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Multi-Channel Assessment Policies for Energy-Efficient Data Transmission in Wireless Underground Sensor Networks

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Abstract: Wireless Underground Sensor Networks (WUGSNs) transmit data collected from underground objects such as water substances, oil substances, soil contents, and others. In addition, the underground sensor nodes transmit the data to the surface nodes regarding underground irregularities, earthquake, landslides, military border surveillance, and other issues. The channel difficulties of WUGSNs create uncertain communication barriers. Recent research works have proposed different types of channel assessment techniques and security approaches. Moreover, the existing techniques are inadequate to learn the real-time channel attributes in order to build reactive data transmission models. The proposed system implements Deep Learning-based Multi-Channel Learning and Protection Model (DMCAP) using the optimal set of channel attribute classification techniques. The proposed model uses Multi-Channel Ensemble Model, Ensemble Multi-Layer Perceptron (EMLP) Classifiers, Nonlinear Channel Regression models and Nonlinear Entropy Analysis Model, and Ensemble Nonlinear Support Vector Machine (ENLSVM) for evaluating the channel conditions. Additionally, Variable Generative Adversarial Network (VGAN) engine makes the intrusion detection routines under distributed environment. According to the proposed principles, WUGSN channels are classified based on the characteristics such as underground acoustic channels, underground to surface channels and surface to ground station channels. On the classified channel behaviors, EMLP and ENLSVM are operated to extract the Signal to Noise Interference Ratio (SNIR) and channel entropy distortions of multiple channels. Furthermore, the nonlinear regression model was trained for understanding and predicting the link (channel behaviors). The proposed DMCAP has extreme difficulty finding the differences of impacts due to channel issues and malicious attacks. In this regard, the VGAN-Intrusion Detection System (VGAN-IDS) model was configured in the sensor nodes to monitor the channel instabilities against malicious nodes. Thus, the proposed system deeply analyzes multi-channel attribute qualities to improve throughput in uncertain WUGSN. The testbed was created for classified channel parameters (acoustic and air) with uncertain network parameters; the uncertainties of testbed are considered as link failures, noise distortions, interference, node failures, and number of retransmissions. Consequently, the experimental results show that DMCAP attains 10% to 15% of better performance than existing systems through better throughput, minimum retransmission rate, minimum delay, and minimum energy consumption rate. The existing techniques such as Support Vector Machine (SVM) and Random Forest (RF)-based Classification (SMC), Optimal Energy-Efficient Transmission (OETN), and channel-aware multi-path routing principles using Reinforcement Learning model (CRLR) are identified as suitable for the proposed experiments.

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1. Introduction

WUGSNs are widely used in the field of object surveillance under the ground surface. WUGSNs need multiple underground sensor nodes deployed sparsely or densely under the surface level. The underground sensor nodes detect the environmental objects and resources (oil substances, water substances, soil materials, etc.). Extensively, these networks help to observe the real-time object movements in defense sectors [1]. WUGSN nodes are operated with a limited set of resources (memory, processor, energy, and lifetime) amongst real-time issues such as vulnerable medium, channel distortions, and uncertain environmental conditions. Amid these network issues, learning and predicting the wireless channel parameters are major problems.

Particularly, a WUGSN channel maintains three types of links for each data transmission. The channel creates the association between underground sensor node and surface sensor node. Next, the channel provides the link between surface sensor node and ground base station. In addition, a third type of link makes the data path between underground sensor nodes [2]. Each type of wireless channel carries network data under unique data traffic parameters and channel quality metrics. The channel qualities and traffic parameters are configured based on signal strength (amplitude), transmission energy, receiving energy, data transfer rate, transmission range, noise rate, interference rate, attenuation rate, traffic type, connection establishment rate, antenna type, medium access control policies, influence rate of legitimate sensor nodes, influence rate of malicious sensor nodes, and other uncertain events.

The channel quality parameters are uncommon for different types of WUGSN mediums established for underground transmission, underground to surface transmission, and surface to base station transmission [3–5]. In this case, the channel parameter analysis model needs suitable channel quality management principles, adaptive learning functions, and reactive backing systems [6,7]. The recent development in computing arena initiates the variants of Machine Learning (ML) and Deep Learning (DL) frameworks to make intelligent decisions against critical problems. Recently introduced channel quality assessment techniques use ML and DL approaches for predicting the channel behaviors. The artificial decision-making systems provide channel metric collection, data preprocessing, classification, decision making, and report generation phases.

The existing solutions contribute better understanding practices against uncertain channel measurements. Rehan et al. [8] proposed ML-based channel quality and stability evaluation procedures for Wireless Sensor Networks (WSNs). This novel channel assessment model achieved baseline channel prediction principles for evaluating channel rank points, signal strength indicator, and connection quality metrics. In this work, the common aggregated channel quality indicator value showed the stability of wireless channels. Similarly, Aldossari et al. [9] analyzed the channel modelling principles for wireless communication. The channel modelling is the process of computing channel measurement quantities using statistical data analysis, stochastic process, and ML principles. This work modelled the wireless channel qualities using signal fading rate, bandwidth rate, Doppler spread, and block error rate.

The ML-based channel measurement functions were computed for observing upper bound and lower bound characteristics of wireless channels. In the same manner, many research works have evolved to track and analyze the wireless channel parameters [10,11]. Moreover, the existing wireless channel models were limited against nonlinear event analysis policies and multi-channel attribute analysis policies. Firstly, the existing channel configuration models and parameter estimation models utilized default attributes of static wireless sensor networks. Secondly, the classification of channel distortions due to environmental issues and malicious events were not identified separately. Finally, the observation of various medium qualities (underground substances and open-air medium) was not attained through optimal ML and DL approaches. These are noted as crucial research problems for feasible data communication.

On the prospect, the proposed DMCAP creates the suitable signaling models, nonlinear channel assessment models, multi-channel interference models, and channel distortion analysis models against uncertain WUGSN channels. Particularly, the proposed research work is motivated to design and implement a reactive nonlinear channel learning models and IDS engines for supporting feasible channel quality estimation. This research work backs higher throughput attainment through the proposed DMCAP model with EMLP, ENLSVM, VGAN-IDS, and nonlinear entropy analysis procedures.

The proposed DMCAP model is significant against existing techniques in terms of differentiated channel assessment procedures. Notably, most of the existing techniques were implemented for analyzing the channel qualities using linear models for WUGSN. The existing techniques were not implemented accurately for evaluating multi-channel quality assessment factors such as nonlinear noise quantity, entropy rate, signal loss rate, and multi-channel interference rate (underground, underground to surface, and surface to surface). According to the motivation, this proposed model classifies the channel under three categories such as underground wireless channels, underground–surface channels and surface wireless channels. The proposed channel models and signal models are created by analyzing wireless channel attributes and signal attributes, respectively.

Particularly, the proposed DMCAP model analyzes the channel quality metrics and nonlinearity issues using EMLP and ENLSVM. In this case, EMLP is used to determine the classified entropy levels for various wireless channels. The development of EMLP (back propagation procedures) is initialized over the configured model of interference and energy optimization. EMLP is a useful procedure for classifying the channel interference on multiple attribute (multi-modal) validation schemes. In this manner, ensemble MLP units are created to learn and classify multi-channel entropy attributes in WUGSN environment.

In the next case, ENLSVM ensures multi-level classifier units for extracting SNIR from multiple channel quality metrics. ENLSVM consists of multi-channel SNIR distribution procedures, SNIR classification, and likelihood analysis procedures under uncertain network conditions. In the final case, VGAN-IDS analyzes the channel distortion rate initiated by malicious sensor nodes. On this basis, the proposed model observes and classifies the channel quality metrics of WUGSN through reactive channel learning and adaptation procedures. Thus, the proposed DMCAP model achieves optimal data transmission pattern and energy saving solution. The proposed DMCAP model has the motivation to optimize overall WUGSN communication quality depends upon real-time multi-channel uncertainties. The technical contributions of proposed model are listed below.

- Development of multi-channel signaling and channel models;
- Development of multi-channel ensemble model and channel attribute classification model;
- Implementing channel entropy classification procedures (EMLP);
- Configuring SNIR distribution and nonlinear regression procedures (ENLSVM);
- Channel distortion analysis against malicious events;
- Supporting optimal wireless channel utilization and data communication solutions through proposed channel behavior learning techniques.

Unlike other existing techniques, the testbed of the proposed model was configured for both surface level channel parameters and underground channel parameters. According to real-time assumptions, the proposed DMCAP model was enriched with a dual channel propagation model such as acoustic (underground) and ground (surface) features. These are the notable features of the proposed DMCAP model compared with existing techniques. On these conditions, the proposed DMCAP model significantly classifies real-time multi-channel attributes based on SNIR, entropy, malicious events, and other nonlinear distortions.

The contributions of the proposed DMCAP model has the benefits such as optimal energy utilization rate, optimal link establishment rate, minimal routing delay, and maximum secure throughput rate compared with existing techniques. Compared with other existing techniques, the proposed model was specially developed for WUGSN. Furthermore, the proposed model was modelled to predict multi-channel quality metrics for reducing the impacts of channel uncertainties in WUGSN. The results provided in Section 4 illustrate the benefits of proposed model against existing techniques practically.

On the basis of research motivation, the manuscript has notable research works that contribute to the channel evaluation and attribute assessment model in Section 2. Section 3 of this manuscript explains the technical contributions and system design of proposed DMCAP model. Section 4 provides the experiment details and performance evaluation. This section shows the implementation details, network configuration parameters, channel configurations, and results. Finally, Section 5 summarizes the crucial contributions of the research work with appropriate future philosophies.

2. Related Works

In wireless networks, channel models perform a major role in implementing a reliable data communication system. Flawless data transmission highly depends on the quality of wireless channels and the rate of distortions. On this basis, any intelligent (ML and DL) communication models should properly learn and predict the active channel conditions. The wireless channel modelling procedures and the data communication models are closely related to each other. There are different types of wireless networks found as wireless sensor networks, mobile ad-hoc networks, wireless personnel area networks, and wireless local area networks.

Among these networks, wireless sensor networks are deployed for collecting the ecological data from various objects on the surface, sea, and underground areas. Compared with other sensor networks, WUGSNs are highly dominated by channel distortions and underground obstacles.

Similarly, WUGSNs consist of both underground links and surface links. On this environment, the nature of each channel is configured uniquely with crucial parameters (antenna type, interference, noise, energy, etc.). Understanding the real-time channel distortions and modelling the channels according to the need aids better reactive communication systems. The proposed DMCAP model implements a realistic WUGSN channel model and channel quality prediction model with the help of multi-channel quality assessment policies. The scope of the proposed research work was initiated from various related research works. This section describes the recently developed channel assessment and channel quality estimation policies.

