evaluate the possibilities of using artificial intelligence (AI) employing support vector regression, also called SVR, as well as several metaheuristic techniques (GWO and PSO) for predicting the vulnerability to wildfire in Sydney, 16 variables pertaining to these disasters were collected. Furthermore, the created algorithm's forecasting potential was evaluated using the 2019–2020 "Black Summer," which was released fire as a test database. The research area's vulnerability to wildfires was then examined using the data ratio of gain (IGR) approach, which revealed that driving variables such woodland type, slope degree, and land use significantly affect the risk of flames. The occurrence ratio (FR) methodology then depicted how each of these variables affect the amount of wildfire. According to the results of the area according to the curve, or AUC, as well as the root mean square error (RMSE) tests, the hybrid-based SVR-PSO models outperformed the independent SVR as well as SVR-GWO models. Wildfire sensitivity modelling in the research region was therefore made more accurate by optimizing SVR using heuristics If you're doing study on the vulnerability of various problems, the recommended structure might serve as a substitute to the modelling technique. [21].

The limitations of conventional microscopes, the need to use external labeling agents, and the state of the art in computational methods all contribute to making the accurate statistical assessment of organelles within cells in 3D imaging data an enormous problem. Our hybrid machine-learning system combines 3D qualitative phase scanning with 3D fluorescent imaging of tagged cells to overcome these obstacles. 3D qualitative phase image of labeled cell information is used for training the learned networks, which uses the correlated image data set to train a random-forest classification as well as a deep neural network that work synergistically [22].

The purpose of this research is to provide a method for detecting brain tumors using MRI data and a machine learning framework. Shape, statistics, color level size zone, dependency, co-occurrence, and final length matrices are all part of the 3D-UNet as well as 2D-UNet segmentation characteristics that we use to train the suggested model. We provide a hybrid approach that uses soft voting criterion to merge the best features of two artificial intelligence models—GBC and the k-nearest-neighbor model (KNN)—in order to maximize efficiency. We merge them because GBC displays remarkable performance when KNN fails to do so for specific information points, as well as KNN outperforms GBC when GBC fails to do so. The model successfully attains a 64% accuracy rate using 2D-UNet segmentation features. We outperform current current algorithms that use 3D-UNet segmented characteristics by learning it on these features, resulting in a considerable accuracy of 71% [23].

In the framework of the so-called fourth industrial revolution (4IR), this study primarily discusses the integration of artificial intelligence (AI) into contemporary power generating grids. Artificial intelligence (AI) has arisen as a potential solution to the growing complexity and need for more effective as well as dependable power systems. To achieve this goal, we looked at three years' worth of user-side real-time data together with the number of both inside and outside grid failures that occurred. In order to forecast and identify faults in power grids, this study investigates the application of cutting-edge artificial intelligence hybrid models at the end-user sites. Convolutional neural network (CNN) mixed models, including CNN-RNN, CNN-GRU, as well as CNN-LSTM, were created in this research. Modern power networks may become more robust, efficient, as well as sustainable by employing AI technologies. This will eventually contribute to a more sustainable and environmentally friendly energy economy [24].

In order to better incorporate renewable energy sources into smart grids, this research investigates the use of sophisticated machine learning methods, with a particular emphasis on the generation of solar energy prediction for the future year. Three separate machine learning (ML) algorithms are utilized: LSTM, Bi-LSTM, and an AE-LSTM hybrid which combines an Autoencoder with Long Short-Term Memory. These models undergo training and evaluation utilizing the mean squared error (MSE) as well as mean absolute error (MAE), two performance measures that are based on real-time data of solar power output that spans an entire year. Because it can capture complex temporal relationships and trends within the data, the combination of the AE-LSTM approach outperforms the LSTM and Bi-LSTM models in terms of accuracy [25].

In order to forecast potential dangers to political stability, this research suggests an innovative theoretical structure that combines a lexicon-based methodology with cyber-based machine learning. As far as threat classification goes, the suggested framework makes use of a decision tree, Naive Bayes, as well as Support Vector Machine. We conducted an experimental investigation to confirm the validity of our suggested paradigm. Results for every approach employed in the studies are detailed. The study's suggested framework shows that the best method for forecasting political security concerns is a mixed Lexicon-based strategy that also makes use of a Decision Tree classification. These results provide important information for future studies on mining opinions for threat prediction in the diplomatic safety area [26].

Cell type the deconvolution is necessary for cellular-level subsequent evaluation of spatial barcoding-based transcriptome (ST) information. In order to deconvolve ST data utilizing standard single-cell DNA sequencing (scRNA-seq) information, we introduce SDePER, a combination of machine learning as well as regression approach. Using a machine learning strategy, SDePER quickly and explicitly eliminates the platform effects—a systemic distinction between ST for scRNA-seq data—to guarantee a linear connection among ST information and a cell type-specific transcriptional profiles. Additionally, it takes into account the spatial connection in various cell compositions across spots as well as the limited number of cell types each capturing spot. In a tissue map with improved resolution, SDePER uses the predicted cell type percentages to infer the expression of genes as well as cell type composition at unknown sites. Compared to previous approaches, SDePER produced more accurate and resilient findings when applied to both coarse-grained simulation information as well as four actual datasets. This highlights the significance of platforms impacts, sparsity, as well as spatial relationship when performing cell type the deconvolution. [27].

In this article, we present the development of a low-frequency wide-band sonar (LFWBS) for the purpose of collecting acoustic response information from a variety of subsea power cable samples with varying inner framework arrangements. The goal is to gather integrity information at various stages of degradation by collecting signatures from caused physical inability settings. Integrity assessment within a hybrid, holistic monitoring paradigm may be accomplished by using a method based on machine learning, such as SVM, KNN, BP, as well as CNN methods. An overall correctness level of 95% + was achieved in detecting various phases of cable deterioration, as well as findings showed that subsea cable could be distinguished by changes of 5 mm in size as well as cable kinds. As a result, crucial undersea power lines may benefit from improved asset administration and forecasting capabilities [28].

