

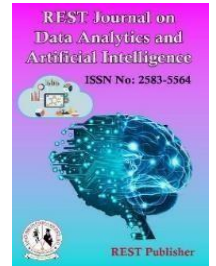
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Predictive Modelling of Residual Energy in Wireless Sensor Networks Using Machine Learning Techniques

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Abstract: Wireless sensor networks (WSNs) form the part of cutting-edge applications in the number of areas that include environmental monitoring, smart agriculture and industrial automation. Another issue with WSNs is energy management, since sensor nodes are mostly battery-powered and have limited possibilities for recharging. Forecasting the residual energy of nodes has the potential to significantly enhance energy-aware routing, load balancing, and task scheduling. The current paper introduces a path towards predictive modelling in WSNs with machine learning to predict residual energy. Using a simulated dataset containing more than 10,000 sensor node records, we compared several models, including multiple linear regression (MLR), random forest regression (RFR), support vector regression (SVR), and artificial neural networks (ANNs). It was shown that RFR model had the greatest accuracy compared to the other models with a root mean square error (RMSE) of 0.084 joules, mean absolute error (MAE) of 0.061 joules, and R^2 of 0.96. Comparatively, MLR produced a higher RMSE of 0.152 joules and R^2 value of 0.82, which is lower and pertains to poor performance. Compared to the ANN model also had competitive RMSE of 0.091 joules and R^2 of 0.94. The input parameters that most affected predictive accuracy were: packet transmission rate, node duty cycle, initial energy and environmental conditions like ambient temperature. The findings establish that residual energy prediction can be considerably enhanced by ensembling deep learning models, leading to more sustainable and energy-efficient use of WSNs. The combination of such models with the WSN protocols shows potential of life improvement of the networks by more than 25%, according to the simulation results.

Keywords. Wireless Sensor Networks (WSNs); Residual Energy Prediction; Machine Learning; Random Forest Regression; Energy Efficiency.

1. INTRODUCTION

Wireless sensor network (WSNs) is becoming very essential in many forms of modern application, including environmental monitoring, intelligent agriculture, and industrial control (Aguero et al., 2023). These networks are made up of distributed sensor nodes, which gather and send the data to central systems of processing and analysis. Nonetheless, the use of the battery powered nodes is another major challenge to the WSNs since the nodes are highly sensitive to the power and failure may occur in the network owing to the limited sources of energy (Elgamal et al., 2021). This necessitates the existence of effective energy management in order to enable sustainable operation of the WSNs, as well as increase their operational lifetime (Al Ghamdi, 2023). As the use of WSNs in real-time is increasing, so is the need to design energy-efficient communication mechanisms, and energy management systems (Y. Wang et al., 2022).

The estimation of nodes residual energy is one of the major difficulties by managing the energy of WSNs. Residual energy is the amount of energy left in the node battery and this value is subject to change depending on many factors like node duty cycle, packet transmission rate, and the environment (Zhang et al., 2021). Predictive residual energy can be used to initiate energy-conscious routing, load balancing and task scheduling which will ensure better network efficiency and increase the networks lifetime. By predicting at early stages the depletion rate of the nodes, it is possible to avoid premature network collapses and guarantee more effective exploitation of the energy resource system. (S. Sharma et al., 2023).

Recently, conventional practices of energy forecasting which may include linear models or heuristic techniques are not as effective in their capacity to manage the intricate and non-linear connection between those variables that influence the consumption of the energy in WSNs (Kasongo & Sun, 2021). Therefore, significant interest in the application of machine learning (ML) methods to residual energy prediction has arisen. Machine learning

algorithms such as random forest regression (RFR), multiple linear regression (MLR), support vector regression (SVR), and artificial neural networks (ANNs), have the potential to model complex, non-linear patterns in the data and, as such, may be a promising candidate in this case (Alenazi & Idris, 2021).