Bogena et al. [12] proposed a novel signal attenuation assessment model against soil contents for hybrid WUGSNs. In this contribution, the low-cost soil surface network was created to estimate the wireless signal transmission. This work evaluated various signaling possibilities against different types of soil thickness. This work stated that the WUGSN can communicate with other nodes via 5 cm soil surface (thickness). This work enabled radio communication channel using ZigBee network protocol to build soil-net environment. In this environment, ZigBee communication channels were created to share the information between underground sensor nodes to evaluate the ability of signal attenuation levels. Similarly, the channels were enabled to connect underground soil nodes and surface nodes. This work stated that the attenuation rate created by soil thickness levels affected the channel ability. However, this work missed the versatile configurations of various uncertainties such as noise, link failures, node failures, and dropped packets.

Sharma et al. [13] analyzed the technical benefits and limitations of Internet of Things (IoT) environment and WSNs. This work provided the details such as network heterogeneity, energy optimization, scalability, routing delay, network security, channel flexibility, and data throughput. This work classified different types WSNs and the characteristics in terms of mobility, energy resources, deployment models, and architectures. Yan et al. [14]

proposed game theory approaches for clustering the sensor nodes in order to reduce the energy consumptions. Game theory is the technique considered for various decision-making systems. In this case, each sensor node of the WSN was treated as a player node on the field. On this deployment model, the sensor nodes were clustered on the basis of their current states (active or passive). This work provided a solution for energy-based clustering solutions in WSNs. The energy-efficient game theory approach and clustering, mechanisms introduced in this work were configure to identify the migration status of active node in to sleep state and vice versa. In the same manner, this protocol introduced penalty principles that were working against greedy nodes or selfish nodes available in sensor networks. Notably, these penalty procedures were applied to control the energy violations created by communicating nodes in the network. However, this technique was not developed with well-defined intelligent approaches, uncertain channel models and ML procedures.

Among the solutions developed against various problems of WSNs, the accurate detection and prediction of channel events play a crucial part. O'Mahony et al. [15] proposed a method of analyzing the channel characteristics of WSNs using Support Vector Machine (SVM) and Random Forest (RF)-based Classification model (SMC). SVM and RF are the ML approaches used in the work to understand the nature of real-time wireless channel qualities. This work developed an experimental base for analyzing the channel noise rates, jamming problems, data transfer difficulties and other signaling properties. This work contributed for wireless channel quality assessment practices. This mechanism provided a proper data point collection principles to observe the channel irregularities and uncertainties of wireless sensor networks. At the same time, the suggested channels with optimal conditions were identified as suitable for data communication. On the other side, the supervised models need nonlinear data analysis support systems.

In addition, the effort of this mechanism did not identify multi-path channel disturbances, underground uncertainties and unique properties of multiple channels. Singh et al. [16] proposed Optimal Energy-Efficient Transmission (OETN) with naked mole-rate principles. The need for channel parameter estimation and the quality of service model are the important features for WUGSN. The provided model in this work integrated naked mole-rat algorithm and cross layer multi-channel assessment policies to improve wireless channel stability. Since the energy-efficient channel stability model was defined properly, this work achieved the reliable data communication. Notably, the mole-rat algorithm was applied with magnetic induction procedures. This work stated that the generic electromagnetic signaling mechanisms were seriously affected by channel uncertainties. In this regard, this work found the magnetic induction technique for the underground sensor network. The influence of the above work found the solution for ensuring better throughput and minimal energy consumption in WUGSN. In contrast, uncertain induction rates were not evaluated for multiple channels of WUGSN.

Di et al. [17] proposed channel-aware multi-path routing principles using Reinforcement Learning model (CRLR) for underwater sensor networks. Compared with previous works, CRLR delivered a complex channel analysis and learning practices towards underwater channel estimations. In this regard, the CRLR model was proposed to improve wireless routing protocol functions and ensure optimal data communication possibilities under single-path and multi-path routing strategies. In addition, this work found Reinforcement Learning model to optimize the channel energy utilization factors. At the same time, this work confirmed real-time rewards for channel events to improve the channel throughput with minimal energy consumption. However, the CRLR was not developed to meet uncertain channel conditions and vulnerable channels.

Similarly, other recent research works proposed various wireless communication strategies, ML applications, data distribution principles, and security measures for WSNs [18–20]. Cortés et al. [21] proposed wireless channel observation techniques against signal jamming attacks with the help of collaborative node mechanisms. The work analyzed the possibilities of jamming problems initiated from other malicious nodes to legitimate sensor nodes. Particularly, the cooperative signal detection model was enabled for maintaining feasible data communication channels for industrial sensor networks. However, this system was limited in terms of heterogeneity features and uncertain network conditions. The existing systems described above found various real-time problems on handling the wireless channels and underground channels. Furthermore, the underground substances, rock displacements, and oil contents were noted as crucial obstacles. Further, the works suggested the applications of suitable ML techniques for channel stability predictions.

Tam et al. [22] proposed multi-objective teaching–learning scheme for handling the problems of sensor networks such as coverage probability and lifetime enhancement. This scheme implemented optimized evolutionary algorithms, genetic algorithm, and multi-objective policies. In the implementation, sensor spacing solutions, sensor dominated solutions, and optimal node quantity solutions were attained through network attribute learning models. This work determined the possibilities of better network lifetime and node coverage. At the same time, this scheme stated the importance of a continuous network optimization problem to determine lifetime and coverage abilities. Though solutions are expected to be improved with well-trained ML and DL approaches. Singh et al. [23] debated wireless sensor underground infrastructures and underground monitoring problems. Particularly, this work discussed soil monitoring methods and other environmental observations using WSNs.

In the same manner, the involvement of the work led to the development of WSN infrastructure using magnetic induction principles that are suitable for underground applications. In addition, the effort of the work was continued with the future scopes of WSN-based underground applications. Yet, this article was incomplete in terms of research innovations.

In the same manner, Sun et al. [24] delivered the potentials of border surveillance using WSNs. As WSNs are manufactured using resource-limited components, the significance of lifetime and energy factors is inevitable. In order to improve the lifetime, energy optimization, and transmission coverage quality, Ehlali et al. [25] and Pal et al. [26] developed different types of coverage analysis models and lifespan improvement strategies for WSNs. However, most of the existing systems were not taking WUGSN characteristics and channel uncertainties under research constraints seriously; this is needed and this problem is estimated to be resolved. Additionally, the available channel assessment techniques and WSN communication protocols were not ensuring feasible data throughput under dynamic channel conditions [27,28]. The literature analysis provides various technical details with the following limitations.

- Multi-channel characteristics are not considered for improving data transmission quality;
- The channels of WUGSNs are not assumed with realistic conditions (acoustic and air-based channel parameters);
- The reasons for data loss are not classified under malicious behaviors and channel behaviors;
- Channel models and attributes are not properly analyzed through multi-classifier units and nonlinear functions. Since WUGSN has heterogeneous channel behaviors (distortions), these are necessary for future channel assessment plans.

The proposed model was implemented with appropriate nonlinear data analysis models, ensemble channel attribute classification models, and malicious event analysis models to improve the entire network communication quality.

Consequently, this proposed model attempts to reduce the number of retransmissions, routing delay, and energy wastages by effectively assessing multiple channel properties of WUGSN. Table 1 shows the comparison of previous works (limitations) and the proposed idea to implement DMCAP. Practically, WSNs, WUGSNs, and other wireless network channels are more vulnerable to uncertain channel qualities. Furthermore, WUGSN channel properties are uncommon for underground mediums and surface mediums with crucial real-time distortions. In this field, the deep multi-channel assessment principles are required to maintain the reliable communication against channel problems and malicious events (intruders). The proposed DMCAP model technically approaches all these issues and ensures the solutions against the mentioned problems.

Table 1. Previous works and motivation of proposed work.

Previous Techniques	Motivations of Proposed Work
Homogeneous wireless channel assessment techniques are proposed.	Multi-channel (heterogeneous) assessment techniques are required.
Linear and moderate channel models are created for implementing the networks.	WUGSNs are expected to be considered with more realistic network parameters.
Uncertain conditions are not produced in the network model effectively.	More uncertain conditions must be imposed on underground and open medium of WUGSN.
Energy optimization is not taken crucially for WUGSN with differentiated channel qualities.	Energy optimization must be taken crucially for WUGSN with differentiated channel qualities.

3. DMCAP System

WUGSN has the collection of UG_N underground sensor nodes that are deployed beneath the surface. Each sensor node UG_i has maximum 5 m of circular transmission range through underground obstacles. The underground obstacles between the sensor nodes can be observed as soil substance, rocks, colloidal surfaces, oil substances, and others. Sensor nodes transmit the data to surface nodes or neighbor nodes through electromagnetic signals or acoustic signals. G_s surface sensor nodes receive the underground data streams continuously from different sensors. This proposed system designs the G_s surface nodes as mobile ad-hoc sensor nodes that can move around the surveillance area gradually. In the next level, BG_s number of ground base stations receive the signals from surface nodes. This hybrid WUGSN has different types of channel environments between UG_N, G_s and BG_s points. According to this network design, each channel link needs significant traffic parameters, signal models, and noise models for different links. UG_N nodes forward the data to neighbor nodes and surface nodes (red nodes). At the same time, surface sensor nodes can detect the neighbor sensor node or nearest base station to deliver the data.

3.1. Signaling and Channeling Models

The proposed system formulates complex signaling parameters and channel distortion factors as provided below. The multi-channel signal models and noise models are provided in the following equations.

Signal Attenuation factor:

$$S\alpha^{i} = \omega\sqrt{\frac{me}{2}}\left(\sqrt{1+\left(\frac{e_{\prime}}{e}\right)^{2}}-1\right) \tag{1}$$

Equations (1) and (2) state ω as signal wavelength. m and e are electromagnetic permeability and real permittivity factor respectively. $e_{\prime}$ indicates imaginary portion of dielectric permittivity factor.

Signal Phase shifting factor:

$$S\beta^{i} = \omega\sqrt{\frac{me}{2}}\left(\sqrt{1+\left(\frac{e_{\prime}}{e}\right)^{2}}+1\right) \tag{2}$$

signal reflection factor:

$$S(R)^{i} = \frac{1-\sqrt{e_{\prime}}}{1+\sqrt{e_{\prime\prime}}} \tag{3}$$

attenuation due to reflection:

$$S(RA)^{i} = 10 \log \frac{2 \cdot S(R)^{i}}{1 + S(R)^{i}} \tag{4}$$

Equations (3) and (4) illustrate reflection models. Similarly, the underground particles such as soil contents, water contents and other particles create signal attenuation between all sensor nodes. The underground sensor signals are affected due to reflection, absorption, refraction, and scattering of electromagnetic signals. The receiving power at different links are derived as provided in Equations (5)–(7).