Improving smart city communication as well as energy management is the goal of this research, which presents a hybrid approach that merges machine learning with modified instructional learning-based optimisation (TLBO). Because of the difficulties caused by their dense populations, optimizing the modified systems is the main goal. The suggested approach combines the benefits of teaching training-based optimization methods with artificial intelligence methods, particularly the LSTM (long short-term memory) method. In response to input from the equipment, it modifies its settings to maximize efficiency in terms of both energy use and data transmission. By analyzing past information on energy usage as well as communication patterns, a case investigation is performed on a test systems to assess the performance of the suggested approach [29].

To enhance the precision of CHF predictions, we presented a hybrid model that relies on an artificial neural network (ANN) in this research. To further narrow the gap between anticipated and actual outcomes, our model uses ANN in conjunction with the information that is already accessible via a search table (LUT). The study's findings show that the suggested hybrid model outperforms other machine learning models, with a rRMSE of only 9.3%. To guarantee the safe and effective functioning of nuclear energy reactors, our suggested method may be used as a continual surveillance tool for forecasting severe circumstances [30].

A novel approach used to investigating how sustainable development and lower carbon emissions might be achieved through green manufacturing techniques. It integrates a number of statistical methods (SEM-PLS, Machine Learning) to validate a model that associates reduced carbon footprints with green procurement, product design, and other practices. The study demonstrates the importance of these practices in achieving sustainability in society and production and emphasizes the necessity for increased leadership focus on their implementation [31]. The variables influencing low carbon emissions in manufacturing companies are being investigated. It looks at how an organization's internal sustainability procedures are impacted by external factors such as investor interest and governmental requirements. Key factors influencing low carbon performance, such as strict environmental laws and well carried out CSR programs, are identified by the study using statistical analysis. These results can help companies create strategies that will effectively lower their carbon impact [32]. A novel strategy for planning agri-food production that takes risks and interruptions into account. To enhance production forecasting and decision-making, it makes use of a strong stochastic optimization model. The methodology, which aims to improve management of the agri-food supply chain, produces better outcomes than conventional methods [33]. This study offers a thorough analysis of the current computer-aided diagnostic (CAD) breast cancer detection techniques rather than suggesting a novel approach. It classifies and examines deep learning, supervised, and unsupervised methods that are applied to picture segmentation in CAD systems. The intention is to inform researchers about the benefits and drawbacks of each segmentation strategy, enabling them to select the best approach for certain breast cancer detection applications [34].

A new method for identifying and segmenting breast tumors in mammography is proposed. It steers clear of intricate deep learning models by using a novel tactic. Initially, the system produces a number of encoded images that highlight various mammography aspects. A shallow Convolutional Neural Network (CNN) is then fed these encoded images to classify each pixel and detect any cancers [35]. In order to address COVID-19 hospital waste management, this study suggests a new structure for HWCNDs, or healthcare waste chain networks. It incorporates capabilities to manage uncertainties and interruptions together with a strong optimization model. For the first time in HWCND, the model incorporates sustainability, agility, and anti-fragility (such as blockchain technology). This all-encompassing strategy seeks to minimize costs and environmental effect while optimizing waste management [36]. A novel framework called Robust and Risk-Averse Medical Waste Chain Network Design (RRMWCNDV) is proposed in this study. It seeks to minimize trash and encourage recycling for the sustainability of the environment, all while optimizing the location of waste management facilities. Using a unique Weighted Value at Risk (WVaR) measure and a two-stage stochastic programming approach, the model integrates risk aversion with robustness. In medical waste management, this approach aids decision-makers in striking a balance between risk, expense, and environmental advantages [37].

A VMI-CS integrated approach for vendor-managed inventory in supply chains is suggested by the study. This approach optimizes inventory levels and addresses issues such as stockouts. It integrates sustainability and resilience against interruptions while minimizing costs through the use of a strong optimization model with a risk measure. The overall goal of this strategy is to increase supply chain efficiency [38]. This study suggests a novel approach to building robust supply chains (VSCNDOIBCT) that makes use of blockchain technology (BCT) and open innovation (OI). In order to minimize expenses and greenhouse gas emissions and to respond to disruptions, it combines an anti-fragility strategy (OI & BCT) with a robust optimization model. By guaranteeing minimal demand satisfaction and adaptable manufacturing capacities, the model also includes agility. In general, the goal of VSCNDOIBCT is to enhance supply chain efficiency through the incorporation of resilience, flexibility, and sustainability [39]. The Net-zero, Resilience, and Agile (NZRA) CLSCND is a unique idea for closed-loop supply chains (CLSCNs) that is proposed in this research. It incorporates resilience, agility, and environmental sustainability (net-zero emissions) into CLSCNs. The objective is to minimize CO2 emissions and ensure disruption resilience while optimizing the flow and positioning of materials within a home appliance CLSCN [40].

3 Proposed work

Think of a MANET where nodes are out in the environment detecting and gathering data. Inside this range, interaction among source and destination nodes takes place via a series of nodes, as well as every node gets its own communications range. Because nodes are movable, their new positions are always occurring somewhere in the interaction context as they move from one spot to another. Therefore, trust as well as distance is taken into account while determining the most effective means of communications. The best possible routes are shown in Eq. 1.

$$p = \{p_1, p_2, \dots, p_j, \dots, p_m\} \tag{1}$$

where m is the sum of all the best routes taken. The movement of nodes in MANET across space is modeled by their mobility models, which also detail their velocity, location, as well as velocity. These models update their locations on a periodic basis within the transmission range. In contrast, MANET safety is largely defined by trust, and the extent to which a network's node confidence one another is a representation of this trust.

