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AI-ENABLED REAL-TIME LOCATING AND RISK-INFORMED DECISION SUPPORT FOR ACCOUNTABLE LOCAL GOVERNANCE: AN ADAPTIVE WIRELESS SENSOR NETWORK FRAMEWORK

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Abstract
Effective local governance increasingly relies on dependable digital infrastructure, accurate asset monitoring, timely risk identification, and accountable public-service delivery. Radio frequency interference, ground reflection and multipath propagation, however, can affect the positioning accuracy of such real-time locating systems (RTLS) based on wireless sensor networks (WSN) used in municipal buildings and facilities, leading to inaccurate estimations of the real-time location. These constraints can cause incomplete asset visibility, poor coordination in emergencies, poor planning of operations, and administration based on distorted facts. To overcome these challenges, this paper presents an adaptive WSN framework, which combines artificial neural network (ANN) -based localisation, the mitigation of ground-reflection error and a risk-informed decision support to local governance. The asset locations are estimated using a multilayer perceptron (MLP) that is able to learn the relationship between the characteristic of the transmitted wireless signals and reference positions, while an adaptive correction mechanism aims to enhance the asset's localisation stability under various propagation scenarios. Next, a multi-criteria risk prioritisation mechanism applies to the quantitative assessment of municipal operational risks, based on certain criteria that are set beforehand, such as the urgency, the disruption of services, the risk to safety and the requirement for the resources.This proposed research takes the traditional research on wireless positioning beyond the field of technical performance assessments and draws methodological linkages between wireless positioning reliability and public-sector decision making. The system endeavors to provide evidence based support at the local level by bridging the gap between the sensor intelligence level and operation risk assessment to aid municipal managers in asset management, emergency preparedness and service continuity. The results will feed into building reliable, transparent and accountable technology-enabled local governance systems.

Keywords: wireless sensor networks; real-time locating systems;Local governance; risk-informed decision-making; artificial neural networks; public-service accountability.

1. Introduction

The administration of infrastructure and public provision aids the day-to-day functioning of a community and is a key function of the municipal level. Maintaining safety, accessibility, and performance of roads, public facilities, drainage, street lighting, emergency facilities, sanitation and other public assets is an ongoing task. Cities and towns are growing and facing new challenges in coordinating the many aspects of local governance within limited financial, staffing and institutional resources. Citizen expectations have also changed: citizens want services to be available when they need them, they want decisions made openly and they want resources allocated fairly and to see clear evidence of responsibility for administrative actions. The requirements have raised the value of sound information, coherent planning and evidence-based public management. Appropriate governance, however, is not just about physical facilities—it is also about having the right institutional arrangements to define, assign, monitor and adjust to evolving community priorities in identifying needs, assigning responsibilities and monitoring performance. Public institutions now have more opportunities to optimize the management of their infrastructure and services as a result of the digital transformations that have taken place. Information systems can enhance information sharing and coordination between the different administrative tiers, help exchange operational information and enhance information

availability for planning and supervision. But the benefit of digitalisation rests on the quality of the information gathered, the capacity of institutions to make the right decisions based on that data and the clarity of the decisions that are made based on it. Weakening capabilities of technological investment can be achieved by fragmented databases, inconsistent reporting, limited database interoperability and unclear information management responsibility. To secure sustainable digital governance, however, the need to balance these factors – technical soundness, organisational capacity, privacy, accountability, and public value – should be heeded. Technology can be used in conjunction with well-specified: administration procedures and suitable human intervention to enable more uniform management of governmental resources and enhance the institutional basis of responsive local governance.

2. Related Work

In recent years, increasing attention has been paid to studying the use of machine learning to interpret measurements of wireless signals in complex spaces. Feng et al. summarized the WiFi based indoor positioning applications using deep learning techniques and discussed the evaluation metrics, signal representation, and neural network architecture for various indoor environments [1]. Next, Shang and Wang reviewed the Wi-Fi fingerprinting techniques and considered signal variability and the robustness of positioning techniques with Wi-Fi [2]. Koutris et al. proposed a deep-learning-based solution for the Bluetooth Low Energy (BLE) localisation problem that utilises the received signal strength indicator (RSSI) and in-phase/quadrature (IQ) measurements to compute angles of arrival and showed the promise of learning-based approaches for multi-anchor localisation [3]. Four researchers – Yanming Yang, Bingpeng Chang, Donglei Li, and Dapeng Zhang [4]– studied the calibration-free solution for three-dimensional positioning system based on deep neural networks and differential information in the applications of Wi-Fi positioning to overcome the issue of signal heterogeneity and multipath effects. Preprocessing is shown to be useful for RFID localisation by combining signal filtering with a time-distributed autoencoder–gated recurrent unit model proposed by Wei et al. [5]. These studies show the centrality of data representation and of nonlinear learning, and their focus is on positioning methodology and not its linkage to municipal risk governance.