Receiving power at UG_N link,

$$P(R)^{Ui-Ui} = P^{tr} + G^{tr} + G^{rx} - Loss^{UG} \tag{5}$$

- P^{tr}–Sensor Node′s Transmission Power;
- G^{tr}–Transmisison Gain;
- G^{rx}–Receiving Gain;
- $Loss^{UG}$–Underground Signal Loss.

Receiving power at G_s and UG_N link:

$$P(R)^{Ui-Si} = P^{tr} + G^{tr} + G^{rx} - \left[Loss^{UG} + Loss^{0} + Loss^{A}\right] \tag{6}$$

- $Loss^{0}$–Free space loss;
- $Loss^{A}$–Loss due to adversarial events.

Receiving power at G_s and BG_s link:

$$P(R)^{Si-Bi} = P^{tr} + G^{tr} + G^{rx} - \left[Loss^{0} + Loss^{A}\right] \tag{7}$$

Over these signaling models, Signal to Noise Interference Ratio (SNIR) is determined for uncertain and lossy conditions under different channels and links. In the determination phase, set SNIR threshold range between $\vartheta 1$ and $\vartheta 2$. In this work, SNIR is adjusted for different channels (Equation (8)). The SNIR is tuned based on novel training algorithm.

$$\text{SNIR}(Ui - Ui,\ Ui - Si,\ Si - Bi) \propto C^{Q} \cdot N^{C} \cdot T^{F}(dt) \tag{8}$$

- $\text{SNIR}(Ui - Ui,\ Ui - Si,\ Si - Bi) < \vartheta 1$, Signal Dropped;
- $\text{SNIR}\ (Ui - Ui,\ Ui - Si,\ Si - Bi) \geq \vartheta 2$, Signal recieved at the sink;
- $\text{SNIR}\ (Ui - Ui,\ Ui - Si,\ Si - Bi) \in R(\vartheta 1,\ \vartheta 2)$, Adversarial block;
- C^{Q}–Channel Type;
- N^{C}–Node Type;
- T^{F}–Learning Factor at regular interval;
- $\vartheta 1$–Lower bound;
- $\vartheta 2$–Upper Bound.

As mentioned in Equation (8), three types of channels (links) are created to transfer the information from set of underground sensor nodes to base station via surface sensor nodes. These channels are configured with separate frequencies, bandwidths, energy limits, and other communication needs. Particularly, the link $Ui - Ui$ is a static under the ground level. At the same time, the links such as $Ui - Si$ and $Si - Bi$ are dynamic surface links in the WUGSN [29,30].

Since the surface nodes are moving from one location to another location randomly, these links are separately maintained with the help of unique mobility patterns. In addition, the communication parameters and interference rates of the links are changed against $Ui - Ui$ link attributes. As illustrated in Figure 1, the brown color nodes are UG_i, the green color node is G_i and the base station is BG_i. Figure 1 shows the channels (links) between the sensor nodes and base station. As multiple channels are needed for this heterogeneous WUGSN, the implementation of multi-channel SNIR model with learning factors is a crucial task. The time bounded streams of signaling and interference factors are collected and packed as individual tuple as provided below. The WUGSN channel parameters and distortion cases are determined continuously through complex mathematical functions. Furthermore, these details are modelled as $T(S)\alpha^{i}$ and $T(P)\alpha^{i}$. These are channel monitoring tuples used as the sequence of inputs to the proposed ML techniques.

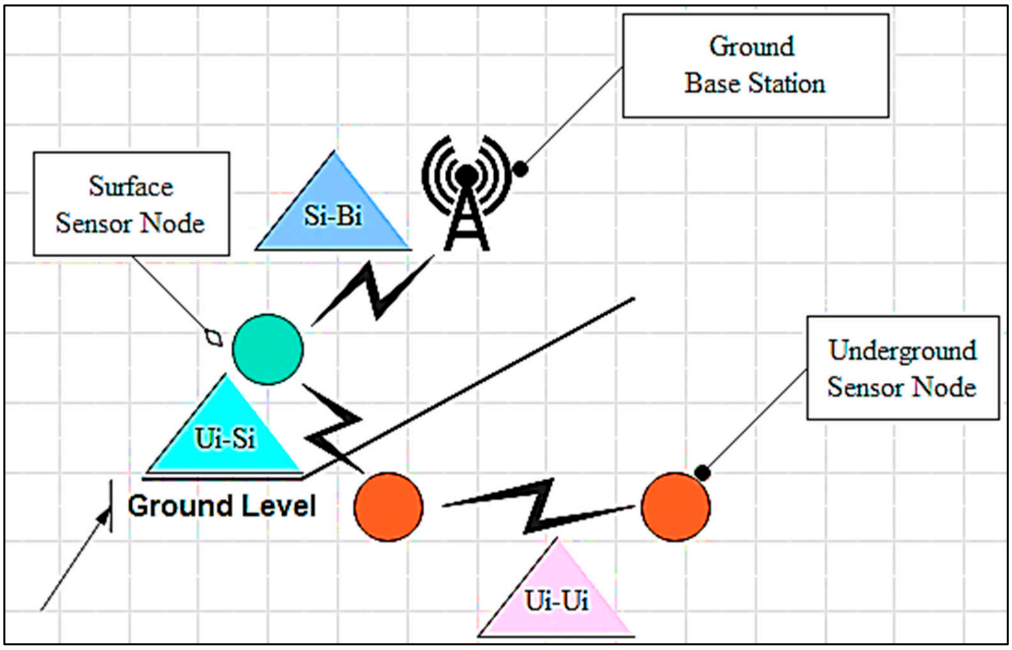

Figure 1. Links and nodes.

Signal attenuation tuple:

$$T(S)\alpha^{i} = \left(S\alpha^{i},\ S\beta^{i}, S(R)^{i}, S(RA)^{i}\right)\cdot\frac{d\tau}{dt}\forall\, L^{N} \tag{9}$$

Signal energy tuple:

$$T(P)\alpha^{i} = \left(P(R)^{Ui-Ui},\ P(R)^{Ui-Si}, P(R)^{Si-Bi}\right)\cdot\frac{d\tau}{dt}\forall\, L^{N} \tag{10}$$

Equations (9) and (10) illustrate the details of $T(S)\alpha^{i}$ and $T(P)\alpha^{i}$. In Equations (9) and (10), τ states signaling interval; L^{N} denotes total number of wireless links in the network. These channel quality management tuples are provided in the ML network layers to compute learning factor and adaptive channel quality weight factor [31–33].

3.2. Multi-Channel Ensemble Model and Channel Attribute Classification Model

As WUGSN needs multi-channel data transmission model, signaling parameters, and channel distortions are dynamically determined at each signaling intervals. The statistical channel analysis models and other conventional models analyze the channel qualities with nominal assumptions. In this case, the requirement of multi-channel ensemble classification model is more crucial.

Algorithm 1 shows the procedure of multi-channel interference and energy model based on channel quality tuples, $T(S)\alpha^{i}$ and $T(P)\alpha^{i}$. Algorithm 1 initiates various classification procedures for analyzing the real-time quality of WUGSN channels. Most importantly, the multi-channel quality evaluation procedures are initialized in each sensor node deployed at either underground locations or surface points.

Algorithm 1: Multi-Channel Interference and Energy Modelling Procedure

Input: Channel Parameters and Identifiers
Output: Ensemble Classifier Activation
1: Get channel parameters as tuple, $T(S)\alpha^{i}$ and $T(P)\alpha^{i}$
2: Get channel identifiers, $Ch^{i}\ \forall\ S(Ui - Ui,\ Ui - Si,\ Si - Bi)$
3: Initiate traffic analyzer for all active nodes
4: Compute ensemble DL engine function, $D^{E}(F)$ and Build ensemble classifier units
 a. Information Entropy Classifier
 b. SNIR Classifier
 c. Attack Classifier
5: Install $D^{E}(F)$ for all active nodes
6: Initiate $D^{E}(F)$ for all active communication under svc mode.
7: Call classifiers of $D^{E}(F)$
8: Redo
End

The subsets of Algorithm 1 lead to enable channel entropy classification practices, SNIR classification practices, attenuation/energy classification practices, and malicious event classifications on each wireless channel. In this deep channel quality analysis and learning model, lightweight ML and DL techniques are utilized for ensuring reliable data transmission conditions [34]. Figure 2 shows the basic signaling model. According to the basic model, the transmitted signal quality, receiving signal quality, channel distortions, and other adversarial factors are evaluated under uncertain mediums. In the first phase of channel quality assessment process, information entropy is determined and evaluated for multiple wireless channels. The information entropy model plays a major role in finding the actual liveliness of each wireless channel of WUGSN. In this regard, the proposed system implements conditional joint entropy functions with Ensemble Multi-Layer Perceptron (EMLP) classifier units in each sensor node. The proposed EMLP procedures are reactive against live channel parameters [35,36].

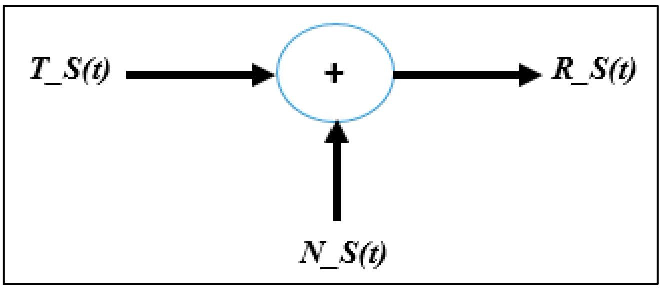

Figure 2. Basic signal model.