In this part, we see how the DRL-HML procedure, which combines DRL-based navigation with HML as a confidence factor, may make MANET navigation more secure. Among the many processing phases in DRL-HML are the following: communication, optimum route choice, as well as k-path discovery. Using DRL, the data that was encrypted broadcasted the message during the RREQ as well as RREP stages. The suggested method finds the best pathways by taking into account trust variables, latency, distance, and connection lifespan. To guarantee security, everything is routed over the chosen path. A simplified representation of the suggested technique for routing is shown in Fig. 1.

3.1 Cluster formation

Once the optimal CHs have been determined, the overall getting is computed using the optimistic aspects of these system nodes [26–30]. It should be noted that property owners are defined as using the sink node in conjunction with the understanding sent into the spew via the CHs to a the nodes (or group associates). The attacker's node is prevented from connecting with the other nodes in the system after the intruder becomes discovered. The sink node has a predetermined threshold value of 0.5 J for anticipating intruders. In any case, the manager is free to tailor that threshold value to requirements. The standard value for the threshold is 0.5 J. We can learn about the transmission power as well as connectivity state of a channel from the remaining power range of individual nodes. If a node has little to no energy, for instance, it may have a decreased chance of linking to a faraway next node, which means it isn't part of a dependability pair. Yet, a node's ability to reach distant nodes is enhanced by increasing its transmission power while its energy is high. Ensuring secure network communication with low consumption of energy as well as transmission latency is the primary purpose of detecting breaches.

3.2 Trust management system

Using a cluster architecture for secure routing, administration, and reliability assessment, this research proposes a trust-based modeling secured routing approach. Nodes' dependability and administration are handled by the trust management nodes as well as the trust agent node, respectively. It is the responsibility of the confidence control node to oversee the dependability of each cluster's nodes as well as supply the necessary data. In order to assist the trust administration node, the trusted broker node gathers the dependability of all neighboring nodes. This study proposes

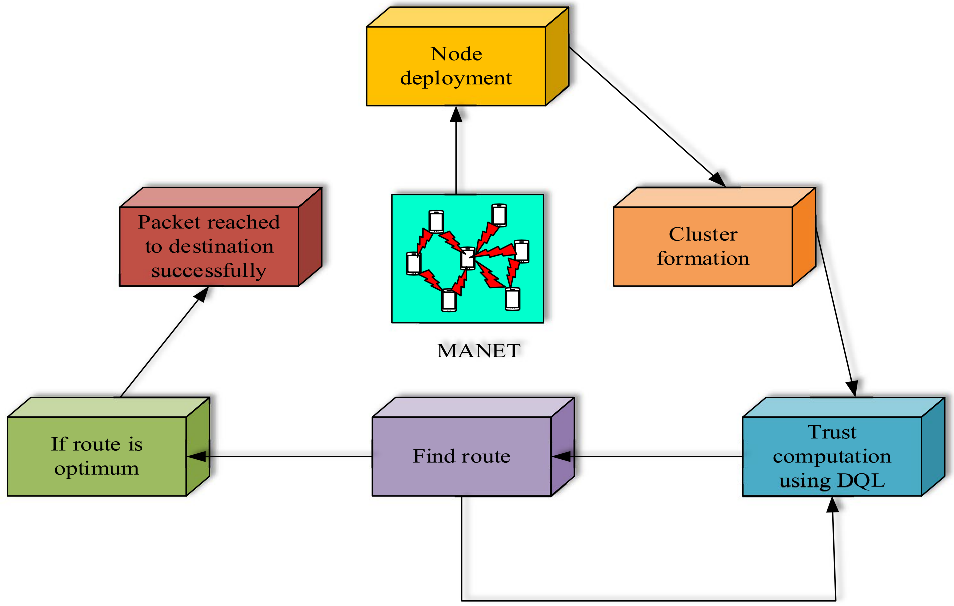

Fig. 1 Trust management in MANETs

a trust-based modeling safety routing approach that has three main components: trust administration, security path, and encrypted data transmission. To start, the reliability values for the nodes gathered by every cluster's trust agent are saved by the confidence administration modules. From time to time, this module also updates the neighboring node's reliability data as well as trust administration status. Nodes' dependability is evaluated by analyzing the traffic they receive from their neighbors and deciding whether it is packets originated by those neighbors or packets that have been relayed. Additionally, the dependability mean for the group's nodes is computed at regular intervals. Second, when a route is defined between two nodes, the safe path modules uses dependability measurements to determine the best course of action for security. When establishing a secure connection among two nodes, it is important to take into account both the individual nodes' dependability as well as the cluster's average consistency rating. And it uses the traffic measurements along the predetermined route to identify nodes that don't belong. Following a secure communication of data key transfer between both sending and receiving nodes, the final component handles actual data transmission.

Using the nodes' interaction patterns as a basis, it calculates the node's trust value. A number between one and zero is given for every node's trustworthiness. In the beginning, 0.1 is the trust value that is given to each node. A node's trust value might increase or decrease more quickly depending on its proportion of the effective ongoing transmission of packets. Here, we consider two kinds of trust values and look at each node's confidence value. Mixed trust assessment describes this kind of assessment. The Trust Computation in MANETs is shown in Fig. 2.

