The neural network adaptive behaviour model for localization and speed control in autonomous rescue mobile robot operation

Muhammad Hafizd Ibnu Hajar[1], Galang Persada Nurani Hakim[1], Ketty Siti Salamah[1], Diah Septiyana[2]
[1]Department of Electrical Engineering, Faculty of Engineering, Universitas Mercu Buana, Jakarta, Indonesia
[2]Department of Industrial Engineering, Faculty of Engineering, Universitas Muhammadiyah Tangerang, Tangerang, Indonesia

Article Info

Article history:

Received Sep 26, 2024
Revised May 31, 2025
Accepted Jul 19, 2025

Keywords:

Adaptive behaviour
Control architecture
Localization
Neural network
Rescue mobile robot

ABSTRACT

In robotic operation, an autonomous operation for a mobile robot is needed to operate smoothly, hence, a control system is needed. Numerous architectures for robotics control systems have been put forth. Regretfully, creating a control system architecture is very challenging and occasionally results in inaccuracy in control. An alternative to conventional mobile robot control has emerged to address this issue: behavior-based control system architectures. This paper addresses the behavior of an autonomous mobile robot (AMR) control system in an outdoor rescue operation. The AMR behavior will be governed by the neural network methods, which are a computational intelligence to generate a dependable control algorithm. The architecture is used to coordinate behavior, especially to localize the victims, and for speed control to find the victim location with fast timing. In localization parameters to find the victim in the disaster area, this neural network adaptive model has the smallest error, which is 3.27, compared with other models such as free space model 43.46, and empirical model 4.735. While in robot speed parameter has a low error value, which is 1.47. With this small error, we can conclude that the neural network adaptive behaviour control architecture model for rescue mobile robot operation has been successfully developed.

Corresponding Author:

Muhammad Hafizd Ibnu Hajar
Department of Electrical Engineering, Faculty of Engineering, Universitas Mercu Buana
Meruya Selatan street No.1, Jakarta, Indonesia
Email: muhammadhafizd@mercubuana.ac.id

1. INTRODUCTION

Robotics is one of the technologies that keeps evolving in Industrial 4.0. One of the most popular robots would be a robotics-based platform called the autonomous mobile robot (AMR) [1]. This AMR can move by utilizing several driving motors and auxiliary sensors [2]. An AMR can navigate, compute, and map the path that the robot will follow [3]. The AMR's sensors and other useful parts enable the robot to comprehend its surroundings and tailor its movements accordingly. Applications of AMR include handling and material processing in manufacturing, hospital services, and so forth [4].

A rescue mobile robot can be used as a specialized robot designed to assist in search and rescue operations [5]. This mobile robot can be use is particularly in environments that are hazardous or inaccessible to humans [6]. These robots are equipped with various technologies such as arm manipulator to extract victims [7], [8], lidar for path planning [9], and many others [10].

Before we rescue the victims, we need to locate them in a disaster area. This can be done using several localization equipment such as GPS [11], Lidar [12], [13], electromagnetic waves [14], and others

[15], and methods such as simultaneous localisation and mapping (SLAM) [16]. The use of GPS, Lidar, and SLAM methods requires an additional sensor device installed in the robot, hence need an additional cost. However, using electromagnetic waves, this can be used existing communication device installed at the robot, and the victim can use wireless body sensor network (WBSN) to emit electromagnetic waves [17] as their beacon. The localization using electromagnetic waves is to hear or detect the missing victims using their electromagnetic wave signature, calculate their distance based on the signature, and determine their location based on its calculation [18]. The localization can be found using a lateration method that uses received signal strength indicator (RSSI) as a radio electromagnetic signature to range the distance to the beacon [19]. In this research output, the model was only used to localize the victims with fast timing, hence the limitation of the model.

Several methods can be used in control, such as proportional integral derivative (PID), fuzzy systems, neural network, evolutionary algorithms, and reinforcement learning. However, there is no single "best" method for all robotic control applications. Instead, the optimal control method depends on system complexity, environment dynamics, available data, and computational resources. Research by Popescu *et al.* [20] compare PID with fuzzy systems in mobile robot control applications, with the best method belonging to the fuzzy system. This is because the fuzzy system doesn't rely on the mathematical model of the system, while PID does. While Lakhmissi [21] compares fuzzy with neural network and anfis for mobile robot path tracking, anfis and neural network are faster compared with fuzzy systems. Research by Neruda *et al.* [22] compare neural network with reinforcement learning for small mobile robots. Neruda implies that it provides a straightforward mapping from input signals to output signals and is robust to noise compared with reinforcement learning. Research by Li and Yang [23] propose to implement a neural network for a topologically adaptable rescue mobile robot. Beckerleg compares the evolvable hardware (EH evolved using a genetic algorithm) with the neural network method. Based on the research, Beckerleg [24] states that the neural network provides a robust controller while EH provides an excellent controller. Research by Firmansyah *et al.* [25] propose to implement neural networks for localization and positioning using ultrasonic, rangefinder, and compass sensors. Based on the literature studies above, in this paper, we present the following contributions compared with other research: i) we address the need for navigation and localization for victim rescue using electromagnetic wave signature, in this case RSSI parameter for the rescue mobile robot and ii) the use of computational intelligence, such as neural network, to build an adaptive behaviour control model for rescue autonomous mobile robot operation with speed and RSSI parameters.