The sensor nodes participating in underground communication and surface communication lead to significant information entropy. The entropy model is defined with joint conditional distribution function as provided in Equation (11).

$$H(t_{n_{ai}}|t_i) = E_{t_{n_{ai}}|r_{n_{ai}}}[-\log p(t_{n_{ai}}|r_{n_{ai}}) = -\sum_{t_i \epsilon t_{n_{ai}}} p(t_{n_{ai}}|r_{n_{ai}}) \log p(t_{n_{ai}}|r_{n_{ai}}) \quad (11)$$

Let the Equation (11) as E_N^i be an entropy pair for active channel at time τ. The information entropy varies continuously for each data transmission. The proposed system implements EMLP network for classifying the continuous streaming of entropy determinations. The training phase of EMLP observes the determinations from Equation (11) and the relationship model for entropy function is provided in Equations (12) and (13). Equation (13) illustrates mutual channel entropy value in the network [37].

$$H(t_{n_{ai}}|r\_n_{ai}) = H(t_{n_{ai}}|r\_n_{ai}) - H(r_{n_{ai}}) \quad (12)$$

$$I(t_{n_{ai}}; r_{n_{ai}}) = \sum_{t_{n_{ai}}, r_{n_{ai}}} p(t_{n_{ai}}, r\_n_{ai}) \cdot \log \frac{p(t_{n_{ai}}, r_{n_{ai}})}{p(t_{n_{ai}}) \cdot p(r_{n_{ai}})} \quad (13)$$

Similarly, the channel data transfer capacity at τ is defined with $I(t_{n_{ai}}; r_{n_{ai}})$ as mentioned in Equation (14).

$$C(I) = \max(I(t_{n_{ai}}; r_{n_{ai}},\ \tau, c)) \quad (14)$$

Equations (11)–(14) are denoting the channel entropy variances and determinations of EMLP (Algorithm 2). In this case, let the sensor nodes in an active communication channel are t_n_{ai} and r_n_{ai}. In this circumstance, t_n_{ai} denotes the active transmitter and r_n_{ai} denotes the active receiver. $E_{t_{n_{ai}}|r_{n_{ai}}}$ denotes joint entropy function related to each active communication pair. $H(t_{n_{ai}}|t_i)$ and $I(t_{n_{ai}}|t_i)$ are denoting joint conditional functions of entropy model and information model. According to Equation (11), $H(t_{n_{ai}}|t_i)$ ensures the data dissemination through other nodes (multi-path) based on logarithmic entropy distribution.

Algorithm 2: EMLP for Entropy Learning and Classification

Input: $H(t_{n_{ai}}|r\_n_{ai}),\ I(t_{n_{ai}}; r_{n_{ai}}), C(I)$
Output: Classified results and Entropy Knowledge Base Creation
1: Get all channel entropy determinations
2: Train the EMLP using training data, $TE(x, y, \tau)$
3: Determine the entropy bias rate, $\varnothing(Ui - Ui)$, $\varnothing(Ui - Si)$ and $\varnothing(Si - Bi)$
4: Set minimal bias function as steepest decent for all data samples
5: EMLP backpropagation unit is modelled as below
Do for all nodes:

$$\frac{d\omega_{x,y}}{d\tau} = -\frac{\partial\varnothing}{\partial\omega_{x,y}},\ \frac{d\delta_{x,y}}{d\tau} = -\frac{\partial\varnothing}{\partial\delta_{x,y}}$$

6: Update the knowledge base, $D(E(x_i, y_i, \tau))$
7: Redo for all nodes in WUGSN.
End

In this case, data shall be fragmented and distributed according to divide and conquer approach since multiple paths are active to destination. The equation is remodeled as indicated to state the relationship between transmitter and forwarding nodes (sink) of multiple paths under logarithmic scale. Equation (12) indicates $H(t_{n_{ai}}|r\_n_{ai})$ as a training function of distributed entropy model with neglected local entropy of each sink (forwarding node) since this proposed model uses EMLP to strictly consider channel entropy conditions for each session. In the same manner, Equation (13) $I(t_{n_{ai}}; r_{n_{ai}})$ represents cumulative channel information distribution probability between t_n_{ai} and r_n_{ai} for each active session in WUGSN. Under this scenario, r_n_{ai} can be considered as any forwarding node (sink) or destination node in multi-path channel model.

In addition, the crucial determination over channel data transfer capacity is defined as $C(I)$ under real-time conditions of WUGSN. Equation (14) has the maximum $I(t_{n_{ai}}; r_{n_{ai}})$ at τ as the real-time data transfer capacity for a particular channel, c. In this manner, the training phase of EMLP for multi-channel entropy model can be expressed for effective WUGSN communication model. This helps to learn the real-time entropy variations for each channel $(Ui - Ui,\ Ui - Si,\ Si - Bi)$.

3.3. SNIR Distribution and Analysis Using Multi-Channel Nonlinear Regression Model

The generic nonlinear channel regression model is determined as shown in Equation (15). Generally, SNIR determined at the channel is nonlinear in nature. Similarly, the production of multi-channel SNIR falls completely under nonlinear functions. In this nonlinear production of timeline data of SNIR, the prediction and determination can be modelled with the help of multi-channel nonlinear regression model. As provided in Equation (15), the nonlinear function of channel quality management tuples shall be determined.

$$y(n) = \theta^0 + (T(S)\alpha^i + T(P)\alpha^i)\cdot\theta^1 + \theta^1\cdot\theta^0 + (T(S)\alpha^i + T(P)\alpha^i)^2 + \ldots \quad (15)$$

$$y(n) = \frac{\theta^0}{1 + \theta^{1(T(S)\alpha^i + T(P)\alpha^i) - \theta^2}} \quad (16)$$

- θ^i–Nonlinear quantity factor.

From the nonlinear model determination, the nonlinear ability of each channel impacts the channel can be calculated. Let the multi-channel nonlinear regression model, $m(y(n))$ be expressed as

$$y(n) \propto C(I) \quad (17)$$

$$m(y(n)) = N\cdot y(n)\cdot\frac{dCi}{d\tau} \quad (18)$$

Equation (18) denotes Ci as channel identifier and N as number of channels. The channel capacity and attenuation/energy nonlinearity determinations are closely coupled with SNIR production rate. As the rates of previous channel qualities and quantities vary, SNIR leads to distortions. At this moment, the learning and classification practices of nonlinear SNIR sequence make significant effects in WUGSN communication. This is modelled with the help of Ensemble Nonlinear SVM (ENLSVM). Generally, SNIR determines the upper bounds in information transferring for a wireless channel. The optimal determination of SNIR for each wireless channel shows the quality of wireless links against various signal distortions [38].

In WUGSN, SNIR is defined as provided Equation (19).

$$SNIR\left(l^i\right) = \frac{P^{sl}}{I^l + Noise^l} \pm \varphi \quad (19)$$

Equation (19) illustrates the SNIR determination at the active link, l^i. In this equation, P^{sl} represents required signal quality, I^l and $Noise^l$ denote interference and noise impacts in the channel, respectively. Equation (20) shows the multi-channel SNIR determination function for all active channels. The distribution of multi-channel $SNIR\left(l^i\right)$ is determined with the Gaussian distribution model with φ as provided in Equation (21).

$$S\left(SNIR\left(l^i\right)\right) = SNIR\left(l^i\right)\cdot ds\cdot d\tau\ \forall\ S(L) \quad (20)$$

- l^i–a link at time τ;
- l^i can be either $Ui - Ui$ or $Ui - Si$ or $Si - Bi$;
- φ–nonlinear event variance, where $0 \le \varphi \le 1$.

In this case, m is the mean and φ^2 is the variance in distribution model. The interference likelihood function is formulated for given distribution model in Equation (21).

$$D(V) = \frac{1}{(2\pi\varphi^2)^{1/2}} \exp\left\{-\frac{1}{2\varphi^2}\left(SNIR\left(l^i\right) - m\right)^2\right\} \quad (21)$$

$$l\left(SNIR\left(l^i\right)/m, \varphi^2\right) = \prod_{n=1}^{N} G\left(\frac{SNIR(l^n)}{m}, SNIR\left(l^i\right)^2\right) \quad (22)$$

$$1\left(\mathrm{SNIR}\left(l^{i}\right)\right) = \sum_{i=1}^{k} \pi_i G(\mathrm{SNIR}\left(l^{i}\right)/m_i, \varphi_i^2) \tag{23}$$

- k—Total number of interference classes;
- i—Interference data class for current channel;
- π_i—Mixing coefficient varies from 0 to 1;
- $\mathrm{SNIR}\left(l^{i}\right)$—SNIR for channel 'i'.

The proposed DMCAP effectively uses both nonlinear regression model with ENLSVM principles to classify SNIR data for multiple channels. Moreover, the effective data distribution function helps to handle the SNIR data space optimally for ENLSVM evaluation procedures. Algorithm 3 describes the multi-channel SNIR evaluation procedures.

Algorithm 3: ENLSVM

Input: $S\left(\mathrm{SNIR}\left(l^{i}\right)\right)$, $D(V)$, $1\left(\mathrm{SNIR}\left(l^{i}\right)\right)$
Output: Classified data distributions
1: Get training samples for k rounds
2: Set threshold for $\mathrm{SNIR}\left(l^{ith}\right), D\left(V^{th}\right)$, $1\left(\mathrm{SNIR}\left(l^{ith}\right)\right)$ -> $\{\mathrm{Ui-Ui\ or\ Ui-Si\ or\ Si-Bi}\}$
3: Do training for i = (1,k)
$\mathrm{SNIR}\left(l^{i}\right)$ for k1 samples/SNIR Classifier
D(V) for k2 samples/Distribution Classifier
$1\left(\mathrm{SNIR}\left(l^{i}\right)\right)$ for k3 samples/Likelihood Classifier
4: Configure φ as nonlinear component for all channels
5: Do testing for i = (1,k), Ensemble Test

$$e = \max \sum_{\varphi,\mathrm{threshold}} \varphi \cdot [\mathrm{SNIR}, D(V), 1(\mathrm{SNIR})]$$

6: Do recurrent training and testing
End

3.4. Channel Quality Distortions Due to Malicious Events

Evaluation of the changes and distortions happens due to abnormal environmental properties, and the distortions initiated due to malicious attacks are the major risks of WUGSN. In this concern, the WUGSN channels are vulnerable to jamming attacks, wormhole attacks, packet dropping attacks, Distributed Denial of Service (DDoS) attacks, and other malicious injections. On the field, the channel security system needs to classify the attacks and other distortions regularly.

The proposed system configures both channel assessment policies and security practices to monitor the wireless communication parameters [39]. Algorithm 4 presents VGAN engine to be active in sensor nodes to monitor the wireless transmissions. The VGAN-enabled IDS works against different types of attacks based on attack knowledge installed in the node's local storage [40]. VGAN-IDS initiates event generator functions and event discriminator functions to monitor the adversarial activities involved in the channels.