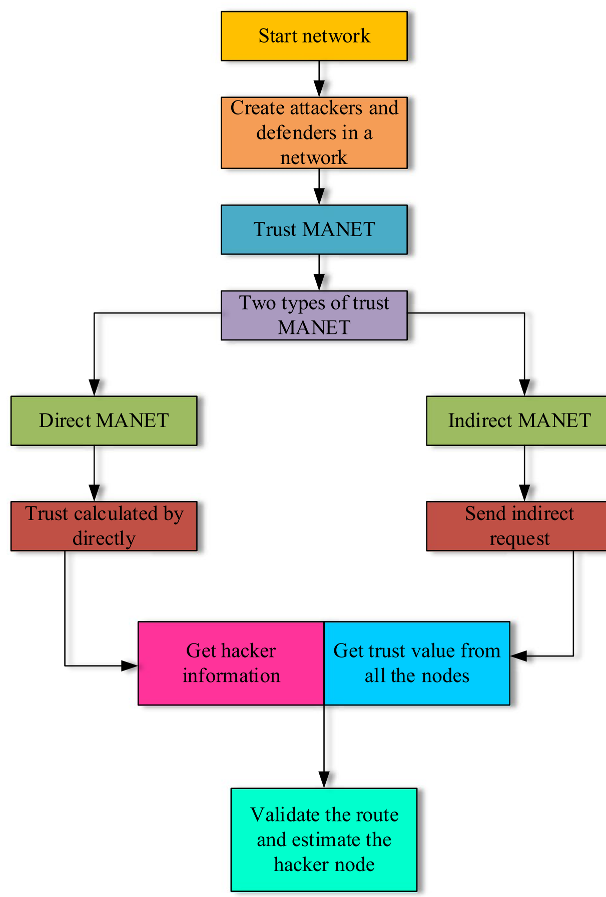

Fig. 2 Trust computation in MANETs

During this stage, a gateway determines the best technique to assess the level of trust. In the event that no other nodes in the vicinity of the suspect node are able to conduct an integrated examination to establish confidence, the gateway will resort to physically inspecting the node utilizing an unmanned node. In order to determine the transmission ratio for a particular duration, the drone node assigned to physical inspections travels to the region around the suspect node and does a task. After the actual examination returns its findings to the entry point, the assessment of trust may proceed. On the other hand, if the suspected nodes are in close proximity to other nodes as well as its trustiness score is more than 0.6, the gateway's firewall will initiate an interactive examination by sending a cooperative examination answer to all of the networks in the vicinity. The nodes in the vicinity of the suspicious node will conduct an interactive inspection to see whether the suspect node uses listening to to forward packets when they get a collaborative inspection answer. The sending ratio, as determined by the collaborative inspection, is used to conduct trust evaluations. On the other hand, the gateway will do a trust assessment using logical inspection if the suspect node's trustiness drops below 0.6 as a result of several false positives notifications or collaborative observations queries. When it detects a suspect node, it assigns the task of conducting a logical examination to the most trustworthy nodes in the vicinity. The overhearing node that is in charge of the logical inspections uses it to do a trust assessment.

The assessing node goes back to the localized observing stage if the suspicious node's trust assessment result is normal. In any case, if an assault is identified, the node proceeds to the inspections results exchange phase, whereby details on the intruding nodes are disseminated all through the network. What follows is a comprehensive breakdown of the procedure accompanied by visual examples.

3.2.1 Direct trust (DT)

The DT is based on the estimated time spent interacting between i^{if} node and d destination n. DT is defined as the difference between the actual as well as predicted time it takes for the i^"th "node to validate using the public key that the d^"th "destination has supplied. Therefore, DT associated with the i^"th" node and the d^"th" endpoint is shown in Eq. 2,

$$DT_i^d(\tau) = \frac{1}{3}\left[DT_i^d(\tau-1) - \left(\frac{\tau_{appx} - \tau_{\text{ast}}}{\tau_{appx}}\right) + \omega\right] \tag{2}$$

where, τ_{appx} gives the rough duration and τ_{est} specifies how long it will take to authenticate the public key.

To put it differently, τ_{app} and $\tau_{\sigma t}$ durations that the node as well as its destination anticipate for the transmission and receipt of the publicly available key. $^{\omega}$ Indicates the opinion variable associated with these nodes.

3.2.2 Indirect trust (IDT)

Based on DT, the node containing the view value is drawn. Nevertheless, the IDT is used for authentication of nodes that do not have an authorized variable, as provided in Eq. 3,

$$IDT_i^d(\tau) = \frac{1}{r}\sum_{i=1}^{r} DT_i^d(d) \tag{3}$$

where, ^{r} Identifies the node's general neighbors ^{i}.

3.2.3 Recent trust (RT)

Their instant will include a calculation of trust using DT and IDT, as well as important validity as well as allowing the location or sink. The RT is created in Eq. 4,

$$RT_i^d(\tau) = \alpha^* DT_i^d(\tau) + (1-\alpha) * IDT_i^d(\tau) \tag{4}$$

where, $\alpha = 0.3$

In this manner, data may be securely sent from one location to another. The suggested hybrid C-SSA method then uses the intended goal characteristic to choose the optimal pathways, taking into consideration the path's ability, throughput, as well as connectivity. Figure 1 shows the hybrid optimization-based trust-conscious, environmentally friendly MANET design.

Here, we improve security by integrating the notions of trust as well as deep packet inspection (DPI). The certification authority also creates a pair of public and private keys to authenticate nearby nodes and start the route agent. The data packet is sent to the intermediary nodes by computing a fake key, which depends on the intermediary host's trust. Afterwards, the DPI is started in order to gather the packet characteristics, and the probability of features similarity is evaluated. The classification of trust is represented in Fig. 3.

3.3 Secure routing

Intentionally harmful nodes in the internet slow down their routing algorithm. To identify the nodes that are acting abnormally throughout the routing process, the following steps are taken during this section. Mechanism of trust based Routing is described in Fig. 4.