2. METHOD

In this section, we would like to explain the experimental setup and method that we used in this work. The experimental setup (field measurement equipment and environment) was designed to collect data (data measurement) that will be used as point of reference by the robot using neural network method to identify the needed speed and the distance between the robot and the victims. The research step can be seen in Figure 1.

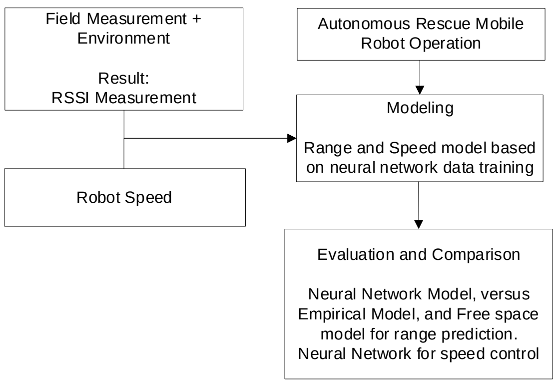

Figure 1. Research block

2.1. Field measurement equipment

In this research, a dataset needs to be generated to develop a neural network model. Unfortunately, although many datasets are available on the internet, they are image-based datasets which for SLAM [16]. This dataset is different from what we need, which is an electromagnetic wave signature. Hence, to imitate mobile robot operation in the disaster area, we propose to do measurement using a long range (LoRa) radio transceiver. The LoRa radio transceiver was used in pairs (transmitter and receiver). The microcontroller was added as a data pre-processing and data transmission control for both the transmitter and receiver. On the transmitter side, the microcontroller was programmed so that it could command the LoRa transceiver to send packet data every 100 microseconds. On the receiver side, the microcontroller was programmed so that it could command the LoRa transceiver to receive incoming packet data, extract the RSSI value, and forward it directly to our recording device. The walk test method was used for every 5-meter measurement point, from 5 meters to 100 meters (please see Figure 2). The LoRa transceiver pair was put on top of the soil. The maximum antenna height from the soil for the LoRa transceiver pair was less than 30 cm [26]. The equipment parameter detail configurations can be seen in Table 1.

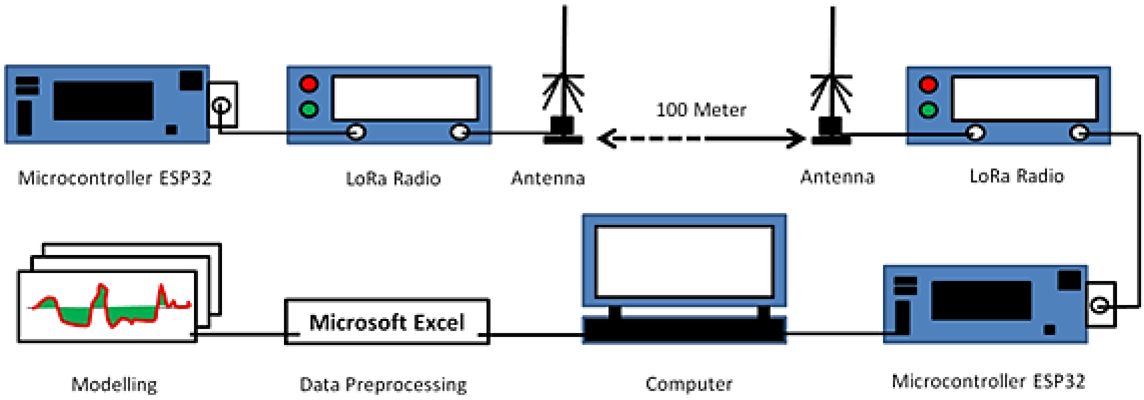

Figure 2. LoRa measurement equipment

Table 1. LoRa setting

Parameter	Value
Frequency	920 MHz
Bandwidth	125 KHz
Spreading factor	12
Antenna gain	0 dBi
Tx-power	20 dBm
Measurement parameter	RSSI

2.2. Field measurement environment

We chose an open dirt road with vegetation growing on the left and the right sides of the road. This site was chosen to simulate a disaster that occurred in the area. The open dirt road environment is located in the western suburbs of Jakarta at GPS coordinates −6.214478, 106.747576. The open dirt road environment situation can be seen from Figure 3.

Figure 3. Open dirt road site

2.3. Received signal strength indicator field measurement result

Figure 4 shows us the result of electromagnetic wave signature measurement in the open dirt road environment (see Figure 3). In Figure 4, we can see the field measurement result. The electromagnetic wave signature uses RSSI methods with decibels millivolt (dBm) as its unit. RSSI measurement in an open dirt road environment using LoRa 920 MHz frequency, 125 KHz bandwidth, and spreading factor 12. From 5 meters to 100 meters, we will take 20 measurements. If we carefully look at the RSSI value has many fluctuations. This fluctuation can be caused by many things, from the Fresnel zone [27] or multipath fading as a side effect of wireless communication [28].