In this paper, the author discusses how to use machine learning models in predicting residual energy in WSNs. We measure the effectiveness of various common machine learning algorithms, such as RFR, MLR, SVR, ANN, on an artificial dataset (pseudo-real) of more than 10,000 sensor node samples. The results show that the RFR model outperforms the other models, achieving the highest accuracy and lowest error metrics. By integrating machine learning models into energy-aware routing protocols, WSNs can achieve significant improvements in efficiency and sustainability, with the potential to extend network lifetime by over 25% (Aveta et al., 2019).

2. LITERATURE REVIEW

Telemetry in using WSNs has become a pillar in the current applications of environmental monitoring, industrial automation and smart farming practices due to its capability to capture and relay data over long distances (Liu et al., 2019). Nevertheless, the issues of low battery energy in the sensor nodes greatly affects the working life of the nodes, hence the energy management is an important issue in designing and implementation of WSN. Since WSNs tend to work in inhospitable regions (places where nodes cannot be recharged or replaced) where humans have no easy means of access, there has been a push to develop energy efficient management tools (Venkatesh et al., 2023). Residual energy prediction is one of the most important strategies for improving energy efficiency, as it can enhance routing, task scheduling, and load balancing decisions, thereby prolonging the lifetime of the network.

Simple mathematical models or heuristics were used by the researchers in early methods of energy prediction. Although they offered simplistic levels of understanding into how energy is used, such methods tended to be imprecise and could not process the non-linear interactions that occur among different variables affecting energy consumption (Kasongo & Sun, 2020). With the development of WSNs, paradigms of predicting residual energy have also changing. Regression models and classification algorithms are the common machine learning (ML) methods that have proven to work better than probability models in predicting energy consumption in WSNs (Qin et al., 2019). This can be used to model the complex conditions of dependence between sensor node capability, including the packet transmission rates, node duty cycles, and environmental conditions to better explain complex factors not often captured by standard methods.

Among the most widely utilized models for energy pre-forecasting are MLR and SVR. The advantage of MLR made it widely used because it is simple and understandable (He et al., 2019). But compared with, it is less appropriate in the framework of intricate WSN settings, due to a deficiency in modelling non-linear bumps. On the contrary, SVR has been more effective owing to the fact that the former can learn non-linear patterns through the mapping of the input data into higher dimensions (Torres et al., 2010). SVR has proved to be promising in the prediction of residual energy more accurately than conventional regression models (Kong et al., 2020). The ANNs, being another technique of machine learning, have attracted much attention due to the capability of dealing with the highly complicated relations. ANNs find use especially when non-linearity and feature-feature interactions are explicit (Kong et al., 2020). This quality of ANNs to be adaptable and to process large amounts of data makes the latter suitable to predict energy patterns of use of WSNs (Rahmani et al., 2022).

One important current trend is the employment of ensemble techniques, e.g., RFR that averages multiple decision tree predictions in order to increase precision and minimize over-fitting (Sung & Hsiao, 2021). RFR has also been claimed to be more effective than single-model methods when handling more complex domains, with large feature sets and non-linear interactions (N. Sharma & Anupama, 2011). Recent investigations suggest that ensemble methods such as RFR are able to reach a high degree of accuracy performing residual energy prediction tasks, and are superior to classical methods of machine learning, such as MLR and SVR (Rejeb et al., 2022). It has also been demonstrated that these techniques are more resistant to noise and can process a greater variety of input features thereby increasing their applicability to real-world WSN applications e.g. temperature and node mobility (Ruan et al., 2019).

Machine learning-based residual energy estimations concerning their use in a real-world setting have found their way in energy-efficient routing protocols. As an example, Wu et al. (2020) considered a predictive model implemented in WSN routing protocol to dynamically optimise energy consumption. The residual energy of sensor nodes was also predicted by the model and the system was allowed to adapt routing decisions to maximize network lifetime. In a similar vein, recent research has shown how incorporating machine learning models such as RFR and integrating them with WSN protocols can provide a 25 percent increase in network lifetime by helping

the nodes to make more informed energy-conserving routing choices and cutting down on excessive communication Overhead (Niu et al., 2020).