3.4 Path compute function

How healthy a route is determined by the total amount of energy remaining among the nodes, the route's overall productivity, as well as the route's availability To that end,

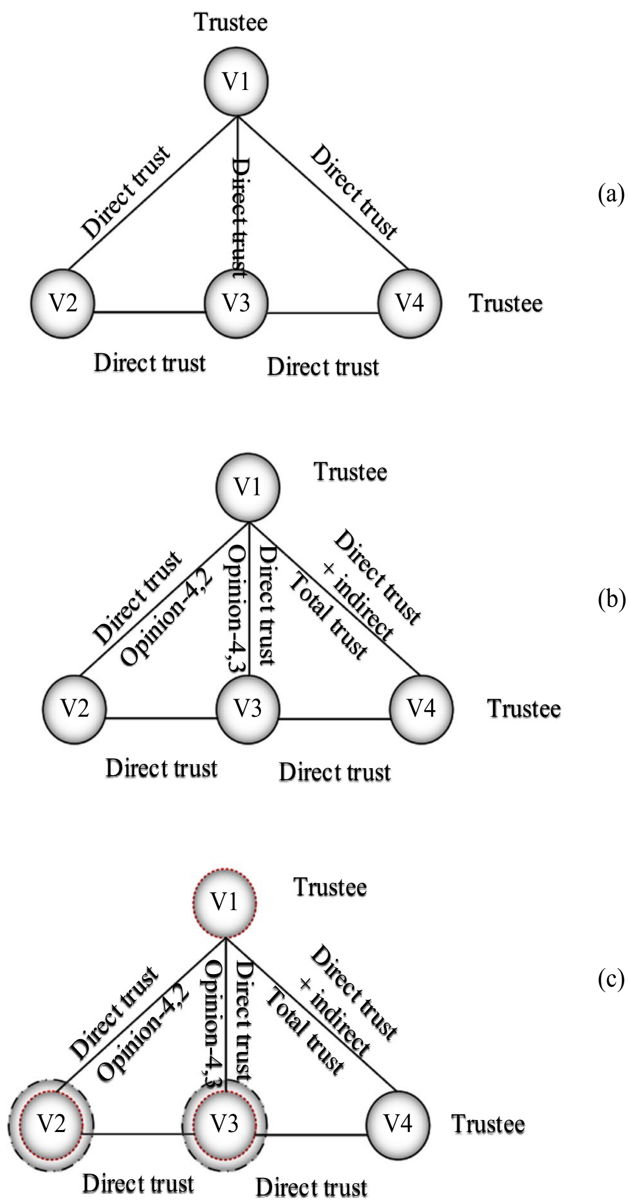

Fig. 3 Direct, indirect and hybrid trust calculation

the function of fitness is a function that maximizes, Which is shown in Eq. 5.

$$F - \frac{1}{3}(e + t + c) \tag{5}$$

These three variables are computed utilizing the path's nodes: e for energy, t for throughput, as well as c for connection. There are equations that may be used to determine how much energy is left in a node after transferring one piece of information. The ratio of total items transmitted through the system every minute is known as throughput, and it may alternatively be represented in Eq. 6,

$$u = \frac{v}{\tau}\,\text{bps} \tag{6}$$

where, $v_{\text{implies no of}}$ carried data packets from origin to destination and ^{t} sets the time in milliseconds. Based on bidirectional interconnections among two nodes, the connectedness may be expressed as in Eq. 7.

$$y = \frac{1}{g}\left[\sum_{i=1}^{R} \cdot \frac{y_l}{cc}\right] \tag{7}$$

Represents overall contacts.

The Markov Decision Process (MDP) provides a helpful theoretical structure for addressing relevant issues within the scope of RL. In order to accomplish a certain control as well as optimization objective, the MDP provides an abstract framework for the issue to be learned via interactions. Here, an MDP environment is built by the network's mind in conjunction with the network's fundamental surroundings, as well as the two work together in an ongoing cycle to provide methods for control. The autonomous AI agent keeps an eye on the network status at all times s_t ffrom the network's foundation and utilizes the present approach to inform a routing choice $\pi(a \mid s)$. When the controller reaches a decision, it communicates that decision to the network's node throughout the forwarded route by issuing the appropriate policy. After then, the system moves on to the next phase s_{t+1}, in this case the natural world promptly bestows an incentive R on the AI agent. In particular, data about network components as well as traffic characteristics may stand in the role of the network's status, while the forwarding route can stand in for the activities. When it comes to optimisation goals like bandwidth guarantees or delay requirements, the reward function determines how well the activities were done in relation to the objective.

The DDPG method, which stands for Deep Definitive Policy Gradient, is used to generate policies in this dissertation [23]. There are two parts to a DDPG agent: the algorithm for a predetermined policy network $\mu(s \mid \theta^{\mu})$ beside the Q – network (analytical) $Q(s, a \mid \theta^{Q})$. The player makes an effort to enhance the existing policy $\mu(s \mid \theta^{\mu})$ according to the policy slope, as well as the opponent assesses the present policy's efficacy using the criteriaθ^{μ}. By alternating among acting as an agent for policy enhancement as well as a critic for policy assessment, the DDPG robot employs an iterative policy process.

The DDPG agent chooses an action according to the present strategy as the initial step in learning is depicted in Eq. 8:

$$a_t = \mu\left(s_t \mid \theta^{\mu}\right) + \mathcal{N}_t. \tag{8}$$

After then, the agent carries out the task a_t keeps an eye on the reward, r_t, and the changed condition s_{t+1} to the