Algorithm 4: VGAN-IDS

Input: Encoded Data Sequences, Channel Quality Metrics
Output: Vulnerability Logs and Attack Classifications

1: Initiate VGAN associated IDS in sensor node
2: Initiate Attack Dataset, Channel attribute dataset
3: Call VGAN (Sample generator, Data discriminator)
4: Set passive capturing mode (low energy) or active capturing mode (optimal energy)
5: Set M = 1 for sensor monitor (VGAN-IDS)
6: Set M = 0 for forwarding nodes
7: Extract the channel data packets and evaluate using VGAN-IDS
8: Classify the data and suspicious events
9: Share alert reports
10: Redo for all sessions

End

VGAN-IDS performs actively over multi-channel neighbor interactions to classify channel distortions into malicious issues and environmental issues separately. Thus, the proposed DMCAP model monitors environmental distortions and malicious events independently to estimate the quality of wireless channels under uncertain conditions. The VGAN-IDS model and channel assessment policies proposed in the article safeguard the multi-channel data transmission against channel distortions and suspicious events. The proposed system was implemented as shown in Section 4. Section 4 provides an immense impact on the development of proposed DMCAP model and performance evaluations. Figure 3 illustrates the overall system model implemented inside each sensor node supports for reliable network communication. The sensor node has hardware internal components and software internal components. As shown in Figure 3, the software module of each WUGSN sensor node contains proposed DMCAP procedures, VGAN-IDS engine, reactive channel estimator, and DMCAP/IDS activator procedures on demand. In addition, Figure 4 illustrates the overall DMCAP system design and the integral phases used for managing reactive data transmission. The proposed internal learning system and channel assessment procedures was initiated for active channels and nodes [41,42].

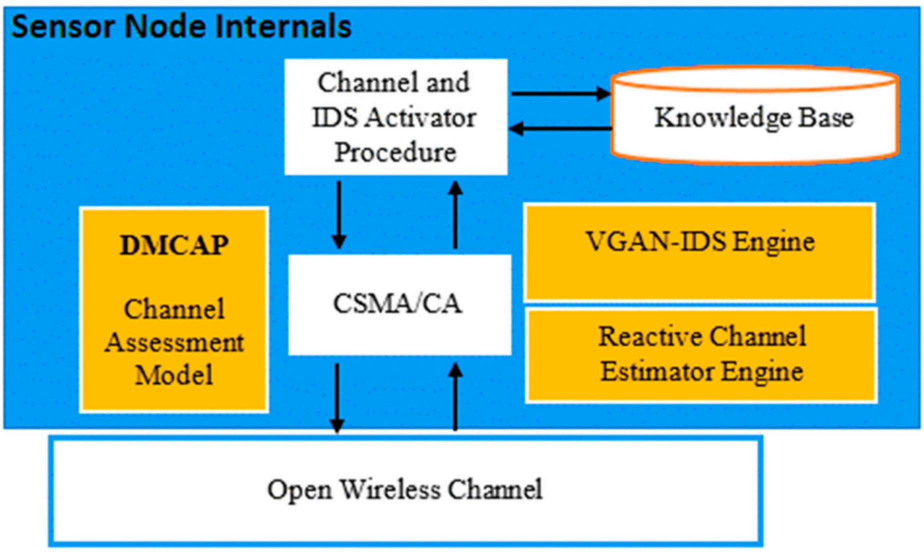

Figure 3. Proposed DMCAP system in sensor node.

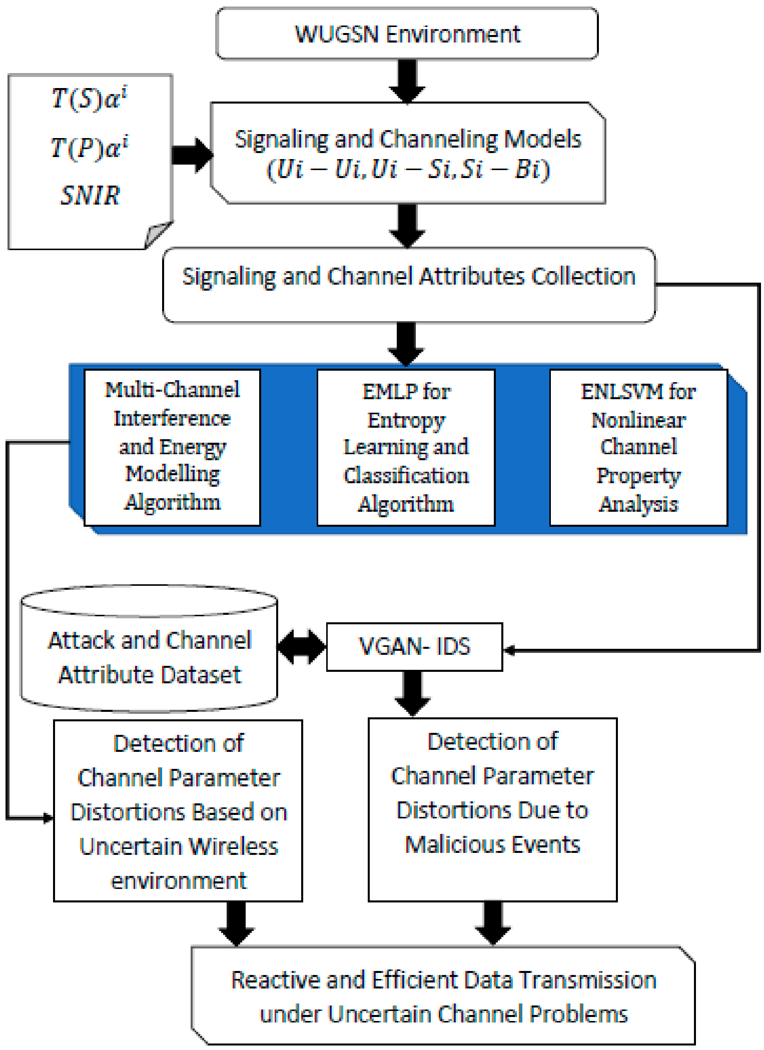

Figure 4. System design of proposed DMCAP phases.

4. Experiments and Results

The experimental circumstance provides the WUGSN design using Network Simulator 3.0 (NS 3.0). In this experiment, wireless sensor network patches are installed and WUGSN parameters are configured as illustrated in Tables 2 and 3. The NS 3.0 sensor network package provides the configuration features related to noise, interference, amplitude, and underground channel constraints. Additionally, the proposed network model consists of electromagnetic signal characteristics and acoustic characteristics. Consequently, the proposed techniques are developed using C++ and Python 3.8 languages in the modelled network base.

Table 2. WUGSN-surface channel configuration parameters.

Test Bed Features	Features
Tool	NS-3.0
MAC	CSMA/CA
Channel Assessment Model	DMCAP
Routing Protocol	AOMDV
Number of Sensor Nodes	40, 80, 100
Attack Dataset	KDD’99
Transmitter Power (W)	0.56
Receiver Power (W)	0.31
Channel Throughput (Kbps)	Variable
Coverage (meters)	50 (maximum)
Channel	Surface (Air)
Mobility	Surface-Random Way Point
Propagation	Two Ray Ground

Table 3. WUGSN configuration parameters.

Test Bed Features	Features
Tool	NS-3.0
MAC	CSMA/CA
Channel Assessment Model	DMCAP
Routing Protocol	AOMDV
Number of Sensor Nodes	40, 80, 100
Attack Dataset	KDD’99
Transmitter Power (W)	0.78
Receiver Power (W)	0.58
Channel Throughput (Kbps)	Variable
Coverage (meters)	25 (maximum)
Channel	Underground
Mobility	Underground-Random Way
Propagation	Two Ray Acoustic

The configured WUGSN has the proposed techniques under Medium Access Control (MAC) policies as inbuilt patches. The network works under 3.5 GHz band around 500 m^2 area. The built-up network area contains the sensor nodes with underground channel characteristics and open surface characteristics. Table 2 shows the WUGSN characteristics of surface sensor nodes and Table 3 illustrates the configurations of underground channel parameters.

The dual-type channel quality configurations ensure close real-time WUGSN channel assumptions [43]. As provided in Figure 3, the knowledge base maintains channel parameter attributes and malicious event attributes (Knowledge Discovery in Databases (KDD’99)). Figure 5 shows the variations in major channel quality parameters such as channel interference rate, channel data transfer rate, and overall channel uncertainty rate. Moreover, Figure 5 denotes the distortion rates at probability scale measurement. The observed measurements present the reduction in data transfer rate as uncertainty and interference rates are increasing over time. The experiment confirms that underground and surface level channel distortions severely affect sensor node’s data communication efforts [44]. The test bed of WUGSN initially observes the wireless channel quality metrics and channel distortions as provided in Figures 5 and 6. Figure 6 relates the quantity of data retransmission rate and channel noise production rate. Generally, noise is defined as unwanted signals that disturb the original data communication.

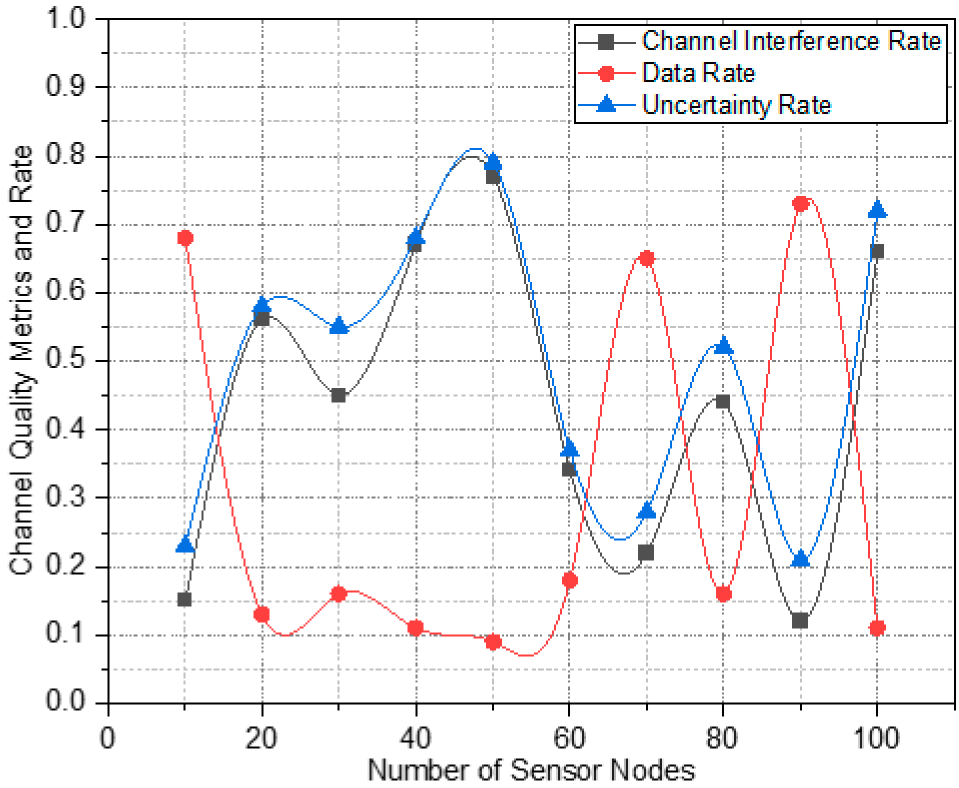

Figure 5. Channel quality measurements.