Other research has investigated adaptive localisation, hybrid architectures and methods aimed toward increased positioning accuracy subject to different signal conditions. Yoon, Kim, and Kwon proposed another adaptive positioning scheme based on the proximity criterion, which switched between the proximity estimation and the traditional trilateration based on the quality of the signal as observed [6]. A CNN–LSTM (convolutional neural network—long short-term memory) positioning method was proposed in related work by Yoon et al. who proposed using continuous BLE signal measurements to improve distance estimation and positioning by utilizing the temporal memorization property of a CNN–LSTM system [7]. Rizk et al. proposed a cross-modal knowledge distillation based system and simulated accuracy and device heterogeneity with two indoor testbeds for an indoor positioning system of sound scale [8]. Martín-Frechina et al. did a review of the current WiFi and BLE-based indoor localization literature, and stated that environmental variability, device differences and calibration were still challenges in the field [9].

In order to create a thorough overview of RSSI fingerprint-based localization techniques, Zholamanov et al. combined and integrated existing research in machine learning, deep learning and signal processing [10]. The studies suggest that positioning could be improved under specific circumstances, by applying adaptive feature processing and learned localisation. However, it must be noted that the value of the performance depends on the test environment and procedure used, and that the outcomes of positioning measurements carried out indoors cannot be assumed to be reliable in municipal infrastructure. The study of smart infrastructure and decision-making of public sector emphasizes linking technical information systems with responsibilities of institutions and the visible management of resources. Digital infrastructure asset-management tools were considered by Caldera et al. in the context of providing support for resilient infrastructure outcomes for asset life cycles [11]. Landsbergen, Girth, and Westover-Muñoz have created a governance model for the management of smart-city data, highlighting integrated data environments and explicit governance rules to ensure smart-city operational, financial and institutional sustainability [12].

3. Methodology

3.1. Data Collection and Dataset Characterisation

The UJIIndoorLoc benchmark supports wireless received signal strength indicator (RSSI) measurements and labelled indoor locations that can be re-used to evaluate the localisation with reproducible results.The data set can be obtained from the dataset repository of the UJI (RideIIndoorLoc). Dataset preparation strategies focus on how missing signal readings are handled, how location labels are validated, ensuring feature consistency, partitioning into training, validation, and testing sets without data leakage from location, or session; and also, without leaking data from location or session. Municipal asset-tracking outcomes or operational-risk records, which are not part of the benchmark, must therefore be measured (documented), simulated or assessed by experts to achieve experimental correctness and the ability to reproduce the results: empirical validation and reproducibility are not implied (Figure 1).