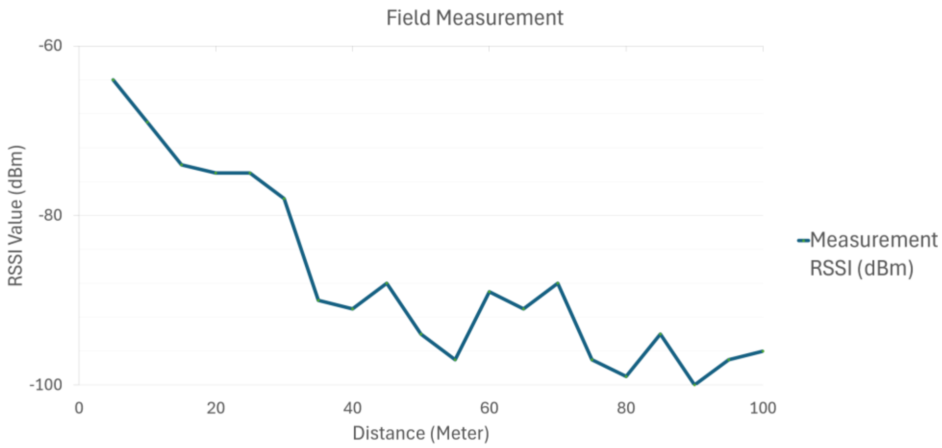

Figure 4. Open dirt road RSSI field measurement

2.4. Free space pathloss model

To do localization, we need to do lateration using the RSSI signal as a measurement of distance. We need to model the electromagnetic wave. Because a drone is flying, the most suitable electromagnetic wave signal propagation model would be the free space path loss (FSPL) propagation model. This model was suitable only when there were no obstacles between the radio receiver and radio transmitter [29]. This environment was suited to drone operation, which is high altitude, hence no obstacle between the drone receiver and the victim's beacon transmitter.

FSPL propagation model is a propagation model that comes from the transmission derivative function of 2 transmitting and receiving antennas (transmission friss) as seen in Figure 3. This function states that the relationship between the power received and the power transmitted between two antennas separated by a fairly large distance r. The friss transmission function is an application of the antenna's far field, with the limitation that the distance must be greater than the wavelength [30].
The gain on the transmitting antenna can be written as (1):

$$S = \frac{P_{in}G_t}{4\pi d^2} \tag{1}$$

Then the power that will be received by the receiving antenna is (2):

$$P_r = \frac{P_{in}G_t}{4\pi d^2} . \frac{\lambda^2}{4\pi} D_r \tag{2}$$

Because the efficiency of the receiving antenna also influences the output power received by the receiving antenna [9], we can write (3):

$$P_{out} = P_r \, \eta_{er} = \frac{P_{in}G_t}{4\pi d^2} . \frac{\lambda^2}{4\pi} D_r \eta_{er} = \frac{P_{in}G_t}{4\pi d^2} . \frac{\lambda^2}{4\pi} \, G_r = \left(\frac{\lambda}{4\pi d}\right)^2 G_t G_r P_{in} \tag{3}$$

So that the transmission function is the power received by the receiving antenna based on the power transmitted by the transmitting antenna, the distance traveled, and the function of the electromagnetic waves on the surface of the transmitting and receiving antennas.

$$\frac{P_r}{P_t} = \left(\frac{\lambda}{4\pi d}\right)^2 G_t G_r \tag{4}$$

Being a function of electromagnetic waves in free air, called free space path loss (FSPL) (5):

$$FSPL = \frac{P_t}{P_r} = \left(\frac{4\pi d}{\lambda}\right)^2 G_t G_r \tag{5}$$

Because the gain of a transmitter power is very difficult to calculate in the usual way, each power at the transmitter and the receiver is then converted into decibels. So we can write (6):

$$FSPL = \frac{P_t}{P_r} = 10\log_{10}\left(\left(\frac{4\pi d}{\lambda}\right)^2\right) + G_t + G_r \tag{6}$$

If we use an isotropic antenna, the gain on the transmitting and receiving antennas is 0, so we can write (7):

$$FSPL = 20\log_{10}\left(\frac{4\pi df}{c}\right) \tag{7}$$

Or we can write [31], [32] (8):

$$FSPL = 20\log_{10}(d) + 20\log_{10}(f) + 32.45 \tag{8}$$

where: d is distance in kilometer unit, and f is frequency in MHz units.

2.5. Mobile robot speed

For the mobile robots speed, we would like to use data provided by Lenain *et al.* [33]. Their experimental mobile robot was classified as a terrain mobility wheeled robot. Their robot are capable of climbing slopes up to 45° with a maximum speed of 8 ms^{-1}. However, we would like to reduce the speed to 1 ms^{-1} when the robot is at least 10 meters near the beacon. This speed reduction was needed so the robot would have enough time to put the brake in front of the victims.

2.6. Neural network method

Artificial neural network (ANN) is a computational intelligence that mimics the biological neural network behavior of living things [34]. ANN methods have been used to solve many problems, such as control [35], detection [36], [37], and forecasting [38]. The method does its job by processing and calculating previously accepted data training [39]. ANN is a collection of nodes called artificial neurons, which model the neurons in the biological brain. Each neuron can send signals to other neurons using synapses, just like in the biological brain [40]. The receiver neuron receives the signal, then processes it, and then signals the next neurons using a synapse that is connected to it. ANN consists of neurons that work as processing elements. These neurons, which are connected to other neurons, are ruled by bias and weights. Its signal calculation is then passed through an activation function to produce an output [41]. One layer of an ANN neuron can be written with a simple (9):

$$C_i = \mathrm{f}_i(IW_i\mathrm{p} + b_i) \tag{9}$$

where: IW_i is scalar weight; p is scalar input; b_i is scalar bias; f_i is transfer function; and C_i is scalar output.