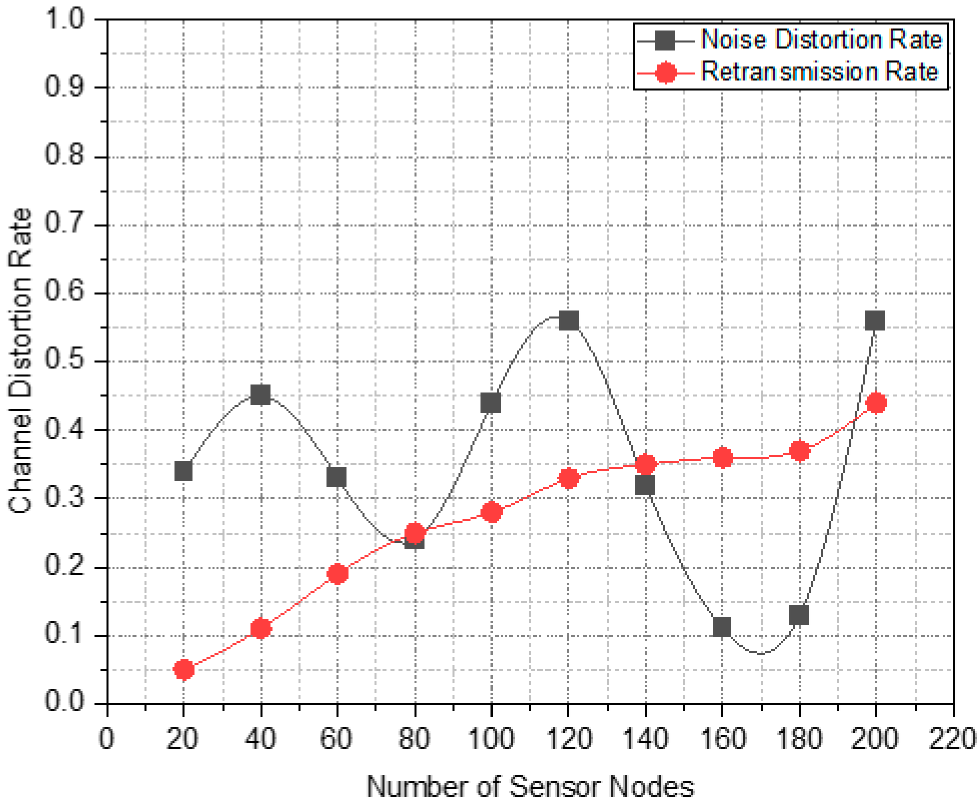

Figure 6. Channel distortion rate.

$$\text{Channel Interference Rate} = \frac{S^I}{S^O} * 100 \quad (24)$$

- S^I-Signal from communicating parties;
- S^O-Signals from other nodes.

$$\text{Channel Data Rate} = \frac{TH}{SD} \quad (25)$$

- TH-Data Transfer Rate between nodes in bits per second;
- SD-Session Duration in seconds.

$$\text{Channel Uncertainty Rate} = \frac{\sum (n^d \cdot l^d) d\tau}{\text{Nactive}} \quad (26)$$

- n^d-Number of node failures in a session;
- l^d-Number of link failures in a session;
- Nactive-Number of active nodes in a session.

$$\text{Channel Noise Distortion Rate} = \frac{\text{Noise (M)} - \text{Noise }(\tau)}{\text{Nactive}} * 100 \quad (27)$$

- Noise (M)-Mean Noise Rate;
- Noise (τ)-Noise rate at time τ.

$$\text{Channel Retransmission Rate} = \frac{\text{NL}}{\text{Number of links in a channel}} * 100 \quad (28)$$

- NL-Total Number of Retransmissions between each link.

Equations (24)–(27) describe the network uncertain conditions enabled in the simulation environment. The uncertain channel conditions can be imposed in the WUGSN testbed as channel interference rate, noise distortion rate, retransmission rate, and overall channel uncertainty rate as denoted in the equations. The detailed illustrations of imposed uncertain conditions are provided in Figures 5 and 6. The changes in channel uncertainties are depicted over the changing number of sensor nodes in the network.

Interference is the signal generated from other sources. Both types of signals crucially interrupt the channel quality measures [45,46]. According to the real-time channel distortions, the proposed network model was configured and experimented for evaluating the system performance. As illustrated in Figures 5 and 6, the total number of sensor nodes in WUGSN varies from 20 to 200. The total number of sensor nodes contains both underground sensor nodes and surface nodes. Figure 6 describes the gradual hike of data retransmission rate against uncertain noise production rate in the wireless channels. In this case, the data retransmission rate increases from 5% (0.05) to 45% (0.45) rapidly against the noise rate (0.35 to 0.55). The network channel characteristics experimented in this section show the competent assumptions of the proposed network model [47].

As illustrated in Figure 6, the rapid hike of sensor nodes' data retransmission rate impacts energy consumption rate and network lifetime. Accordingly, the need for efficient channel assessment and learning system is mandatory to activate channel-aware data transmission principles for uncertain WUGSNs. The proposed DMCAP model and the existing models compete to provide reactive data transmission procedures against channel distortions. The models are evaluated using various learning-support performance metrics. In this regard, the proposed and existing techniques are evaluated using system precision, link quality prediction, routing delay, and secure channel throughput against channel uncertainty rate and other factors.

Figure 7 clarifies precision rate of different channel assessment techniques. Generally, system precision rate is determined as provided in Equation (29).

$$\text{Prec(System)} = \frac{\text{C\_t}}{\text{T\_t}} * 100 \quad (29)$$

- $C_t \rightarrow$ Correctly predicted True channel distortion events;
- T_t $\rightarrow$ Total predicted events as true channel distortions.

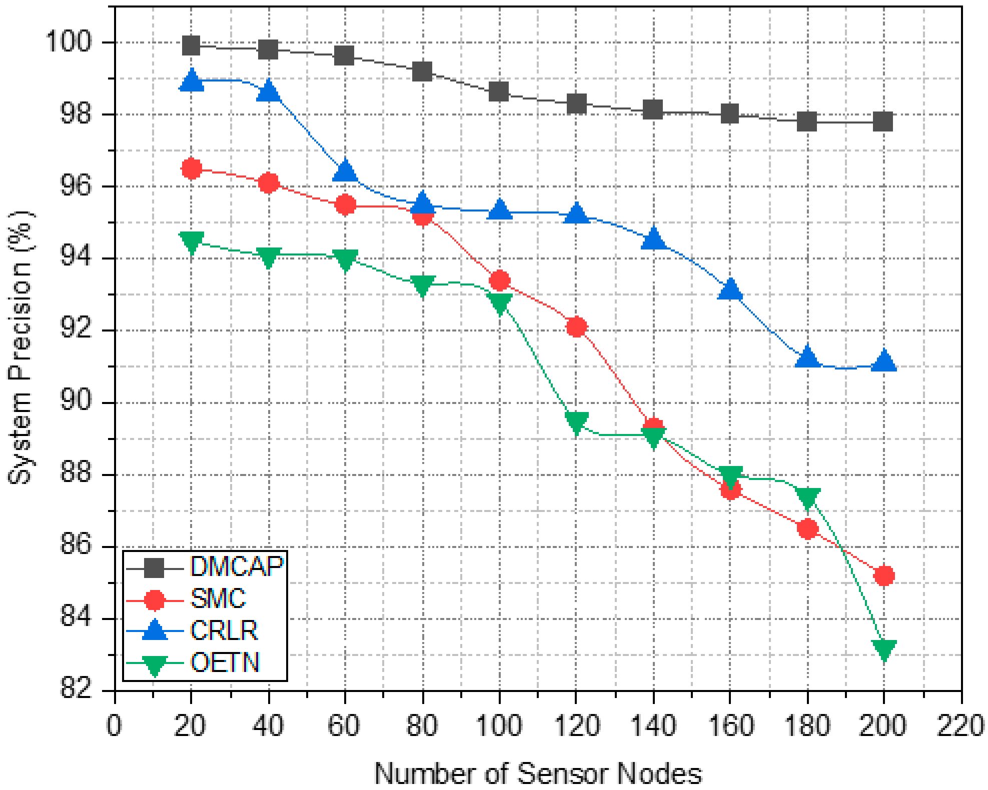

Figure 7. System precision rate.

The system precision rate justifies the actual perfectness of the proposed technique (Equation (29)). In this case, the DMCAP outperforms the existing techniques (SMC, CRLR, and OETN). The maximum precision rate of DMCAP is measured as 99.9% where other techniques fall between 94% and 98.5%. Similarly, the minimal system precision rate is recorded as 97.8% for the DMCAP model. At the same time, the existing techniques secure the precision rate from 80% to 91%.

In the existing techniques, SMC is identifying optimal channels based on signal phase parameters (in-phase and quadrature phase) through software-enabled radio signaling mechanisms. The samples collected from in-phase and quadrature phase (I and Q) are applied in to SVM and RF functions. The supervised learning approaches such as SVM and RF are conventional for analyzing the phase samples of signals deeply. In the developed testbed, this proposed article assumes more complex uncertain conditions for channel optimization. Under this case, the existing SMC is not qualified to obtain better precision and prediction rate (link quality) compared with the proposed model. It attains 85% of precision rate and 82% of link quality prediction rate. This is lower than the proposed DMCAP and CRLR (91% of precision and 87% of prediction). The reason behind the better performance of CRLR is related to effective training procedures of reinforcement network over channel parameters. At the same time, OETN attains minimal growth in terms of system precision and link quality prediction. Since the OETN procedures and following baseline node evaluation procedures to optimize the channel utilization and energy utilization, the result is not significant under uncertain underground conditions.

As provided in Figures 8 and 9, the testbed was adapted to evaluate the performance of all techniques against changing uncertainty rate (Equation (26)). Link quality predictions can be observed against channel distortions and malicious events. Comparably, the proposed DMCAP shows 8% of better precision rate than other techniques.

In this experiment, the proposed techniques observe the major channel distortion issues using multi-channel assessment principles and channel quality tuple analysis procedures. Additionally, the proposed DMCAP ensures multi-level ML and DL evaluation schemes for predicting noise, SNIR, entropy, and other significant distortions [48,49]. The absence of deeply trained evaluation procedures affects the existing techniques against uncertain WUGSN channels.

Figures 8 and 9 show the measurements of link quality prediction rate against environmental distortions and malicious event distortions. Predicting the link quality to transmit the data without loss is a primary goal of this proposed system. The goal can be achieved when the sources of data loss are detected properly. The liveliness of channels is affected due to either environmental disturbances or malicious events. Finding and treating the issues ensure the better link prediction rate. Considering the practical issues of link quality management, the proposed DMCAP system initiates dual case channel quality monitoring practices. In this manner, DMCAP implements both environmental property assessment models and malicious event assessment models. The experiments show the benefit of resilience proposed DMCAP system as provided in Figures 8 and 9. Figure 8 depicts link quality prediction rate against environmental issues.