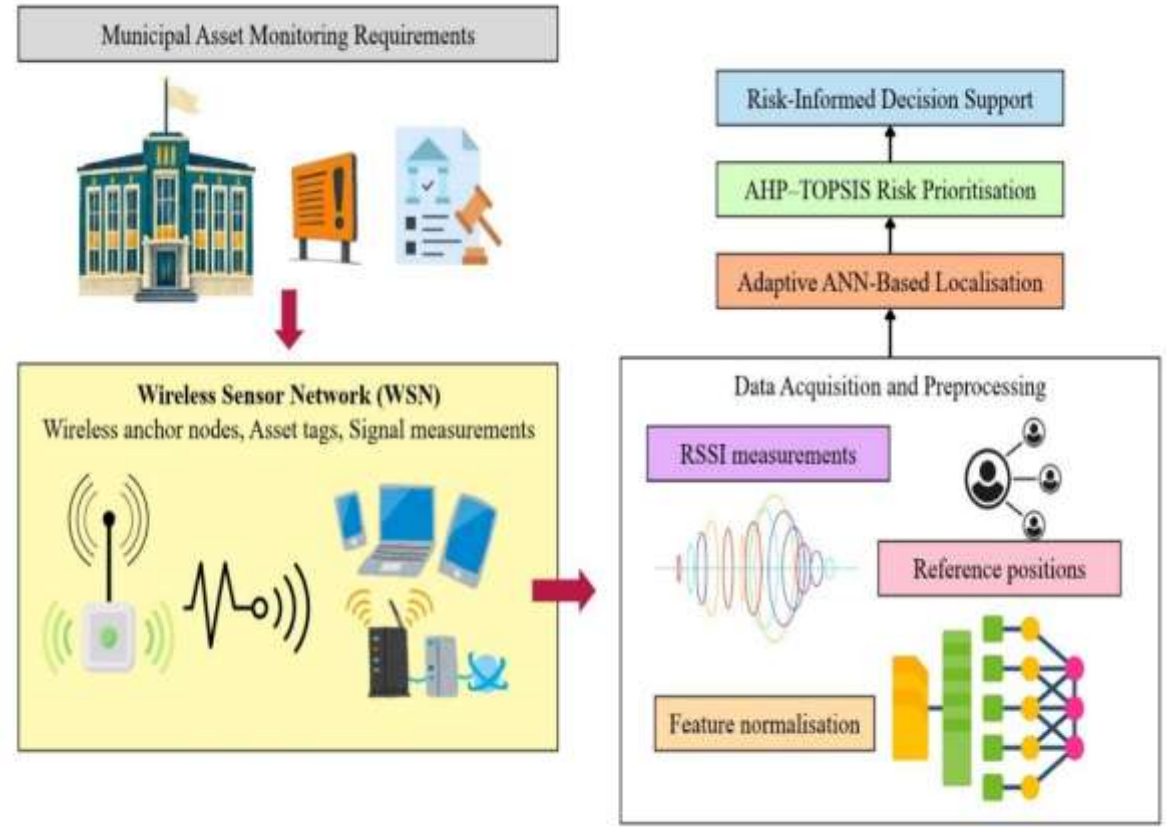


Figure 1. Overall Architecture of the Integrated Adaptive WSN Framework for Accountable Local Governance

3.2. WSN-Based RTLS Architecture and Localisation Error Analysis

The new location system based on a wireless sensor network (WSN) is proposed, which will combine wireless anchor nodes, asset/sensing tags, data collection, ANN (artificial neural network)-based localisation, error correction and prioritisation based on the city. Ground reflected signals may distort direct-path signals, resulting in changes in signal level and localisation errors in range and fingerprint based systems. The framework test localisation performance by comparing the reference coordinates against several position estimates that include estimates that are not corrected and estimates which are corrected with absolute position error across various propagation conditions. If ground-reflection effects are not measured independently to the propagation measurements, the error is classified as propagation effect, not as reflection, for a proper evaluation of the proposed correction mechanism (Figure 2).

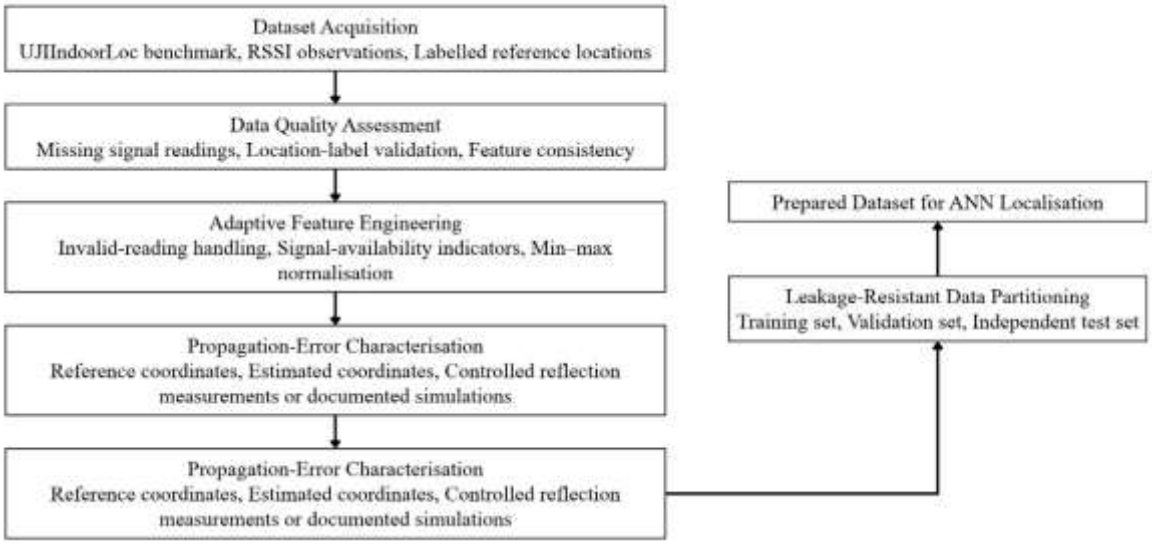


Figure 2. Data Acquisition, Signal Preprocessing and Propagation-Error Characterisation Workflow