3. RESULT AND DISCUSSION

3.1. Empirical model based on received signal strength indicator field measurement result

In this section, we would like to derive the model from the FSPL model to become an empirical model for localization. The comparison between the field measurement result and versus empirical model can be seen in Figure 5.

In Figure 5, we can see the comparison of the empirical model with the measurement result, which shows little difference. This is because the FSPL model in (8) has a different 43.21 dB in average with the field measurement result, then based on that comparison, we derive the FSPL model to become an empirical model as we stated in (10):

$$Empirical\ model = 20\log_{10}(d) + 20\log_{10}(f) + 32.45 + 43.21 \tag{10}$$

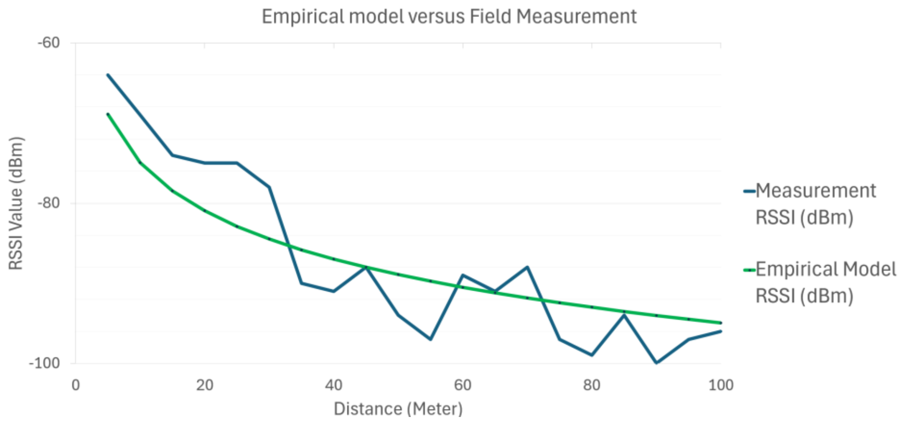

Figure 5. Comparison between the empirical model versus field measurement for localization

3.2. Neural network adaptive model

In this section, we would like to present our proposed model, which is the neural network adaptive behaviour control architecture rescue mobile robot. To do this, we need to input field measurement data as training data for the neural network. The data training was based on field measurement in the open dirt road, as we can see in Figure 3, which is the average RSSI measurement versus distance and speed. The data has been divided to become 70% for training, 15% for validation, and 15% for testing, and its output produces mean squared error (MSE) with a value of 6 for training and validation using 8 hidden neurons. The neural network adaptive behaviour control architecture model for the rescue mobile robot can be shown in Figure 6.

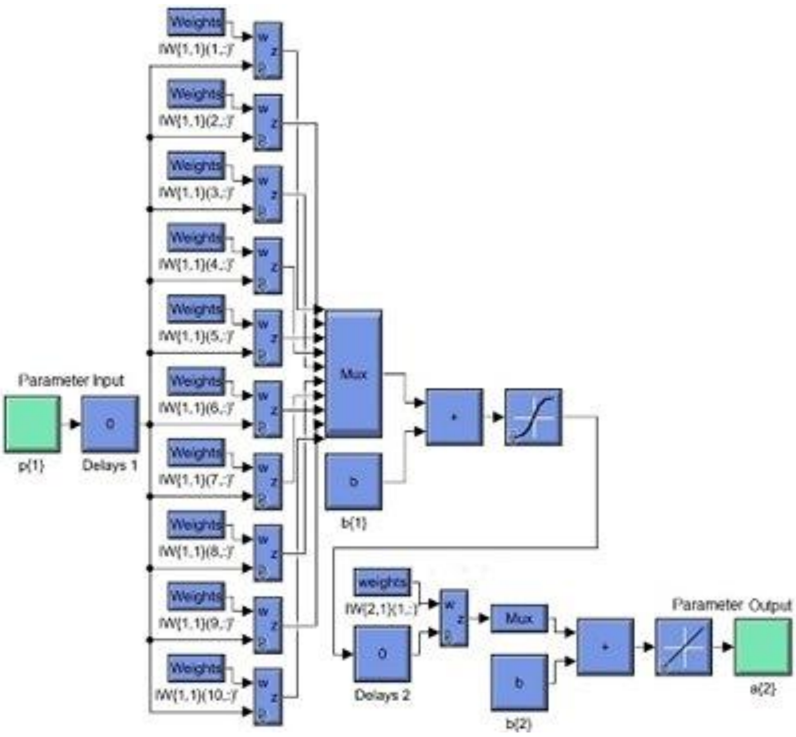

Figure 6. The neural network adaptive behaviour control architecture model for the rescue mobile robot

In Figure 6, we can see the neural network architecture used in this research. The neural network has 3 layers, which are the input, the hidden layer that acts as a processing neuron, and the output layer. The input layer has 2 parameters, which are speed and RSSI, while the output neuron has a range parameter. For the rescue mobile robot adaptive model, we can write a new mathematical model using (9), such as (11):

$$C_i = tansig(\sum_{i=1}^{ni}(IW_{i,n}p_i + b_i) \quad (11)$$

Therefore, for the output layer, we can write (12):

$$C_i = purelin(IW_{i,n} \sum_{i=1}^{ni}(tansig(\sum_{i=1}^{ni}(IW_{i,n}p_i + b_i)\,)) + b_i) \quad (12)$$

where: IW_i is scalar weight; b_i is scalar bias; p is scalar input such as average RSSI; and C_i is scalar output such as distance for localization, and robot movement speed.