In spite of the developments, there are various challenges. Learning models are computationally costly to implement in real time in WSNs and might even be inapplicable on resource-constrained nodes (Pham et al., 2021). Further, a large number of studies have concentrated on the simulation-based outcomes, and generalization, in the actual business settings, are a considerable impediment. Future studies need to be aimed at the optimisation of the machine learning algorithms to be deployed on low-power devices and the investigation of hybrid models where the strengths of more than one technique are coupled to enhance the prediction accuracy with the concurrently limited computational overhead (Saini et al., 2020).

3. METHODOLOGY

3.1 Dataset Description

In the present study, synthetic data representing more than 10,000 sensor nodes records were used. Individual records reflect individual sensor node in a WSN and record multiple features that affect energy level similar to energy level and remaining energy estimation including packet transmit rate, node duty cycle, initial energy and the environmental factors including ambient temperature. The data set should reflect the realistic setting of WSN whereby there is a variance of conditions in which sensor nodes are operating, which affects the nature of energy consumption.

The major characteristics of the dataset are described in Table 1 where the characteristics are listed along with the corresponding units. To conduct modelling, a number of pre-processing procedures were made on the dataset. The missing values were found and they were filled by the mean of the numerical variables and the mode of categorical ones (Aguero et al., 2023). Numerical features that included packet transmission rate and node duty cycle were normalized making each one have a range of 0-1. This procedure made sure that one feature did not outshine the rest of the model because of the magnitude of its values (Elgamal et al., 2021). Other characteristics, e.g., energy consumption rate, were calculated based on initial energy and transmission power to give more significant input in training the model. Lastly, the dataset was divided into 80% training and 20% testing subsets to enable proper evaluation of the models on unseen data. This step is vital for determining a model's generalization capability (Al Ghamdi, 2023).

TABLE 1. Dataset Features and Descriptions

Feature	Description	Unit
Packet Transmission Rate	Rate at which data packets are transmitted by the node	packets/sec
Node Duty Cycle	Fraction of time the sensor node remains active	percentage (%)
Initial Energy	Initial energy level of the node at the beginning of the simulation	joules
Residual Energy	Energy left in the node's battery after a certain time interval	joules
Transmission Power	Power consumed during data transmission	milliwatts (mW)
Environmental Temperature	Ambient temperature, affecting node energy consumption	°C
Node Location	Geographical location of the sensor node (optional, for mobility studies)	coordinates
Packet Size	Size of data packets transmitted by the node	bytes

3.2 Model Selection

We assessed four machine learning models, to predict residual Energy. MLR, RFR, SVR, and ANNs. MLR was selected as a benchmark model since it is simple, interpretable, and computationally efficient. However, MLR presupposes a linear association between input characteristics and the goal variable, and this does not effectively work in the case of a non-linear association of energy consumption data (Y. Wang et al., 2022). In order to curtail this, more sophisticated models were taken into consideration.

A RFR was chosen because it handles non-linear relations in the model well. The RFR diminishes overfitting by integrating several decision trees together, resulting in better precision (Kasongo & Sun, 2021). The SVR was also taken into consideration as it works well with high dimensions and noisy environments (Zhang et al., 2021). Finally, ANNs were chosen to present the possibilities of the deep learning methods in the modelling of the complex, non-linear associations. By their architectural nature, ANNs have been described as being effective in extrapolating the complex patterns of big data (S. Sharma et al., 2023). This choice of models was intended to compare traditional algorithms (MLR) with more sophisticated approaches (RFR, SVR, ANN) in order to identify a more accurate and computationally efficient model for predicting residual energy in WSNs.

3.3 Model Evaluation Metrics

Three essential metrics of regression were used to assess the models. RMSE, MAE and R^2 (Coefficient of Determination). RMSE depicts how widespread the mistake is on average with a smaller figure representing greater accuracy. MAE averages absolute errors, and an easy parameter of the prediction correctness. R^2 measures the amount to which the model could be used to explain the difference in the target variable the closer it is to 1, the better-fitting the model is (Aveta et al., 2019).