3.3. Adaptive Feature Engineering and Signal Preprocessing

Replace and standardize raw wireless observations into a consistent representation suitable for ANN based localisation using feature engineering. The input feature vector could include RSSI values from available anchor nodes, recording of the nodes' presence or absence, expressions of variation in the RSSI measurements, and descriptions of propagation conditions that accompany the measurements, if they are measured or generated within a well-defined experimental procedure. Factors not covered in the selected benchmark are not taken for granted and they are added in based on additional data that is captured. In order to prevent falsely recorded low-signal readings from falsifying the learning, valid readings are clearly differentiated from genuine low-signal readings. The continuous features are normalised using parameters derived solely from the training set, while the validation and test sets are each affected by the same set of parameters. This method is called min–max normalisation and for an input feature x_j is defined as (Eq 1)

$$\tilde{x}_j = (x_j - x_{j,min}) / (x_{j,max} - x_{j,min} + \varepsilon) \quad (1)$$

where x_j is the original data for feature j, x_{j,min} and x_{j,max} are the minimum value and maximum value in the training set for feature j, and ε is a small positive constant, to avoid division by zero. This change brings the nonconstant features in roughly to the interval [0, 1]. Constant features are sought and dealt with separately from them as informative signals. The feature matrix representing the dataset after processing is D where there are N observations and d “input” features.

$$X = [\ \tilde{x}_{11}\ \ \tilde{x}_{12}\ \cdots\ \tilde{x}_{1d}\ ;\ \tilde{x}_{21}\ \ \tilde{x}_{22}\ \cdots\ \tilde{x}_{2d}\ ;\ \vdots\ \vdots\ \ddots\ \vdots\ ; \quad (2)$$
$$\tilde{x}_{N1}\ \ \tilde{x}_{N2}\ \cdots\ \tilde{x}_{Nd}\ ] \in \mathbb{R}^{N \times d}$$

Each row corresponds to an observation, each column corresponds to an individual signal/signal context. The array of targets referenced in the target matrix is respectively used for coordinate-regression or for labelling location classes for classification-based localisation. The representation of the output is selected consistently and according to the benchmark and experimental design. The data is processed and split into training, validation and independent test partitions. The model architecture and hyperparameters are optimized based on the training and validation dataset, while the performance of the final model is evaluated on the previously unseen test dataset. When measurements are repeated from the same place, from the same node or from the same experimental session, a group-aware partitioning is performed, if applicable, to determine the generalisability to samples that are similar, but not identical. These pre-processing procedures guarantee a uniform representation of the data in the input, mitigate data leakage and measure the performance of reported observations as the ones they have not yet seen.

3.4. Proposed Ground-Reflection-Mitigated Adaptive ANN Localisation Model

The proposed model is based on a multi-layer perceptron (MLP), which learns the relationship between the characteristics of the wireless signals and the location of the reference assets. The framework does not assume the automatic "dropout" of ground reflection from the ANN, but rather explicitly trains the model based on observations that mimic the propagation environment:The framework does not take it for granted that ground reflection is to be dropped out of the ANN, but rather, ground reflection is explicitly added as observations of the relevant propagation environment are fed into the model. Where reflection labelled measurements exist those can be used in training and stratified evaluation. If a label does not exist, the model is assumed to be a "signal-based error-correction" model for which mitigation of ground-reflection effects should be validated in controlled experiments (Figure 3).