The neural network model performance compared with field measurement is presented in Figure 7. In Figure 7 we can see the comparison from neural network model with measurement result that has little in difference. This because the neural network model in (12) has different 0.245 dB in average with field measurement result. Therefore compare with free space pathloss model and empirical model, this neural network model is very accurate.

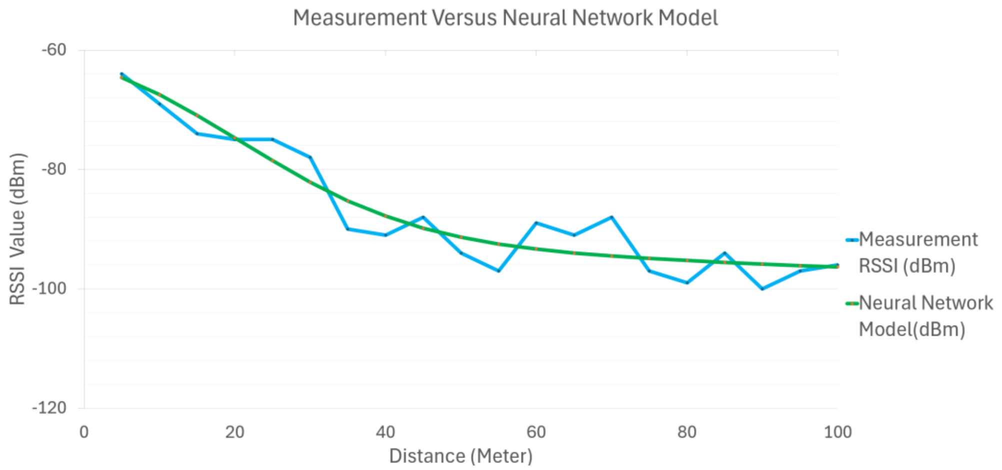

Figure 7. Comparison between neural network model versus field measurement for localization

3.2. Comparison between models for localization and robot speed based on proposed design

In this section, we would like to compare the free space model, the empirical model, and the neural network model for victim localization based on the RSSI signal. The comparison between each model will be presented in Figure 8.

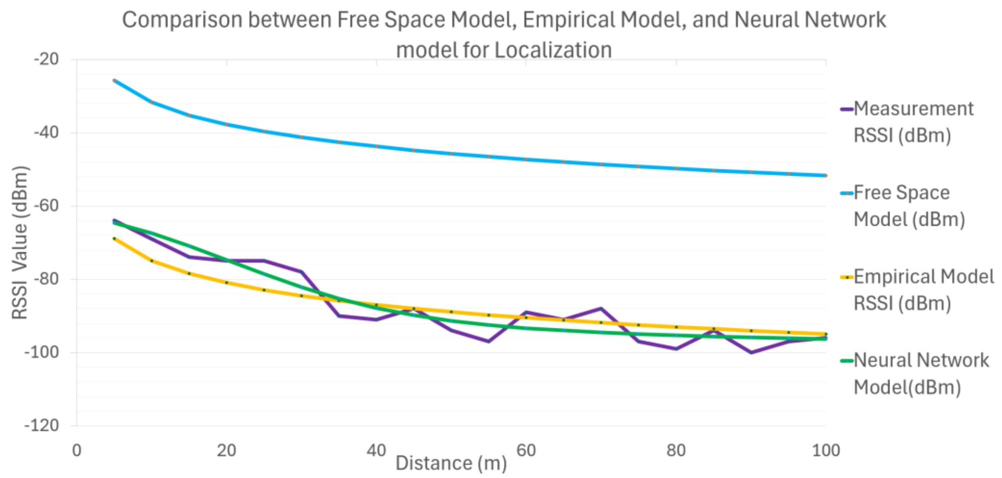

Figure 8. Comparison between each model for localization

In Figure 8, we present our proposed (neural network) model for locating the victim using the RSSI signal level. We compare our neural network model with field measurement, FSPL model, and empirical model. In this comparison, we are using 20 test points of RSSI from the beacon victim's transmitter. To validate our simulation, we would like to calculate the error using the root mean square (RMSE) method. The RMSE was popular in statistics to validate model evaluation [42]. Based on Table 2 data, the RMSE validation can be presented in Table 2.

Table 2. RMSE comparison for the localization parameter of each model

No	Item	RMSE
1	Free space model	43.46
2	Empirical model	4.735
3	Neural network adaptive model	3.27

Based on the RMSE shown in Table 2, we can see that on the robot localization parameter, the neural network adaptive model has a low error value, which is 3.27, compared with other models. The small error compared with other models indicates that the localization parameter of the neural network adaptive model is more accurate compared with other models. After we finish comparing localization control then we compare robot control for speed concerning distance with the victim with our proposed design. The RMSE for robot speed can be seen in Table 3.

Table 3. RMSE for speed parameter based on design

No	Item	RMSE
1	Neural network adaptive model	1.47

Based on the RMSE shown in Table 3, we can see that the simulation on the robot speed parameter has a low error value, which is 1.47. The small error for the robot speed parameter was because it only has 2 values, which are 1 m/s in distance between 0 to 10 meters and 8 m/s in distance between 15 to 100 meters, hence it produces very low error. Based on the simulation validation on robot speed parameter and robot localization to find the victim in the disaster area, we can conclude that the neural network adaptive behaviour control model for rescue mobile robot has been successfully developed.