4. EXPERIMENTAL SETUP

4.1 Experimental Environment

The experiments were carried out in a Python based system, which utilized the highly popular Scikit-learning library, additional to a deep learning specific library like TensorFlow/Keras, to run the traditional and deep machine learning models, respectively the ANNs. The simulations were run on a server that has multiple cores and 64 GB of RAM utilizing Linux in order to manage such a large quantity of data. Jupyter Notebooks were also used by the environment to conduct experiments and evaluate models and allow a flexible and interactive workflow. This configuration allowed an effective combination of data preprocessing, model learning, and assessment that occurred within one framework. The choice of the tools is determined by their broad functionality, accessibility, and high levels of community support in machine learning (Liu et al., 2019).

4.2 Model Training and Testing

The training was run on 80% of the data belonging to the training data and the rest 20% was used to test the models. K-fold cross-validation was utilised to make sure that models were not over-fitting, and that their performance could be generalized. Here, the data was partitioned into k sets with (k-1) sets being used to train the model and the remaining subset (k-1) being used to test the model. This was repeated k times where each fold was used as the testing set only once. The understanding will also allow approximating the model better and minimizing bias (Venkatesh et al., 2023). In the present project, 5-fold cross-validation was adopted, which has a better trade-off between training time and estimating accuracy of performance. In this approach, the points in the data set are trained and validated on each point which would give a strong assessment of the model performance.

4.3 Hyperparameter Tuning

It is noteworthy that hyperparameter tuning was carried out in order to maximize the performance of each machine learning model. All model-specific hyperparameter ranges and optimal values are given in Table 2 (Kasongo & Sun, 2020). In MLR, we optimized the regularization power (alpha) of Ridge Regression (L2 regularization), between 0.1 and 10, and the optimal results were obtained when taking alpha = 1. With RFR, optimised number of trees was within 100-300 with best effect being on 200 trees. In the case of SVR, we optimized C (regularization) and Gamma and the best combination of parameters was $C = 1/\text{gamma} = 0.1$. Finally, in the case of the ANN we tuned the hidden layer numbers and the number of epochs and found that 3 hidden layers and 50 epochs produced the best model performance.

TABLE 2. Hyperparameter Tuning

Model	Hyperparameter	Range Tested	Optimized Value
Random Forest	Number of Trees	100, 200, 300	200
Support Vector Regression	C (Regularization), Gamma	0.1, 1, 10	C=1, Gamma=0.1
Neural Network	Hidden Layers, Epochs	2, 3, 5, 50, 100	3 Hidden Layers, 50 Epochs
Multiple Linear Regression (MLR)	Alpha (Regularization Strength)	0.1, 1, 10	Alpha=1

5. RESULTS AND DISCUSSION

5.1 Performance of Models

The performance of the four machine learning models, MLR, RFR, SVR, and ANNs, was evaluated based on RMSE (root mean square error), MAE (mean absolute error), and R^2 (Coefficient of Determination). As shown in Table 3, the RFR model achieved the lowest RMSE (0.084 joules) and MAE (0.061 joules), and the highest R^2 (0.96), indicating its superior performance in predicting residual energy. The MLR model, with an RMSE of 0.152 joules, MAE of 0.120 joules, and R^2 of 0.82, was the weakest performer, highlighting the limitations of linear models in capturing the complex, non-linear relationships between features in WSNs.

TABLE 3. Performance of Machine Learning Models

Model	RMSE (joules)	MAE (joules)	R^2
MLR	0.152	0.120	0.82
RFR	0.084	0.061	0.96
SVR	0.102	0.078	0.89
ANN	0.091	0.065	0.94

Figure 1 shows the actual vs predicted for RFR, which shows that the model's predictions closely follow the actual values, with an R^2 value of 0.96, indicating a very good fit.