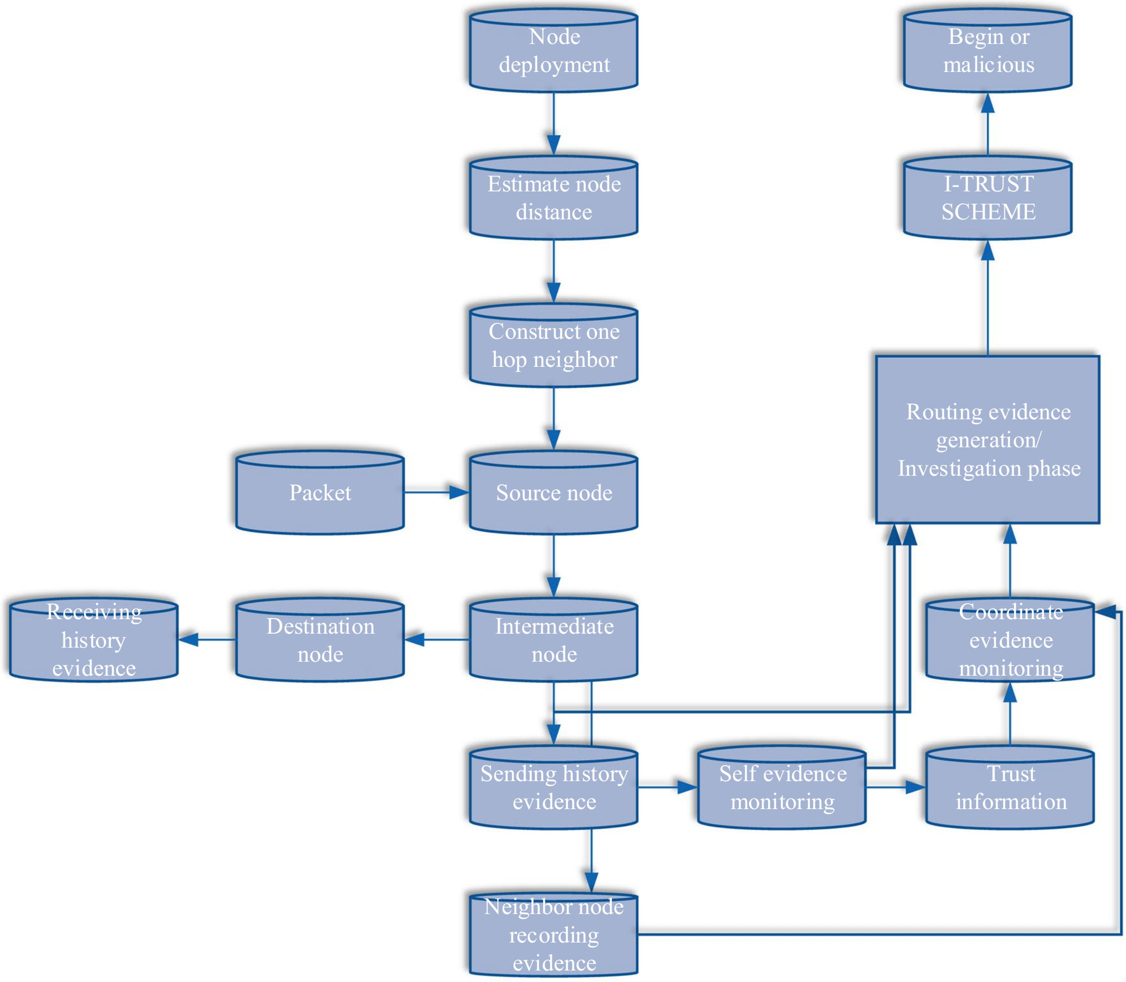

Fig. 4 Trust based routing mechanism

network's foundation. By using a replay memory R, time-dependent correlation among information may be eliminated throughout the training process. Information on the change (s_t, a_t, r_t, s_{t+1}) are kept in R for the present step, and thereafter, a minibatch of N transitions at random (s_i, a_i, r_i, s_{i+1}) in order to refresh the critic the network, data is taken from the replayed storage using the ADAM optimization to minimize subsequent loss is shown in Eq. 9 [24]:

$$L = \frac{1}{N}\sum_i \left(\gamma_i - Q\left(s_i, a_i \mid \theta^Q\right)\right)^2 \tag{9}$$

where we set γ_i to

$$y_i = r_i + \gamma Q\left(s_{i+1}, \mu\left(s_{i+1} \mid \theta^\mu\right) \mid \theta^Q\right) \tag{10}$$

The following is an explanation of how a sampled policy gradients is used to update an actor's policy in order to maximize the discount continuous reward, which is described in Eq. 11:

$$\nabla_{\theta^\mu} J \approx \frac{1}{N}\sum_i \nabla_a Q\left(s, a \mid \theta^Q\right)\Big|_{s=s_{i,a}=\mu(s_i)} \nabla_{\theta^\mu}\mu(s \mid \theta^\mu)\Big|_{s_i} \tag{11}$$

The benefits of DRL for controlling networks outweigh those of more conventional heuristic-based techniques. For starters, DRL doesn't need assumptions or reductions to produce information straight from complicated, high-dimensional, chaotic networking systems; this is all because to neuronal networks' remarkable generalizability. Secondly, DRL permits a rewrite of reward functions to accommodate various networking aims without altering the algorithm approach, making it a black-box optimization strategy. Finally, after training, a DRL agent just needs one step to choose a nearly ideal forward course. As soon as the state of the network changes, heuristic-based systems need to go through a long process of convergence to find a new optimum solution. Serious non-convergence will result from the ensuing computational complexity, which is especially problematic in massive, extremely volatile systems. A MANET's normal routing is depicted in Fig. 5.

4 Results & discussion

The simulator has been enhanced with one hundred nodes at a simulated atmosphere as well as was made use of from the NS-2 instrument. In this case, we are using simulation duration of 40 ms for the results. Here is the setup for the simulation's experimental surroundings: The experimental mobile node is a randomized way point architecture that moves freely across the network. We did not account for the nodes' electrical usage in our simulation, which included mobile speeds of 5, 10, 15, as well as 20 m/s. Over the course of the 300-s trial, five such attacks—one each of Hello flooding, jellyfish, and jamming—took place. The study utilized a kind of Jamming attack that operated on the network's layer and utilized misleading tactics. All of the variables that were tested may be seen in Table 1.