4. CONCLUSION

In this paper, we propose the neural network adaptive behaviour control model for rescue mobile robot ground operation. This model control architecture was developed to localize and find the disaster victims with haste by using electromagnetic wave signatures generated from victims' beacons. This model has been tested successfully using simulation. The neural network adaptive behaviour control model consists of 2 main parameters, which are localization and speed robot control. In localization parameters to find the victim in the disaster area, this neural network adaptive model has the smallest error, which is 3.27, compared with another model, such as free space model 43.46, and empirical model 4.735. The robot speed parameter has this model has a low error value compared with our proposed design, which is 1.47. Although we can conclude that the neural network adaptive behaviour control model for rescue mobile robot has been succesfull develope, however in the future there the needs to add SLAM feature to the model, and another additional parameter to be insert into the model so the robot not just only to find victims in the open ground but also buried in the ruins of buildings or buried in the ground also obstacle detection, and real-world trials.

FUNDING INFORMATION

Authors state the funding for this works was given by Universitas Mercu Buana using Internal research grant with domestic cooperation scheme at 2023-2024.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Muhammad Hafizd Ibnu Hajar	✓		✓	✓	✓	✓		✓	✓					
Galang Persada Nurani Hakim		✓	✓	✓						✓		✓	✓	
Ketty Siti Salamah						✓	✓		✓		✓			
Diah Septiyana					✓					✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [initials: GPNH], upon reasonable request.

REFERENCES

[1] V. De Silva, J. Roche, and A. Kondoz, "Robust fusion of LiDAR and wide-angle camera data for autonomous mobile robots," *Sensors*, vol. 18, no. 8, pp. 1–21, 2018, doi: 10.3390/s18082730.

[2] A. Adriansyah, E. Ihsanto, C. Anam, S. Indriyanto, A. Baihaqi, and J. Andika, "Autonomous Mobile Robot Design with Behaviour-based Control Architecture using Adaptive Neuro-Fuzzy Inference System (ANFIS)," in *2022 FORTEI-International Conference on Electrical Engineering (FORTEI-ICEE)*, 2022, pp. 11–16, doi: 10.1109/FORTEI-ICEE57243.2022.9972931.

[3] M. S. Nwe and H. M. Tun, "Implementation of Multisensor Data Fusion Algorithm," *International Journal of Sensors and Sensor Networks*, vol. 5, no. 4, pp. 48–53, 2017, doi: 10.11648/j.ijssn.20170504.11.

[4] M. A. K. Niloy *et al.*, "Critical Design and Control Issues of Indoor Autonomous Mobile Robots: A Review," *IEEE Access*, vol. 9, pp. 35338–35370, 2021, doi: 10.1109/ACCESS.2021.3062557.

[5] S. Habibian *et al.*, "Design and implementation of a maxi-sized mobile robot (Karo) for rescue missions," *ROBOMECH Journal*, vol. 8, no. 1, pp. 1–33, Dec. 2021, doi: 10.1186/s40648-020-00188-9.

[6] Y. Zhang *et al.*, "Earthshaker: A mobile rescue robot for emergencies and disasters through teleoperation and autonomous navigation," *Journal of University of Science and Technology of China*, vol. 53, no. 1, pp. 1–13, 2023, doi: 10.52396/JUSTC-2022-0066.

[7] A. C. Yoo, G. R. Gilbert, and T. J. Broderick, "Military robotic combat casualty extraction and care," *Surgical Robotics: Systems Applications and Visions*, pp. 13–32, 2011, doi: 10.1007/978-1-4419-1126-1_2.

[8] Z. Sun *et al.*, "BIT-DMR: A Humanoid Dual-Arm Mobile Robot for Complex Rescue Operations," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 802–809, 2022, doi: 10.1109/LRA.2021.3131379.

[9] X. Zhang, J. Lai, D. Xu, H. Li, and M. Fu, "2D Lidar-Based SLAM and Path Planning for Indoor Rescue Using Mobile Robots," *Journal of Advanced Transportation*, pp. 1–14, 2020, doi: 10.1155/2020/8867937.

[10] R. P. Saputra, N. Rakicevic, D. Chappell, K. Wang, and P. Kormushev, "Hierarchical Decomposed-Objective Model Predictive Control for Autonomous Casualty Extraction," *IEEE Access*, vol. 9, pp. 39656–39679, 2021, doi: 10.1109/ACCESS.2021.3063782.

[11] C. Kang, S. H. Lee, and C. C. Chung, "On-Road Vehicle Localization with GPS under Long Term Failure of a Vision Sensor," *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, pp. 1638–1643, 2015, doi: 10.1109/ITSC.2015.266.

[12] A. Budiyarto, S. C. Abadi, and Naufaldo, "Autonomous navigation system for hexa-legged search and rescue robot using LiDAR," *IAES International Journal of Robotics and Automation*, vol. 13, no. 1, pp. 50–64, 2024, doi: 10.11591/ijra.v13i1.pp50-64.

[13] R. J. Kannan *et al.*, "A low-cost localization method in autonomous vehicle by applying light detection and ranging technology," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 36, no. 3, pp. 1739–1749, 2024, doi: 10.11591/ijeecs.v36.i3.pp1739-1749.

[14] H. Gietler and H. Zangl, "A Real-time Electromagnetic Localization System," in *2022 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, 2022, pp. 1–6, doi: 10.1109/I2MTC48687.2022.9806498.