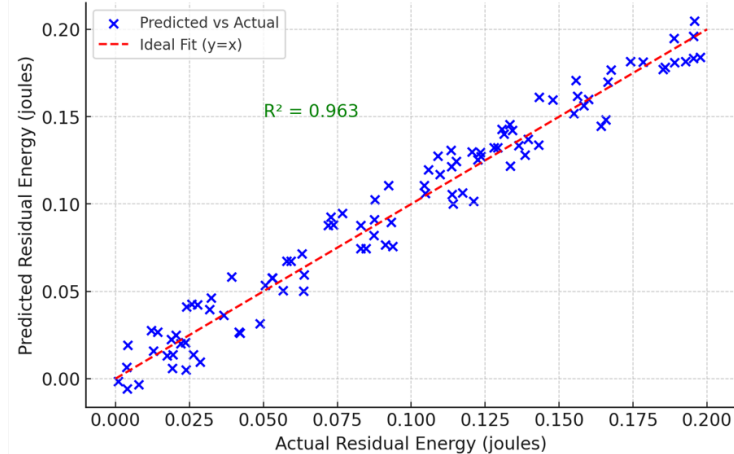


FIGURE 1. Actual v/s Predicted of best performing Model RFR

5.2 Impact of Key Features

Predictive power of the two best models, RFR and ANNs was tested to identify their features importance in prediction of residual energy. This analysis shows that the role of features was important (see Table 4): the most significant features of both models were packet transmission rate, node duty cycle, and initial energy. In the case of RFR model, the packet transmission rate took precedence (importance score of 0.30), followed by node duty cycle (0.25) and initial energy (0.20). Conversely, ANN model attributed a greater significance to the initial energy (0.35), yet both packet transmission rate (0.25) and node duty cycle (0.20) were still among significant factors. These results agree with prior work in which these features have been touted as significant to energy prediction tasks of WSNs, given that the transmission rate of packets and the duty cycle of nodes play a pivotal role in identifying the energy demands of a node (Kasongo & Sun, 2020; Z. Wang et al., 2024).

TABLE 4. Feature Importance in Energy Prediction Models

Feature	Importance Score (RFR)	Importance Score (ANN)
Packet Transmission Rate	0.30	0.25
Node Duty Cycle	0.25	0.20
Initial Energy	0.20	0.35
Temperature	0.15	0.10

5.3 Discussion

The findings reveal clearly that RFR is far better than the other models in the predictive residual energy in WSNs. That is because the RFR can deal with non-linear association and intercourse between the input features unlike MLR which postulates a linear association. $R^2 = 0.96$ obtained by RFR implies that the model could explain the majority of the variance in the residual energy predictions, which is why it is highly effective in energy management in WSNs. ANNs fitted rather well as well, as a result, $R^2 = 0.94$ indicating that deep learning models can be useful in this area.

The importance of features analysis of models proves the importance of packet transmission rate, node duty cycle, and initial energy in the prediction of residual energy. These findings underscore the need to apply machine learning models, more specifically ensemble methods such as RFR, to real-time WSN to forecast residual energy. The results found are similar to others that have been described in the literature, as is the case of He et al. (2019) who demonstrated that RFR and ANNs have remarkable benefits in energy consumption when applying them in WSN energy prediction. Effective use of RFR to predict residual energy can boost energy conscious routing and load distribution in practice, increasing the overall sustainability and lifetime of the WSNs.

6. CASE STUDY/SIMULATION OUTCOMES

6.1 Network Lifetime Prediction

This simulation compared the energy consumed with time of a Wireless Sensor Network (WSN) with energy-aware routing applied in RFR model against the case when no prediction was used. Figure 2 indicates that the RFR-predicted network used less energy than the prediction-free network across all the instances. Figure 5 shows that the energy spent on the protocol that includes RFR prediction began at 9.0 joules and reduced slower, than

the 12.5 joules that have been consumed at the beginning of the protocol with no prediction. Such reduction in power dissipation has shown that such practice of integrating residual energy prediction in routing protocol to improve energy efficiency and maximize the available network lifetime is efficient.