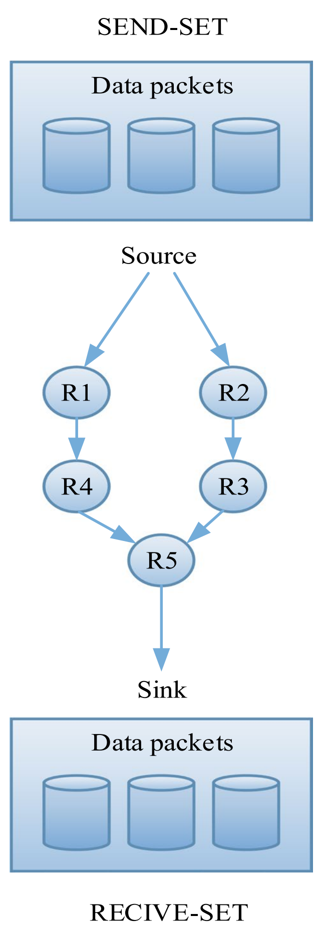

Fig. 5 Normal routing in MANETs

Table 1 Simulation parameters

Parameters	Values
Simulation area	100 m × 100 m
Mobility speed	30 ms
Size of packet	16 bytes
Number of nodes	50,75
Number of sources	75 (nodes 1–75)
Number of sinks	1
Mobility model	Random waypoint model
Channel type	Wireless channel
Node placement	Random
Antenna type	Omni-directional
Simulation time	50 rounds
Radio model	Two-way ground

4.1 Performance metrics

Using characteristics such as energy consumption, detection rates, throughput, and delay, the research compares the suggested approach to all current methods based on competency criteria, regardless of whether there is an assault. As a maximum value to assign the device's period, the apparatus energy is the energy that remains behind each node after transmission is ceased. While the duration indicates the whole time it may take for this specific data to be conveyed, the result signals of this device is connected to the accumulated quantity of data supplied by its components within a certain time period. Performance of PDR, PLR, average end-to-end delay and throughput is shown in Eq. 12, 13 and 14.

Here we get into the specifics regarding the approaches' comparison study, which is based on evaluation criteria as well as continues with nodes both with and without nodal assaults to show how successful the suggested approach is.

4.1.1 Packet delivery ratio (PDR)

The packet-to-transmit ratio is the ratio of the total packet acquired compared to the total packets transmitted. Performance of Packet Delivery Ratio vs. Time is shown in Fig. 6.

$$\mathrm{PDR} = \frac{\text{Total no. of packets received}}{\text{Total no of packets sent}} \tag{12}$$

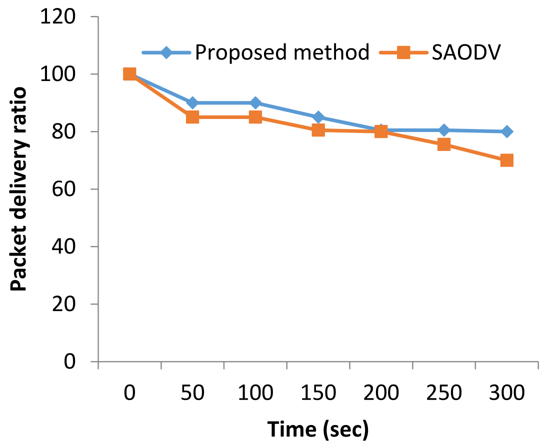

Fig. 6 Packet delivery ratio versus time

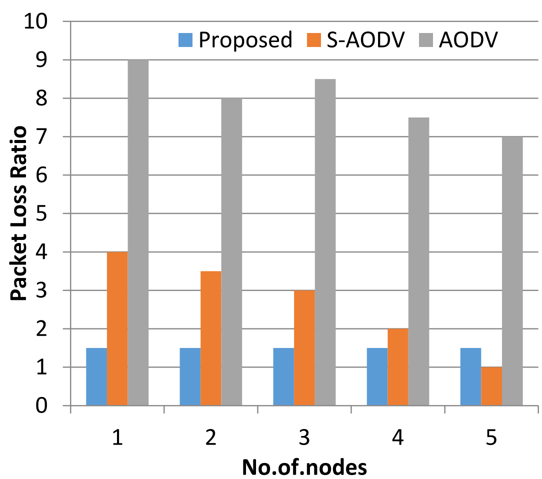

Fig. 7 Packet loss ratio versus no of nodes

4.1.2 Packet loss ratio (PLR)

It stands for the entire amount of packets that were dropped while being sent. It is calculated as the ratio of all the lost packets to the total payload received. Performance of Packet Loss Ratio vs. No of Nodes is described in Fig. 7.

$$\mathrm{PLR} = \frac{\text{Total no. of packets lost}}{\text{Total no of packets received}} \tag{13}$$

4.1.3 Average end-to-end delay

The term refers to the sum of all the times that packet spend traveling from their origin to their final destination, taking into account factors such as transmission time, delay

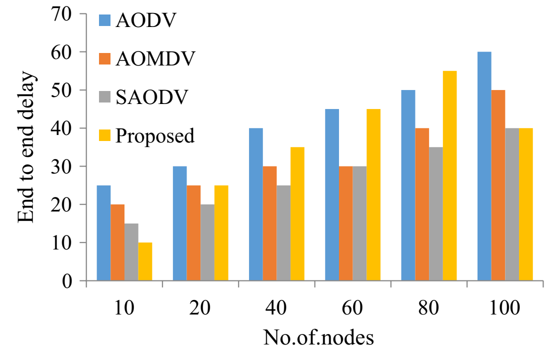

Fig. 8 End to end delay versus no of nodes

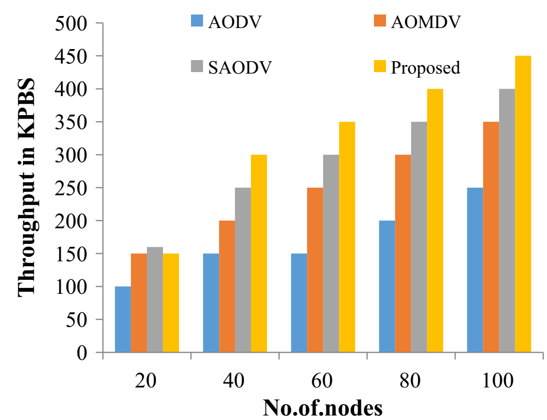

Fig. 9 Throughput versus no of nodes

in propagation, waiting time, as well as processing period. Performance of End to End Delay vs. No of Nodes is shown in Fig. 8.