[15] T. J. S. Chowdhury, C. Elkin, V. Devabhaktuni, D. B. Rawat, and J. Oluoch, "Advances on localization techniques for wireless sensor networks: A survey," *Computer Networks*, vol. 110, pp. 284–305, 2016, doi: 10.1016/j.comnet.2016.10.006.

[16] Z. Yang, N. Naz, P. Liu, and M. N. Huda, "Evaluation of SLAM Algorithms for Search and Rescue Applications," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 14136 LNAI, pp. 114–125, 2023, doi: 10.1007/978-3-031-43360-3_10.

[17] J. A. Rocha *et al.*, "Human Activity Recognition Through Wireless Body Sensor Networks (WBSN) Applying Data Mining Techniques," *Smart Innovation, Systems and Technologies*, vol. 253, pp. 327–339, 2022, doi: 10.1007/978-981-16-5036-9_31.

[18] C. Isaia and M. P. Michaelides, "A Review of Wireless Positioning Techniques and Technologies: From Smart Sensors to 6G," *Signals*, vol. 4, no. 1, pp. 90–136, 2023, doi: 10.3390/signals4010006.

[19] N. D. R. Rose, L. T. Jung, and M. Ahmad, "3D trilateration localization using RSSI in indoor environment," *International*

Journal of Advanced Computer Science and Applications, no. 2, pp. 385–391, 2020, doi: 10.14569/ijacsa.2020.0110250.
[20] C. Popescu, N. Paraschiv, and O. Cangea, "Comparison between PID and fuzzy controllers used in mobile robot control," in *Annals of DAAAM and Proceedings of the International DAAAM Symposium*, 2011, pp. 223–224, doi: 10.2507/22nd.daaam.proceedings.111.
[21] C. Lakhmissi, "Comparison between fuzzy, neural and neuro-fuzzy controllers for mobile robot path tracking," in *IEEE 3rd International Conference on Control, Engineering and Information Technology (CEIT'15)*, 2015, pp. 1-6, doi: 10.1109/CEIT.2015.7233166.
[22] R. Neruda, S. Slušný, and P. Vidnerová, "Performance comparison of relational reinforcement learning and RBF neural networks for small mobile robots," in *2008 Second International Conference on Future Generation Communication and Networking Symposia*, 2008, pp. 29–32, doi: 10.1109/FGCNS.2008.133.
[23] J. Li and S. X. Yang, "A Novel Feature Learning-Based Bio-Inspired Neural Network for Real-Time Collision-Free Rescue of Multirobot Systems," *IEEE Transactions on Industrial Electronics*, vol. 71, no. 11, pp. 14420–14429, 2024, doi: 10.1109/TIE.2024.3370939.
[24] M. Beckerleg, J. Matulich, and P. Wong, "A comparison of three evolved controllers used for robotic navigation," *AIMS Electronics and Electrical Engineering*, vol. 4, no. 3, pp. 259–286, 2020, doi: 10.3934/ElectrEng.2020.3.259.
[25] R. A. Firmansyah, W. S. Pambudi, T. Suheta, E. A. Zuliari, S. Muharom, and M. B. S. Hidayatullah, "Implementation of Artificial Neural Networks for Localization System on Rescue Robot," in *2018 Electrical Power, Electronics, Communications, Controls and Informatics Seminar, EECCIS 2018*, 2018, pp. 305–309, doi: 10.1109/EECCIS.2018.8692861.
[26] G. P. N. Hakim *et al.*, "Near Ground Pathloss Propagation Model Using Adaptive Neuro Fuzzy Inference System for Wireless Sensor Network Communication in Forest, Jungle and Open Dirt Road Environments," *Sensors*, vol. 22, no. 9, pp. 1–18, 2022, doi: 10.3390/s22093267.
[27] P. D. P. Adi and A. Kitagawa, "Performance evaluation of E32 long range radio frequency 915 MHz based on internet of things and micro sensors data," *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 11, pp. 38–49, 2019, doi: 10.14569/IJACSA.2019.0101106.
[28] W. Stark, "The effects of multipath fading in wireless communication Systems," in *The RF and Microwave Handbook: RF and Microwave Applications and Systems*, pp. 556-574, 2018, doi: 10.1201/9781420006711.ch31.
[29] J. J. Popoola, A. A. Ponnle, Y. O. Olasoji, and S. A. Oyetunji, "Investigation of the need for specific propagation model for specific environment based on different terrain characteristics," *IIUM Engineering Journal*, vol. 19, no. 2, pp. 92–104, 2018, doi: 10.31436/iiumej.v19i2.886.
[30] H. T. Friis, "A Note on a Simple Transmission Formula," *Proceedings of the IRE*, vol. 34, no. 5, pp. 254–256, 1946, doi: 10.1109/JRPROC.1946.234568.
[31] Z. El Khaled, W. Ajib, and H. McHeick, "Log Distance Path Loss Model: Application and Improvement for Sub 5 GHz Rural Fixed Wireless Networks," *IEEE Access*, vol. 10, pp. 52020–52029, 2022, doi: 10.1109/ACCESS.2022.3166895.
[32] M. K. Elmezughi and T. J. Afullo, "An Efficient Approach of Improving Path Loss Models for Future Mobile Networks in Enclosed Indoor Environments," *IEEE Access*, vol. 9, pp. 110332–110345, 2021, doi: 10.1109/ACCESS.2021.3102991.
[33] R. Lenain, B. Thuilot, O. Hach, and P. Martinet, "High-speed mobile robot control in off-road conditions: A multi-model based adaptive approach," in *Proceedings - IEEE International Conference on Robotics and Automation*, 2011, pp. 6143–6149, doi: 10.1109/ICRA.2011.5979664.
[34] S. C. Peter, J. K. Dhanjal, V. Malik, N. Radhakrishnan, M. Jayakanthan, and D. Sundar, "Quantitative Structure-Activity Relationship (QSAR): Modeling Approaches to Biological Applications," *Encyclopedia of Bioinformatics and Computational Biology*, pp. 720–734, 2019, doi: 10.1016/b978-0-323-95502-7.00311-0.
[35] Z. Dzulfikri, S. T. Nuryanti, and Y. Erdani, "Design and implementation of artificial neural networks to predict wind directions on controlling yaw of wind turbine prototype," *Journal of Robotics and Control (JRC)*, vol. 1, no. 1, pp. 20–26, 2020, doi: 10.18196/jrc.1105.
[36] I. Y. Pratama, A. Wahab, and M. Alaydrus, "Deep learning for assessing unhealthy lettuce hydroponic using convolutional neural network based on faster R-CNN with Inception V2," in *2020 Fifth international conference on informatics and computing (ICIC)*, 2020, pp. 1–6, doi: 10.1109/ICIC50835.2020.9288554.
[37] R. Alfanz, R. Fahrizal, T. P. Utomo, T. Firmansyah, F. Muhammad, and I. M. Muztahidul, "Implementation of wavelet method and backpropagation neural network on road crack detection based on image processing," *Sinergi*, vol. 28, no. 3, pp. 489–496, 2024, doi: 10.22441/sinergi.2024.3.005.
[38] I. Izzati, I. K. Sriwana, and S. Martini, "Drug forecasting and supply model design using Artificial Neural Network (ANN) and Continuous Review (r, q) to minimize total supply cost," *Sinergi*, vol. 28, no. 2, pp. 219–230, 2024, doi: 10.22441/sinergi.2024.2.002.
[39] S. Sinha, U. Srivastava, V. Dhiman, P. S. Akhilan, and S. Mishra, "Performance assessment of deep learning procedures: Sequential and ResNet on malaria dataset," *Journal of Robotics and Control (JRC)*, vol. 2, no. 1, pp. 12–18, 2021, doi: 10.18196/jrc.2145.
[40] L. Vanneschi and S. Silva, "Artificial Neural Networks," in *Natural Computing Series*, Springer Nature Switzerland AG, 2023.
[41] Z. E. Mohamed, "Using the artificial neural networks for prediction and validating solar radiation," *Journal of the Egyptian Mathematical Society*, vol. 27, no. 1, pp. 1–13, 2019, doi: 10.1186/s42787-019-0043-8.
[42] T. Chai and R. R. Draxler, "Root Mean Square Error (RMSE) or Mean Absolute Error (MAE)," *Geoscientific Model Development*, vol. 7, pp. 1525–1534, 2014.