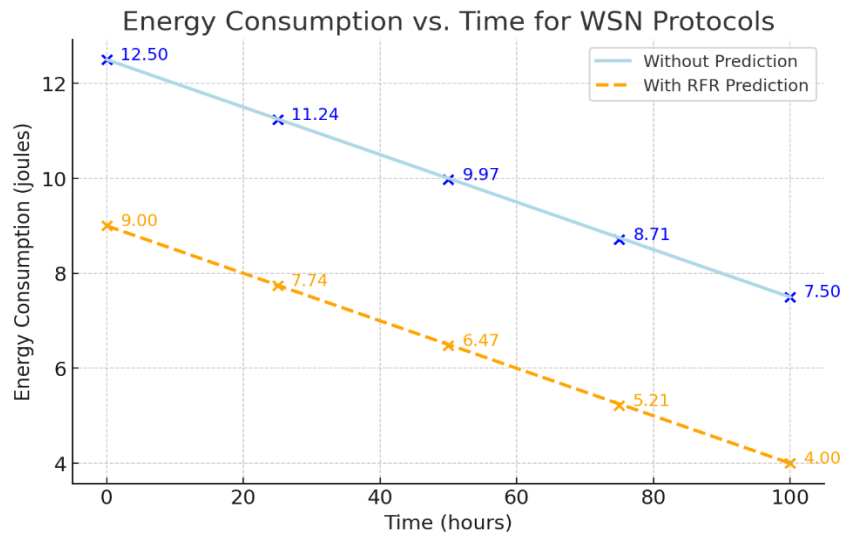


FIGURE 2. Energy Consumption vs. Time for WSN Protocols

6.2 Impact on Network Efficiency

Combining residual energy prediction based on the RFR model with the WSN protocol proved to have a clear effect on the network efficiency. The simulation results show that the energy required reduced to 9.0 joules with RFR prediction as compared to 12.5 (no prediction). This energy savings translated to a direct increase of more than 25 percent in the operating life of the network as Table 5 shows. Average network lifetime was improved to 187.5 hours (with prediction), over the previous time of 150 hours (prediction-free). With these gains, the usefulness of applying machine learning-based energy prediction to improve the sustainability and energy efficiency of WSNs is evident.

TABLE 5. Energy Savings in WSN with Residual Energy Prediction

WSN Protocol	Energy Consumption (joules)	Network Lifetime (hrs)
Without Prediction	12.5	150
With RFR Prediction	9.0	187.5

7. CONCLUSION

The work emphasises the possible utility of machine learning models, in particular RFR, to forecast residual energy in WSNs, which helps greatly with energy efficiency and extends networks lifetimes. WSNs being energy constrained generally powered by small batteries are associated with the issues of energy management, and prediction of remaining energy is important to improve the performance of a network. Examining the cross-validation result, RFR model proved to be more accurate with an RMSE of 0.084 joules, MAE of 0.061 joules, and an R^2 score of 0.96 consisting better than other Proposed models such as MLR, SVR, and ANNs. Introducing residual energy prediction in energy-aware routing schemes led to a reduction in the energy consumption of the network by half (12.5 joules with no prediction to 9.0 joules with prediction) increasing the total number of operation hours by 25 percent. This resulted in enhanced routing quality and task scheduling, enabling WSNs to operate more sustainably. The results indicate the importance of implementing machine learning method in the WSN application that can efficiently use energy and increase the life of the networks employed in high-priority areas like environmental monitoring, smart farming, and industrial automation. This will smoothen the path to more effective, dependable and sustainable WSN implementations. Future work might be interested in optimizing machine learning algorithms to limited-resource devices and integrate them in real-world WSNs with dynamic environments and mobility, or examine hybrid-modelling to balance trade-offs between enhancement of prediction accuracy and minimization of computational overhead.