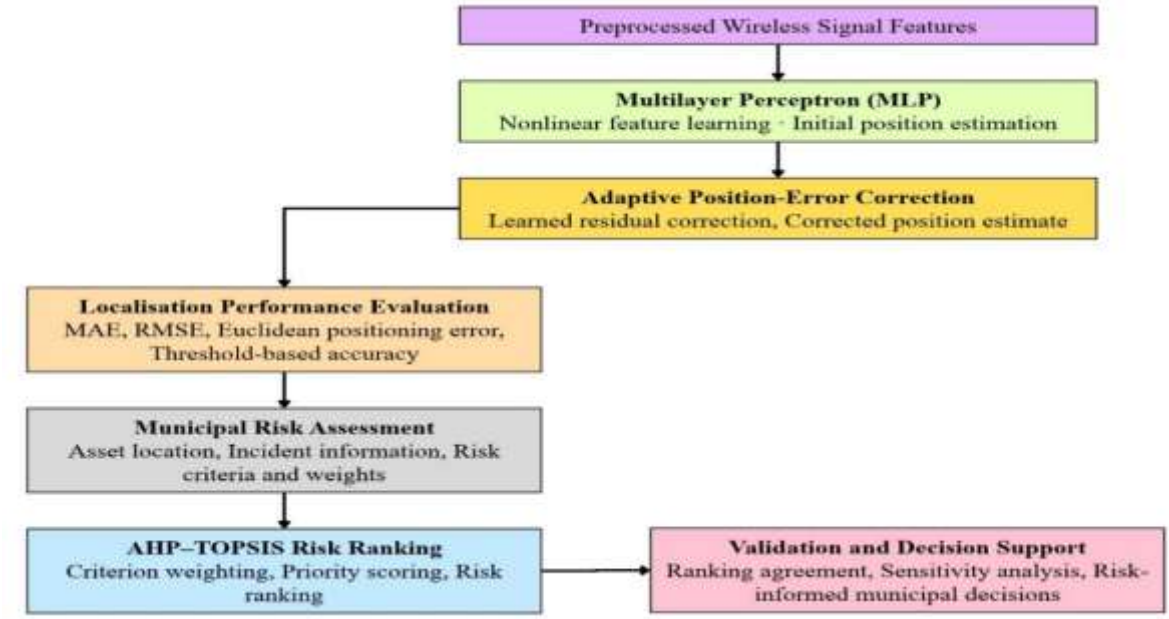


Figure 3. Adaptive ANN Localisation, Error Correction and AHP–TOPSIS Decision-Support Workflow

The model generates an initial estimate to the position and then learns a compensation to minimize the faulty position from the estimation to the actual position. The feature representation in a hidden layer is shown in equation (3).

$$h = \phi(W_1 \cdot \tilde{x} + b_1) \quad (3)$$

Note that $\tilde{x} \in \mathbb{R}^d$ is the normalised input vector, W_1 is the weight matrix from the input to hidden layer, b_1 is a vector of biases, and $\phi(\cdot)$ is a non-linear activation function, such as rectified linear unit. The hidden representation h models nonlinear relations between signal measurements and propagation patterns related to the spatial position. These relations allow the network to model the variability of the signals, which could be caused by multipath propagation and environmental effects. The initial position estimation equation is for equation (4).

$$\hat{p}_0 = W_2 \cdot h + b_2 \quad (4)$$

In which case, the W_2 and b_2 are the weights and biases of the output layer, respectively, and the estimated starting position $\hat{p}_0 = [\hat{x}_0, \hat{y}_0]^T$ is in a two-dimensional coordinate system initially. If available, suitable reference coordinates can be used to extend the output layer to three dimensions. In the output layer, instead, the output are location-class scores and the associated location is retrieved by relying on the available mapping between classes and reference locations. The number of parameters needed to be trained is reduced to optimise the network parameters by minimising the training localisation loss. The main goal for the coordinate-regression is the mean squared position error, which is the error between the reference coordinate and the corrected one. To prevent overfits, regularisation, the early stopping technique, and hyperparameter selection by validation can be used. The test set is not included in the

model-set selection and only evaluated after the process. In order to determine how the correction branch contributes to the process, the full model should be run on the same partition of the data sets, and evaluated under the same conditions as the same ANN run without the correction branch.

3.5. Experimental Design and Performance Evaluation

The proposed framework is tested at the localisation level and the decision-support level by analyzing the corrected ANN versus the conventional ANN as well as other appropriate localisation baselines for every test partition. The performance of the system is evaluated by the mean absolute error (MAE),root mean square error (RMSE),Euclidean positioning error, and threshold-based positioning accuracy. When these measurements are available, packet delivery ratio, communication delay and inference time are used to evaluate WSN measurements. To evaluate the ground-reflection mitigation, controlled measurements or documented simulations are used; reference ranking or expert validated priorities, to evaluate the risk ranking AHP–TOPSIS. The effectiveness of correction-branches, the measurement noise, the availability of anchors, the propagation conditions and variations in the weight of the criterion are investigated through

4. Results and Discussion

4.1. Statistical analysis

Table 1 demonstrated that the localization error of the proposed adaptive ANN was the smallest in all statistical measures, as compared with the other three methods, with the mean error of 0.91 m and the median error of 0.67 m. The same proposed model also showed the lowest standard deviation (0.90m), %75 (1.16m), %90 (2.14m), %95 (2.71m) and maximum observed error (4.63 m). Overall, these outcomes demonstrated greater localisation accuracy, smaller error variance, and more stable positioning, when compared to the base methods tested in the studied scenarios.