BIOGRAPHIES OF AUTHORS

Muhammad Hafizd Ibnu Hajar received the B.Eng. Degree in electrical engineering from Universitas Mercu Buana Jakarta, in 2014, the M.Sc. degree in electronics science and technology from Beijing Institute of Technology, China, in 2017. He subsequently joined Universitas Mercu Buana, where he is currently a lecturer in the Department of Electrical Engineering. His principal research interest is robotics, electronics and control systems. His current research interests include internet of things and path planning of robots. He teaches some courses such as research methods, telecommunications electronics, robotics and transmission line. In addition, he was also active in Community Service activities and as a journal managing editor of electrical engineering at Universitas Mercu Buana Jakarta. He can be contacted at email: muhammadhafizd@mercubuana.ac.id.

Galang Persada Nurani Hakim was born in Jakarta, Indonesia 1985. He received his B.S. and M.S. degrees in electrical engineering from Universitas Mercu Buana in 2017 and his Ph.D. degree from International Islamic University Malaysia (IIUM), Malaysia, in 2023. From 2019 until the present, he was a lecturer at Universitas Mercu Buana. Currently he work as a postdoc member at IIUM. His research interests include fuzzy systems, agricultural sensors, wireless sensor networks, microenergy harvesting, and electromagnetic wave propagation. He can be contacted at email: galang.persada@mercubuana.ac.id.

Ketty Siti Salamah is currently a Lecturer in the Department of Electrical Engineering, Universitas Mercu Buana, Jakarta, Indonesia. She graduated from the Universitas Mercu Buana in 2016 with a Master's in Electrical Engineering. Her research interest is wireless sensor network, internet of things, and image processing. She can be contacted at email: kettysitisalamah@mercubuana.ac.id.

Diah Septiyana was born in Tangerang, Banten Province, Indonesia 1988 received the B.S. degree in Industrial Engineering from Universitas Mercu Buana, Indonesia, in 2013 and the M.S. degree also in Industrial Engineering from Universitas Mercu Buana, Indonesia, in 2015. Her research interests include electrochemical, operational management, control of product/service quality and supply chain systems and mapping of risk analysis. For sectoral interests include chemistry, water utility company, logistic, manufacture and service systems. Methodological focuses include quantitative and qualitative approaches such as approaches such as structural equation modelling, surveys, case studies, and action research. She can be contacted at email: dee.septie@gmail.com.