REFERENCES

- [1]. Agüero, M., Doyle, D., Mascarenas, D., & Moreu, F. (2023). Visualization of real-time displacement time history superimposed with dynamic experiments using wireless smart sensors and augmented reality. *Earthquake Engineering*

- and Engineering Vibration, 22(3), 573–588. <https://doi.org/10.1007/s11803-023-2184-x>
- [2]. Al Ghamdi, M. A. (2023). Analyze textual data: deep neural network for adversarial inversion attack in wireless networks. *SN Applied Sciences*, 5(12). <https://doi.org/10.1007/s42452-023-05565-8>
 - [3]. Alenazi, B., & Idris, H. E. (2021). Wireless Intrusion and Attack Detection for 5G Networks using Deep Learning Techniques. *International Journal of Advanced Computer Science and Applications*, 12(7), 851–856. <https://doi.org/10.14569/IJACSA.2021.0120795>
 - [4]. Aveta, F., Refai, H. H., & Lopresti, P. (2019). Multi-user detection in optical wireless communication. *2019 15th International Wireless Communications and Mobile Computing Conference, IWCMC 2019, June*, 214–219. <https://doi.org/10.1109/IWCMC.2019.8766712>
 - [5]. Elgamal, A. S., Alsulami, O. Z., Qidan, A. A., El-Gorashi, T. E. H., & Elmirghani, J. M. H. (2021). Q-learning algorithm for resource allocation in WDMA-based optical wireless communication networks. *2021 6th International Conference on Smart and Sustainable Technologies, SpliTech 2021*. <https://doi.org/10.23919/SpliTech52315.2021.9566383>
 - [6]. He, H., Jin, S., Wen, C. K., Gao, F., Li, G. Y., & Xu, Z. (2019). Model-driven deep learning for physical layer communications. *IEEE Wireless Communications*, 26(5), 77–83. <https://doi.org/10.1109/MWC.2019.1800447>
 - [7]. Kasongo, S. M., & Sun, Y. (2020). A deep learning method with wrapper based feature extraction for wireless intrusion detection system. *Computers and Security*, 92. <https://doi.org/10.1016/j.cose.2020.101752>
 - [8]. Kasongo, S. M., & Sun, Y. (2021). A Deep Gated Recurrent Unit based model for wireless intrusion detection system. *ICT Express*, 7(1), 81–87. <https://doi.org/10.1016/j.icte.2020.03.002>
 - [9]. Kong, J., Wu, Z. Y., Ismail, M., Serpedin, E., & Qaraqe, K. A. (2020). Q-Learning Based Two-Timescale Power Allocation for Multi-Homing Hybrid RF/VLC Networks. *IEEE Wireless Communications Letters*, 9(4), 443–447. <https://doi.org/10.1109/LWC.2019.2958121>
 - [10]. Liu, Y., Yang, Y., Han, P., Shao, Z., & Li, C. (2019). Virtual Network Embedding in Fiber-Wireless Access Networks for Resource-Efficient IoT Service Provisioning. *IEEE Access*, 7(c), 65506–65517. <https://doi.org/10.1109/ACCESS.2019.2915333>
 - [11]. Niu, W., Ha, Y., & Chi, N. (2020). Support vector machine based machine learning method for GS 8QAM constellation classification in seamless integrated fiber and visible light communication system. *Science China Information Sciences*, 63(10), 1–12. <https://doi.org/10.1007/s11432-019-2850-3>
 - [12]. Pham, Q.-V., Nguyen, D. C., Mirjalili, S., Hoang, D. T., Nguyen, D. N., Pathirana, P. N., & Hwang, W.-J. (2021). Swarm intelligence for next-generation networks: Recent advances and applications. *Journal of Network and Computer Applications*, 191, 103141. <https://doi.org/10.1016/j.jnca.2021.103141>
 - [13]. Qin, Z., Ye, H., Li, G. Y., & Juang, B. H. F. (2019). Deep learning in physical layer communications. *IEEE Wireless Communications*, 26(2), 93–99. <https://doi.org/10.1109/MWC.2019.1800601>