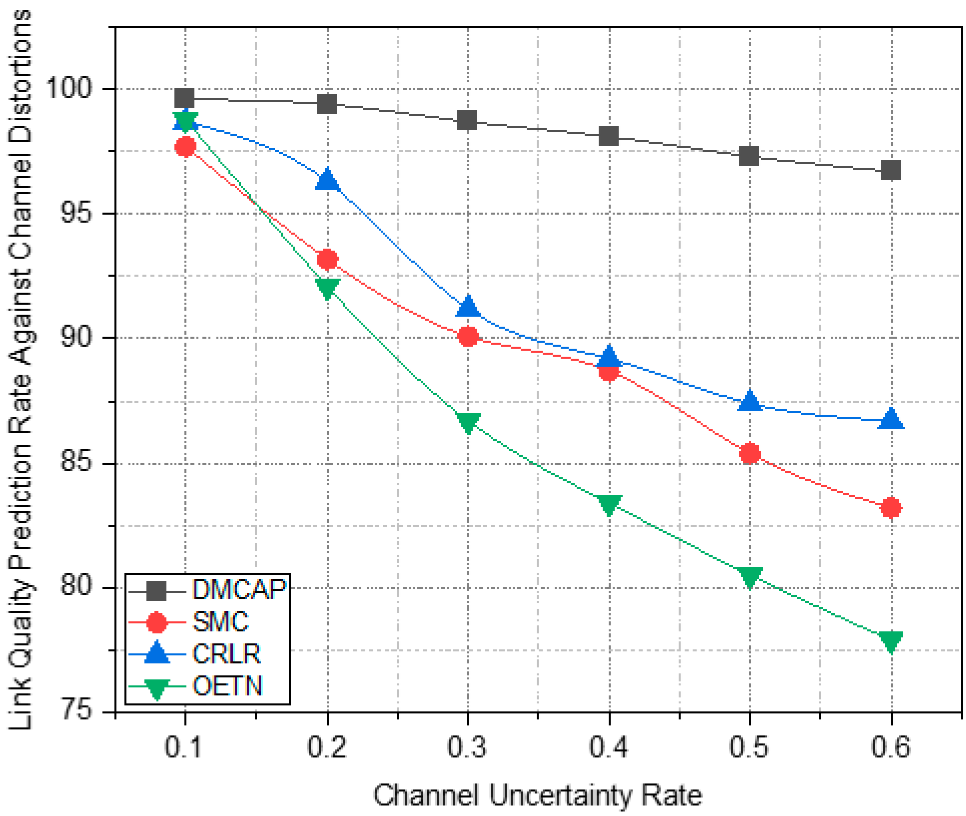

Figure 8. Link quality prediction rate against channel distortion.

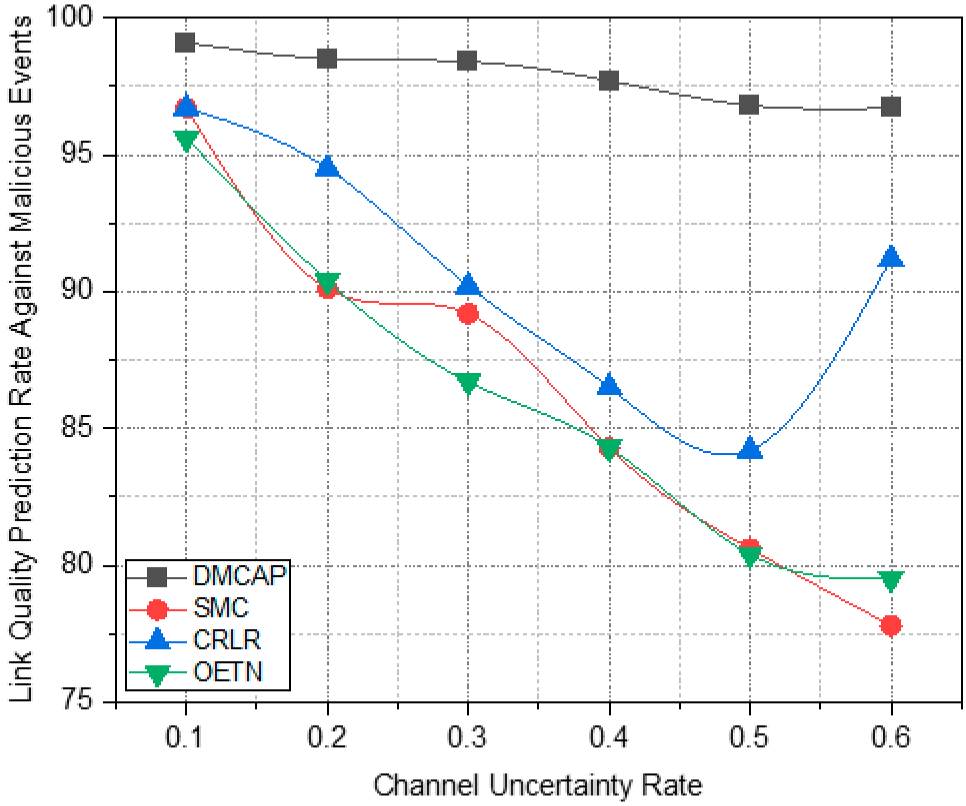

Figure 9. Link quality prediction rate against malicious events.

Compared with other techniques, the performance of DMCAP is commendable (96% of prediction rate against maximum uncertainty rate). On the other hand, CRLR produces optimal prediction and security benefits against OETN and SMC. As CRLR has channel-aware RL engines in each node, the impact shows on better results (92%). At the same time, the existing techniques such as SMC and OETN are not efficient against malicious events under uncertain wireless networks. SMC and OETN are the good procedure for analyzing the channel metrics under limited channel assumptions with minimal rate of dynamic network conditions. However, the development of multi-channel assessment and reactive route selection are primary goals for next generation networks. On the scope, the proposed DMCAP is performing uniquely compared with other techniques.

DMCAP maintains the link quality prediction rate between 99.8% and 96.6% against raising uncertainty rate. The uncertainty rate of each link denotes the overall signal interruptions produced as noise, interference, link failures, node failures, and intruder activities on the channel. Likewise, DMCAP holds 99.7% to 97% of link quality prediction rate against malicious events (Figure 9).

Correspondingly, the proposed DMCAP achieves a better link prediction rate at the optimal time complexity (milliseconds) as illustrated in Table 4. As shown in Table 4, the time complexity of DMCAP for initiating reactive transmission falls between 328 and 489 milliseconds.

Table 4. Time complexity.

Number of Active Links	DMCAP (ms)	SMC (ms)	CRLR (ms)	OETN (ms)
1000	328	444	399	456
1200	356	558	446	567
1400	389	720	478	787
1600	435	780	498	810
1800	468	897	525	940
2000	489	1116	578	1208

The measurements are huge for existing techniques compared with the proposed model. The time complexity denoted in Table 4 is calculated in milliseconds (time taken to complete the operations). Each channel has multiple links between source node and destination node. In this experiment, the number of channel links are varied from 1000 to 2000. As proposed, DMCAP uses suitable nonlinear regression models and multi-channel ensemble classifiers, channel assessment operations taken in each sensor node are evenly balanced. Consequently, the time taken to complete channel assessment procedures is minimized (328 ms to 489 ms) compared with other works.

In this evaluation, SMC and OETN struggle to analyze the real-time channel data using conventional approaches. Hence these existing techniques are consuming more time to obtain classified attributes of multiple channels (1116 ms and 1208 ms, respectively). At the same time, the precision rate of these systems are not optimal. On the other side, the CRLR is consuming procedure operational time between 399 ms and 578 ms which is comparably closer to the proposed method. In this case, the proposed method utilizes the efficiency of multi-channel classifiers (ensemble) over reinforcement procedures to reduce the time complexity around the network.

Figure 10 and Table 5 show the average routing delay (ms) and reactive link establishment rate (%) against channel uncertainties, respectively. As provided in Figure 10, the routing delay for each channel shall be reduced with proposed active channel assessment and reactive channel handling policies. Initiating the reactive data transmission in the network is impossible when the channel assessment system is not reactive and inefficient against channel interruptions. At this moment, the existing techniques produce 280 ms to 220 ms of routing delay for each channel.

Table 5. Reactive link establishment rate (%).

$e(\tau)$	DMCAP	SMC	CRLR	OETN
20	97.1	79.1	86.3	78.4
40	97.5	79.7	86.9	78.5
60	98.2	80.6	87.8	78.9
80	98.9	81.7	88.2	79.2
100	99.4	82.4	90.2	80.1
120	99.7	83.2	90.8	82.3

Significantly, the routing delay is directly proportional to the reactive link establishment rate during node or link failures on the channel. As indicated in Figure 10, the routing delay of the proposed model is minimal compared with other techniques for various iterations (10 iterative experiments). This can be related to Table 5 results of the proposed model. The results provided in Table 5 show the successful link establishment rate during failures.

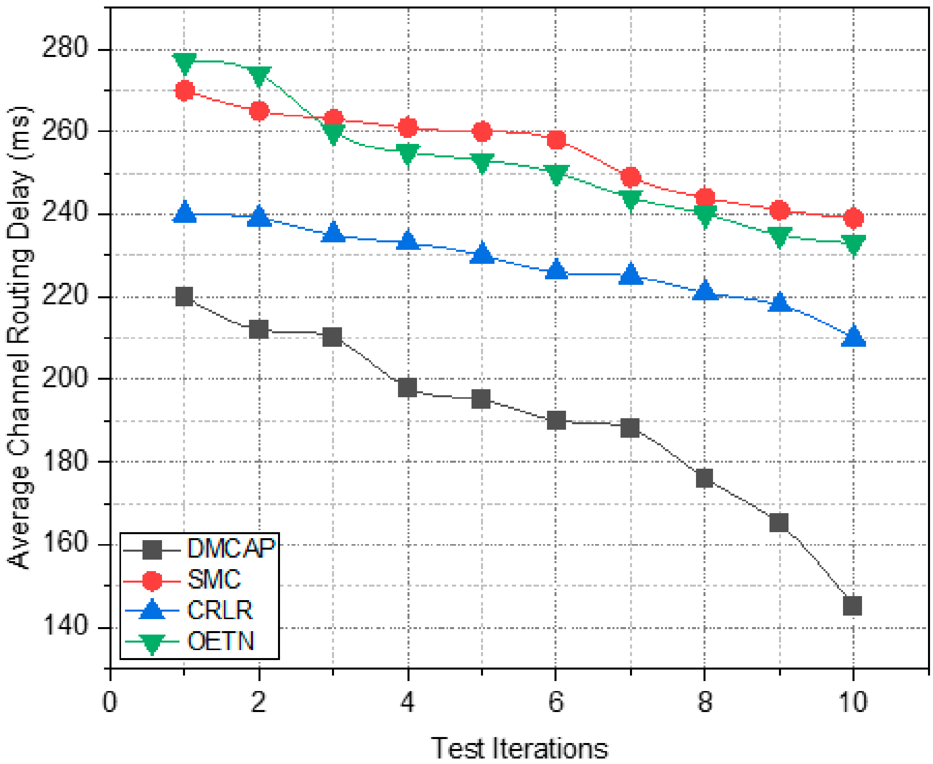

Figure 10. Average routing delay.