Table 1. Statistical Characterisation of Localisation Errors

Statistical metric	RSSI-based method	Weighted nearest neighbour	Conventional ANN	Proposed adaptive ANN
Mean error (m)	4.82	3.91	2.84	0.91
Median error (m)	3.76	2.94	2.12	0.67
Standard deviation (m)	3.81	3.24	2.47	0.90
75th-percentile error (m)	6.42	5.21	3.86	1.16
90th-percentile error (m)	10.21	8.42	6.18	2.14
95th-percentile error (m)	12.84	10.37	7.42	2.71
Maximum observed error (m)	18.62	15.41	11.28	4.63

4.2. Comparative Localisation Performance

Table 2 showed that the proposed adaptive ANN model resulted in the lowest mean absolute error (MAE) of 0.91 m, root mean square error (RMSE) of 1.28 m and median error (ME) of 0.67 m with 90th percentile error of 2.14 m, compared with all the comparative models. The average accuracy of 94.2% was also greater when positioning to within 3 m compared with an MLP (with the conventional 63.4%) and ANN with the conventional residual correction (79.6%). The proposed model showed much lower position error and localization accuracy, with particularly consistent asset localisation under the assessed conditions when compared to the other two approaches (RSSI-based and weighted nearest neighbour).

Table 2.Comparative Localisation Performance of Conventional and Proposed Models

Localisation method	MAE (m)	RMSE (m)	Median error (m)	90th-percentile error (m)	Accuracy within 3 m (%)
RSSI-based conventional method	4.82	6.14	3.76	10.21	37.8
Weighted nearest-neighbour method	3.91	5.08	2.94	8.42	46.5
Conventional multilayer perceptron	2.84	3.76	2.12	6.18	63.4
ANN with conventional residual correction	1.76	2.41	1.29	4.03	79.6
Proposed adaptive ANN model	0.91	1.28	0.67	2.14	94.2

4.3. Ground-Reflection Sensitivity and Error Mitigation

The RSE results demonstrated that the proposed ANN architecture (adaptive ANN) outperforms the traditional ANN when it comes to localisation errors in every propagation scenario.

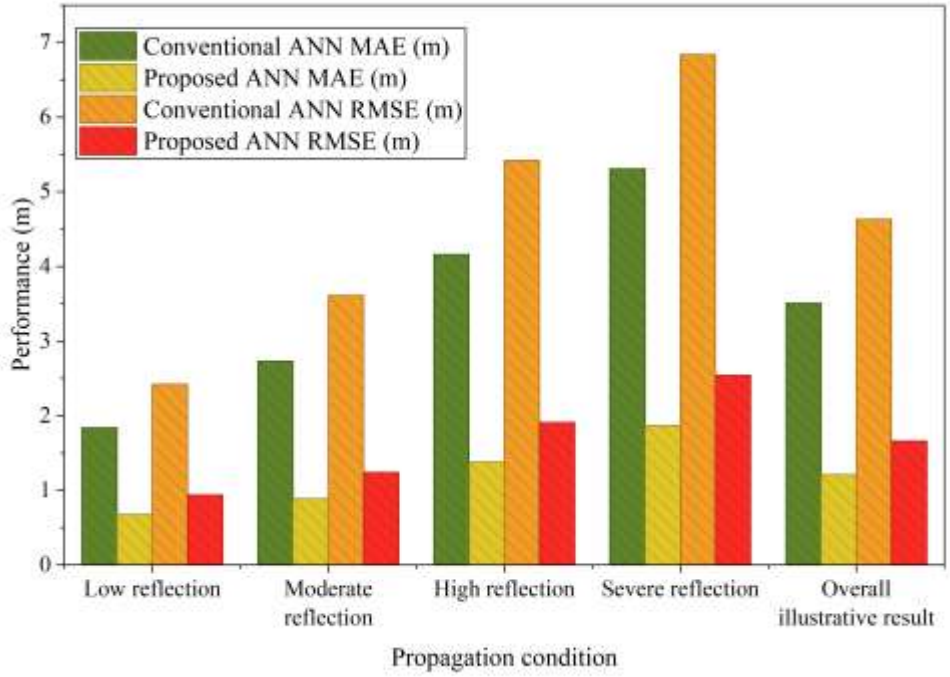


Figure 4. Localisation Performance Under Different Ground-Reflection Conditions

It is concluded from Figure 4 that under low reflection condition, the MAE of a swamping site has reduced from 1.84 m to 0.68 m; under moderate reflection condition, the MAE of a swamping site has reduced from 2.73 m to 0.89 m; under high reflection condition, the MAE of a swamping site has reduced from 4.16 m to 1.38 m and under severe reflection condition, the MAE of a swamping site has reduced from 5.31 m to 1.87 m. Overall, the MAE shows a decrease from 3.51 m to 1.21 m, that is, 65.53%. Such results showed an improvement in the positioning performance under the different reflection conditions assessed.