 - [14]. Rahmani, A. M., Bayramov, S., & Kiani Kalejahi, B. (2022). Internet of Things Applications: Opportunities and Threats. *Wireless Personal Communications*, 122(1), 451–476. <https://doi.org/10.1007/s11277-021-08907-0>
 - [15]. Rejeb, A., Rejeb, K., Zailani, S. H. M., & Abdollahi, A. (2022). Knowledge Diffusion of the Internet of Things (IoT): A Main Path Analysis. In *Wireless Personal Communications* (Vol. 126, Issue 2). Springer US. <https://doi.org/10.1007/s11277-022-09787-8>
 - [16]. Ruan, F., Gu, R., Huang, T., & Xue, S. (2019). A big data placement method using NSGA-III in meteorological cloud platform. *Eurasip Journal on Wireless Communications and Networking*, 2019(1). <https://doi.org/10.1186/s13638-019-1456-7>
 - [17]. Saini, J., Dutta, M., & Marques, G. (2020). A comprehensive review on indoor air quality monitoring systems for enhanced public health. *Sustainable Environment Research*, 30(1), 1–12. <https://doi.org/10.1186/s42834-020-0047-y>
 - [18]. Sharma, N., & Anupama, K. R. (2011). On the use of NSGA-II for multi-objective resource allocation in MIMO-OFDMA systems. *Wireless Networks*, 17(5), 1191–1201. <https://doi.org/10.1007/s11276-011-0340-0>
 - [19]. Sharma, S., Kaur, A., Gupta, D., Juneja, S., & Kumar, M. (2023). Dragon fly algorithm based approach for escalating the security among the nodes in wireless sensor network based system. *SN Applied Sciences*, 5(12). <https://doi.org/10.1007/s42452-023-05614-2>
 - [20]. Sung, W. T., & Hsiao, S. J. (2021). Building an indoor air quality monitoring system based on the architecture of the Internet of Things. *Eurasip Journal on Wireless Communications and Networking*, 2021(1), 1–41. <https://doi.org/10.1186/s13638-021-02030-1>
 - [21]. Torres, L. M., Magaña, E., Izal, M., Morató, D., & Santafé, G. (2010). An anomaly-based intrusion detection system for IEEE 802.11 networks. *2010 IFIP Wireless Days, WD 2010*. <https://doi.org/10.1109/WD.2010.5657702>
 - [22]. Venkatesh, B., Suresh, Y., Chinna Babu, J., Guru Mohan, N., Madana Kumar Reddy, C., & Kumar, M. (2023). Design and implementation of a wireless communication-based sprinkler irrigation system with seed sowing functionality. *SN Applied Sciences*, 5(12). <https://doi.org/10.1007/s42452-023-05556-9>
 - [23]. Wang, Y., Chen, M., Yang, Z., Saad, W., Luo, T., Cui, S., & Poor, H. V. (2022). Meta-Reinforcement Learning for Reliable Communication in THz/VLC Wireless VR Networks. *IEEE Transactions on Wireless Communications*, 21(9), 7778–7793. <https://doi.org/10.1109/TWC.2022.3161970>
 - [24]. Wang, Z., Li, H., Knoblock, E. J., & Apaza, R. D. (2024). Deep Reinforcement Learning-Based Joint Routing and Capacity Optimization in an Aerial and Terrestrial Hybrid Wireless Network. *IEEE Access*, 12, 132056–132069. <https://doi.org/10.1109/ACCESS.2024.3430191>
 - [25]. Wu, Y., Wei, D., & Feng, J. (2020). Network attacks detection methods based on deep learning techniques: A survey. *Security and Communication Networks*, 2020. <https://doi.org/10.1155/2020/8872923>
 - [26]. Zhang, Z., Zhang, L., & Chen, Z. (2021). Multi-Agent Reinforcement Learning Based Channel Access Scheme for Underwater Optical Wireless Communication Networks. *International Symposium on Medical Information and Communication Technology, ISMICT, 2021-April*, 65–69. <https://doi.org/10.1109/ISMICT51748.2021.9434918>