4.1.4 Throughput

Bits per time period is the measure of how quickly data can be sent to a target in a network. The unit of measurement is kbps. As shown in the image, the suggested TBSMR procedure outperforms the current methods in terms of PDR. Performance of Throughput vs. No of Nodes is described in Fig. 9.

A technique's rate of detection may be defined as the percentage of hostile attackers that the suggested approach successfully recognized out of every node in the network. This is expressed as

$$\text{Detection Rate } = \frac{M}{a}, \tag{14}$$

where M names the bad nodes that have been discovered.

Tables 2, 3, and 4 indicate the results of the study that were conducted using metrics for performance regardless of the attacks. Without the assaults, the suggested strategy

Table 2 Performance comparison of network based on 100 nodes with a black hole attack

Methods	Evaluation measures			
	Average throughput	Delay	Packet drop	Detection rate
AODV	0.2564	0.0119	0.6378	0.9719
AOMDV	0.2979	0.0123	0.6556	0.9719
SAODV	0.5871	0.0116	0.4422	0.9881
Proposed	0.7593	0.0110	0.2956	0.9881

Table 3 Performance comparison of network based on 100 nodes with Sybil attack

Methods	Evaluation measures			
	Average throughput	Delay	Packet drop	Detection rate
AODV	0.2759	0.0119	0.6553	0.9585
AOMDV	0.4543	0.0121	0.5805	0.9585
SAODV	0.5035	0.0117	0.4399	0.9926
Proposed	0.6366	0.0112	0.3605	0.9961

Table 4 Performance comparison of network based on 100 nodes without an attack

Methods	Evaluation measures			
	Average throughput	Delay	Packet drop	Detection rate
AODV	0.3864	0.0121	0.6222	0.9778
AOMDV	0.2111	0.0121	0.6822	0.9763
SAODV	0.5141	0.0114	0.4667	0.9896
Proposed	0.6531	0.0107	0.3267	0.9898

achieved an average bandwidth of 0.6531, a latency of 0.0107, a packet loss percentage of 0.3267, as well as a rate of detection of 0.9898. When compared to the current approaches, the suggested approach achieved superior results. With the black holes assault present, the comparison of the results is shown in Table 3, below. Productivity, latency, packet loss, and detection rate were all averaged out to be 0.7593, 0.011, 0.2956, as well as 0.9881, accordingly, using the suggested approach. When a Sybil assault is present, a comparison is shown in Table 4. On average, the suggested technique achieved bandwidth of 0.6366, latency of 0.0112, packet loss of 0.3605, as well as recognition speed of 0.9961. Tables 2, 3, and 4 show that the suggested technique outperformed the state-of-the-art in terms of throughput, latency, packet loss, as well as detect rates.

5 Discussion

A safe and energy-efficient routing protocol for MANETs is suggested by the study. Known parameters like throughput, packet delivery ratio (PDR), latency, and detection rate are used to assess performance. For a thorough assessment, the evaluation takes into account a variety of scenarios with and without harmful attacks. This study sets itself apart by utilizing an unusual set of methods. Trust management finds trustworthy nodes, fuzzy clustering guarantees effective cluster head selection, and hybrid Cat Swarm Optimization (CSO) with Salp Swarm Algorithm (SSA) optimizes route selection. Compared to current methods, this integrated approach offers a number of important advantages (AODV, AOMDV, SAODV). When compared to conventional approaches, the results clearly show improvements in PDR, latency reduction, and detection rate. This demonstrates the efficacy of the suggested strategy for safe and effective routing in MANETs and holds true even in the face of Sybil and black hole assaults. To ensure long-term resilience, future research should concentrate on real-world testing to confirm these findings and investigate the behavior of the system against a wider spectrum of threats.

6 Conclusion

The potential applications of ad hoc networks that are mobile have attracted a lot of interest from the scientific community. However, these networks are vulnerable to a wide variety of attacks due to their inherent characteristics. A key barrier to widespread adoption of these wireless connections remains their energy and security. The safe energy-efficient routing system addresses both the power crisis and the security challenges. The cat and salp swarm optimisation computations were used to successfully implement a routing strategy. In the first step, we use the fuzzy clustering technique and the highest values for indirect, direct, as well as recent trust to identify the CHs. Additionally, intruded nodes are detected based on a set threshold value. Data packets are essentially routed across numerous hops to reach the drain by the CHs. One hybrid optimization approach, C-SSA optimization, which combines CSO and SSA, has shown to be the most effective in MANET for selecting novel routing protocols. The proposed method has a much faster convergence process and the hybrid vehicle prioritizes storage, productivity, as well as route link constraints. The suggested technique achieved a 90% detection rate, an ideal packet delivery rate of 0.99%, a minimum energy of 0.11 m joules, a maximum speed of 0.74 bps, and a negligible delay of 0.005 ms when tested with 100 nodes. Similarly, the suggested method yielded respectable results regarding the selected dropping of packets attack when compared to existing techniques. For the most part, this study is based on simulation results. To confirm the method's efficacy in diverse settings, real-world testing is required. It is necessary to look into how the system responds to more sophisticated network attacks. Future system performance assessments should involve exposing the recommended system to a wider range of security threats.

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Declarations

Conflict of interest Conflict of Interest is not applicable in this work.

Ethics approval and consent to participate No participation of humans takes place in this implementation process.

Human and animal rights No violation of Human and Animal Rights is involved.

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