Against the performance of existing techniques, the proposed model shows limited routing delay as it is predicting the channel uncertainties actively. On the same way, Table 5 provides the ability of successful link establishment rate among uncertain channel problems and link disabilities. As the number of epochs increases, the proposed DMCAP model updates reactive channel management quality by obtaining the channel assessment attributes. This mechanism works better than other systems and DMCAP obtains 99.7% of reactive link establishment rate. At the same time, CRLR is the only existing technique producing average routing delay (210 ms as minimum) and better link establishment rate (90.8%) compared with other existing techniques.

The reinforcement learning system of CRLR is the reason for optimal performance. In contrast, SMC and OETN are evenly generating more routing delay as they are not deeply understanding the channel behaviors through crucial learning and classification principles. Thus, they are attaining maximum routing delays of 230 ms and 240 ms, respectively. Similarly, the performance is not optimal for link recreation phase as provided in Table 5.

Figure 11 and Table 6 illustrate closely related performance metrics such as secure throughput achievement rate and retransmission reduction rate for each channel. Nevertheless, secure throughput rate shows the amount of successful data transmission against malicious interruptions. The secure throughput of each channel is ensured and obtained with VGAN-IDS engine installed in each sensor node. In this experiment, the proposed DMCAP achieves secure throughput from 17.2 Kilobits Per Seconds (Kbps) to 23.9 Kbps when the number of training epochs are increasing gradually. Moreover, the throughput of CRLR obtains better states compared with OETN and SMC. OETN and SMC maintain only nominal security against malicious event (15.6 Kbps and 13.1 Kbps). This experiment reveals that the proposed technique securely manages the data transmission under VGAN-IDS initiatives and alert systems. Due to the immense experiment-based observations, the number of retransmissions initiated at each link is crucially reduced in WUGSN (DMCAP).

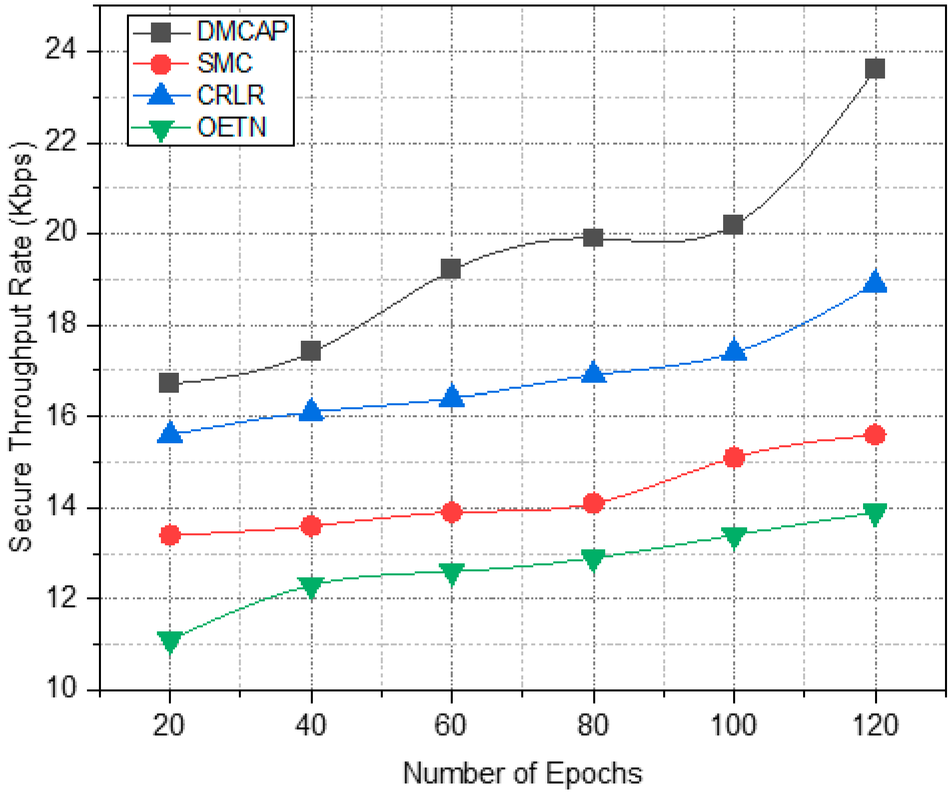

Figure 11. Secure throughput rate.

Table 6. Retransmission reduction rate (%).

e(τ)	DMCAP
20	90.1
40	96.7
60	97.3
80	97.9
100	98.9
120	99.5

Table 6 shows the observed results for the DMCAP system's retransmission reduction rate. The rate of retransmission is reduced as the number of epochs increases. The retransmission reduction rate is defined as the number of retransmissions required at each sensor node against environmental interrupts and malicious interrupts on the link. As illustrated in Table 6, the proposed system reduces the retransmission rate (%) from 90.1% to 99.5% successfully. This indicates that the energy and lifetime of each sensor node on the link is saved with the benefit of proposed DMCAP procedures.

As per the theoretical and experimental clarifications, the proposed system was implemented as distributed multi-channel assessment and activation protocol in each sensor node. The proposed DMCAP is a light-weight protocol installed in both underground and surface sensor nodes for ensuring reliable data communication under uncertain WUGSN conditions. This protocol is fast and reactive in the uncertain channel environment. Particularly, DMCAP uses ensemble multi-channel attribute assessment procedures (ENLSVM) and VGAN-IDS engines as sensor internal procedures. Thus, the proposed DMCAP overcomes data communication problems that happen due to nonlinear productions and channel uncertainty issues optimally compared with other techniques (SMC, CRLR, and OETN). Notably, the proposed model effectively detects and predicts the channel attributes for managing the quality of wireless communication. The contributions and advantages of the proposed DMCAP model was illustrated through various testbed experiments against channel uncertainties.

To achieve significant benefits from proposed channel assessment policies, the testbed was configured with dual-link characteristics to meet the conditions of underground channel assumptions and surface level channel assumptions. The configuration of classified channel configuration parameters helps to observe the crucial and real-time performance of proposed DMCAP model (Tables 2 and 3). However, these dual-link configuration properties are not used in existing techniques. On the realistic testbed, experiments are taken to illustrate the real-time uncertainty conditions of WUGSN using the measured quantities of noise distortion rate, retransmission rate, channel interference rate, data rate, and other uncertainties (link and node failures).

Figures 5 and 6 infer the dynamic nature of the WUGSN setup. On the simulation platform, the performance metrics such as link quality prediction rate, system precision rate, average routing delay, and secure throughput rate are measured for the proposed model and the existing models (SMC, CRLR, and OETN). In addition, the reactive link establishment rate and retransmission reduction rate are considered as crucial factors for ensuring the stability and efficiency of proposed DMCAP model against exiting techniques.

$$\text{Reactive Retransmission Rate} = \frac{\text{DMNR\_t}}{\text{UTt}} * 100 \tag{30}$$

- $DMNR_t$-Number of Retransmission taken at one iteration by DMCAP;
- UTt-Number of network or link failures happens at one iteration.

$$\text{Retransmission Reduction Rate} = \frac{\text{DMNR\_t}}{\text{NRTt}} * 100 \tag{31}$$

- NRTt-Total number of retransmissions taken without proposed DMCAP.

Equations (30) and (31) illustrate the importance of the growth shown in Tables 5 and 6 for the proposed DMCAP model. As discussed, the proposed model uses more unique multi-channel modelling schemes for differentiating the characteristics of each wireless channel (air medium or acoustic medium). In addition, the combination of channel distortion analysis and malicious turbulences over the channel are taken seriously to predict the link stability to initiate multi-path transmission in WUGSN. The detailed channel analysis and attribute assessment schemes improve the data throughput over uncertain channels.

Consequently, Table 7 illustrates the energy optimization rate achieved through the reduction in retransmission rate. Furthermore, this article found the coverage problems during wireless communication in the WUGSN and near ground sensor networks. Likewise, a few notable works are considered under this technical scope [50,51]. As the uncertain channel qualities and coverage irregularities create crucial network problems, these are expected to be considered as major parts under any research cases [52].

Table 7. Energy optimization rate.

e(τ)	DMCAP
20	0.21
40	0.26
60	0.29
80	0.32
100	0.36
120	0.39

5. Conclusions

Generally, WSNs and WUGSN are massively applied at defense, industrial, medical, and environmental monitoring conditions. The existence and the deployment condition of WUGSNs create more channel interruptions. WUGSNs maintains both deep underground medium and air medium to lead multi-hop wireless links. According to the link nature, the channel configuration parameters change from one link to another link in the same channel. Correspondingly, the impact of underground channel distortions and surface channel distortions create major problems for WUGSN communication. The channel is disturbed due to underground noise, interference, and malicious interactions. The rate of channel interruptions is not common for surface transmission with widely varying uncertainty rates [53–55].

Against the significant problems, the proposed DMCAP model was developed as a distributed sensor agent. The DMCAP model contained multi-channel signaling models, EMLP, ENLSVM, and VGAN-IDS procedures for providing reactive data transmission against critical channel distortions. The procedures developed inside the sensor node initiated channel attribute evaluation functions, reactive channel activation functions, malicious event monitoring functions, and reactive channel estimator functions. The proposed novel functions and complex data analysis models guarantee the channel protection and reliable communication [56–58]. Consequently, the proposed DMCAP commits the reduction in the retransmission rate, time complexity, and routing delay as illustrated in Section 4 against the existing systems such as CRLR, OETN, and SMC. Consequently, the DMCAP saves overall network energy and lifetime under uncertain channel conditions [59]. However, the proposed DMCAP procedures are lacking lightweight encryption mechanisms to enable data confidentiality and channel masking facilities. Additionally, this proposed model was not evaluated for multiple sensor nodes applied in WUGSNs. These are considered as the limitations of this proposed article. In future, the secure DMCAP is estimated to be designed and implemented for WUGSNs.

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