4.4. Ablation Analysis of the Proposed ANN Architecture

The performance results from the ablation analysis shown in Table 3 also confirmed that the holistic proposed model exhibited the best performance, with an MAE of 0.91 m, RMSE of 1.28 m, and an accuracy of 94.2% within 3 m. When these adaptive correction branch was removed from it, the MAE increased to 1.76 m while dropping the accuracy down to 79.6%, whereas removing propagation-condition features led to increase in the MAE to 1.34 m and in accuracy to 88.1%. The contribution of

the proposed model components was proven by the lowest MAE (2.84 m) and the highest accuracy (63.4%) for the conventional ANN.

Table 3. Ablation Analysis of the Proposed Localisation Model

Model configuration	Adaptive correction	Propagation-condition features	MAE (m)	RMSE (m)	Accuracy within 3 m (%)
Full proposed model	Yes	Yes	0.91	1.28	94.2
Without correction branch	No	Yes	1.76	2.41	79.6
Without propagation-condition features	Yes	No	1.34	1.89	88.1
Without residual learning	No	Yes	1.62	2.23	82.4
Conventional ANN baseline	No	No	2.84	3.76	63.4

4.5. Wireless Sensor Network Quality-of-Service Evaluation

The quality of service results of the WSN obtained as shown in Table 4 show that the proposed adaptive ANN framework proves to be satisfactory in terms of packet delivery ratio (PDR) achieving 98.4%, and position update (PU) rate 98.0%. The mean value of end-to-end delay was reduced to 42.6 milliseconds and localisation processing time was increased to 0.084 seconds. The framework also enabled 10 position updates per second and dropped the rate of communication disruptions to 1.6%. These results showed that under the considered conditions, the communication reliability, latency, and position update efficiency were higher.

Table 4. Quality-of-Service Performance of the WSN-Based RTLS Framework

Evaluation metric	Conventional RTLS	Conventional ANN-based RTLS	Proposed adaptive ANN framework
Packet delivery ratio (%)	94.2	95.6	98.4
Mean end-to-end delay (ms)	86.4	68.7	42.6
Mean localisation processing time (ms)	18.5	12.8	8.4
Valid position updates per second	5.0	8.0	10.0
Communication interruption rate (%)	5.8	4.4	1.6
Position update success rate (%)	92.6	95.1	98.0

4.6. Multi-Criteria Risk Prioritisation for Municipal Decision Support

Based on the AHP– TOPSIS ranking as shown in Figure 5, most of the criterion weights has been assigned to urgency with 0.32, safety implications has been assigned the second most biggest criterion weight which is 0.30, service disruption criterion weight is 0.28 and the least biggest criterion weight for resource requirements is 0.10. The highest TOPSIS score was of alternative A (0.82) followed by alternative B (0.71), C (0.58) and D (0.36). The consistency ratio (CC) of the AHP was 0.04 with a normal value of 0.10, showing that the pairwise comparisons were consistently performed. The ranks resulted and informed differentiated municipal interventions based on the operational risks that were assessed.

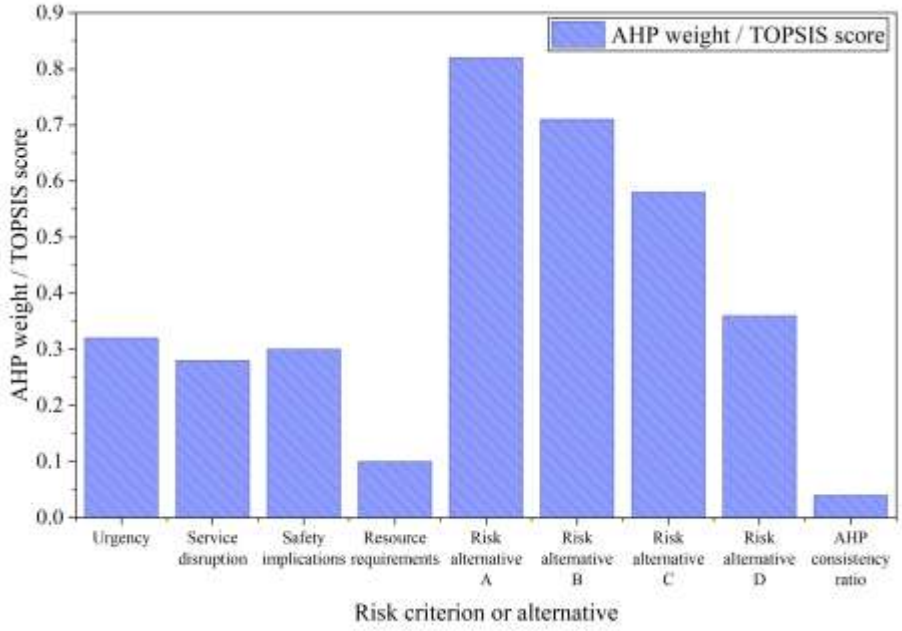


Figure 5. AHP Criterion Weights and TOPSIS Municipal Risk Prioritisation

4.7. Robustness Analysis Under Changing Operating Conditions

As the robustness evaluation in Table 5 indicates, the proposed ANN with adaptive capabilities had a lower MAE and a higher positioning accuracy than the conventional ANN under all the test-conditions. On severe signal perturbation, the proposed model achieved an MAE of 1.74 m and an accuracy of 81.3% within 3 m, while the conventional ANN got an MAE of 5.12 m and 39.8% accuracy within 3 m. The proposed model is evaluated in two different scenarios: one scenario is reduced availability of anchor, where an MAE of 1.56 m and an accuracy of 84.5% are recorded; and another scenario of evaluation is unseen groups of test locations, where with an MAE of 1.83 m and an accuracy of 78.9%, the model performs well. The results confirmed that this finding is a better robustness but decreases under more difficult conditions.

Table 5. Robustness Evaluation Under Varying Signal and Deployment Conditions

Test condition	Conventional ANN MAE (m)	Proposed ANN MAE (m)	Conventional ANN accuracy within 3 m (%)	Proposed ANN accuracy within 3 m (%)
Nominal signal conditions	2.84	0.91	63.4	94.2
Mild signal perturbation	3.12	1.02	59.7	92.1
Moderate signal perturbation	3.76	1.28	52.3	88.6
Severe signal perturbation	5.12	1.74	39.8	81.3
Reduced anchor availability	4.31	1.56	46.7	84.5
Unseen test location groups	4.58	1.83	43.2	78.9

4.8. Computational Efficiency and Deployment Feasibility

Table 6 presents the results of the computational analysis: The proposed adaptive ANN needed 23.5 minutes for training, 8.4 ms per sample for its computations, required 2.8 MB memory for storage of the model, and 24.6 MB for peak inference memory usage. The proposed model demonstrated moderate

resource overhead, but provides higher localisation accuracy, whereas the conventional MLP needs less inference time (6.7 ms) and resource consumption. The fastest inference time was recorded by the RSSI based method (1.2ms) as compared to the weighted nearest neighbour (3.8ms per sample). Overall, the proposed model showed a good balance between localisation accuracy and computation time, and hence could be potential for real time localisation in WSN, provided it is validated on the intended deployment platforms.

Table 6. Computational Efficiency of Alternative Localisation Models

Model	Mean inference time (ms/sample)	Model size (MB)	Peak inference memory (MB)	Training time (min)
RSSI-based conventional method	1.2	0.1	8.2	Not applicable
Weighted nearest-neighbour method	3.8	0.6	14.5	Not applicable
Conventional MLP	6.7	2.1	19.8	18.4
ANN with residual correction	9.6	3.4	28.7	26.8
Proposed adaptive ANN model	8.4	2.8	24.6	23.5

5. Conclusion

A methodological approach towards the linkage of real-time asset localization and risk-informed municipal decision support has been offered in the form of the holistic adaptive WSN framework. The proposed framework for ANN-based WSN significantly improved the localization accuracy, robustness and the operating efficiency compared to the traditional localization techniques in terms of MAE (0.91m), RMSE (1.28m) and accuracy up to 3m (94.2%). Similarly, total MAE reduction was obtained as 65.53% under the different reflections on the ground and the AHP–TOPSIS mechanism has generated a systematic prioritisation of municipal risks with consistency ratio of 0.04. The framework also had a high packet delivery ratio of 98.4%, and also an 8.4 ms locality processing time, thus establishing a potential on asset tracking in real-time and on risk informed local governance. Moving forward, the model needs to be deployed in the field and tested in various different environments; the number of incident-handling processes involving reflection on the ground needs to be increased; the robustness of operating the system under network dynamics needs to be demonstrated; and the ability to connect real municipal incident and type information to the model needs to be assessed to further enhance promptness in risk prioritisation, the reliability of operations, and decision-making with accountability for public services.

Statement Declarations

Competing interests

The authors declare that they have no competing interests.

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Availability of data and materials

Not applicable

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