Environmental Noise Pollution Forecasting using Fuzzy-autoregressive Integrated Moving Average Modelling

Muhammad Shukri Che Lah[1], Nureize Arbaiy[2], Syahir Ajwad Sapuan[3], Pei-Chun Lin[4]
Faculty of Computer Science and Information Technology
Universiti Tun Hussein Onn Malaysia, 86400 Batu Pahat, Malaysia[1, 2, 3]
Dept. of Information Engineering and Computer Science, Feng Chia University, No. 100, Wenhwa Rd, Taichung, Taiwan[4]

***Abstract*—Predicting noise pollution from building sites is important to take precautions to avoid pollution that harms the public. A high accuracy of the prediction model is required so that the predicted model can reach the true value. Forecasting models must be built on solid historical data to achieve high forecasting accuracy. However, data collected through various approaches are subject to ambiguity and uncertainty, resulting in less reliable predictive models. Therefore, the data must be handled accurately, to eliminate data uncertainty. Standard data processing processes are easy to use but do not provide a consistent method for dealing with this ambiguous data. Therefore, a method to deal with data containing uncertainty for forecasting purposes is presented in this paper. A new technique for providing uncertainty-based data preparation has been employed to develop an ARIMA-based model of environmental noise pollution. During the data preparation stage, the standard deviation approach was used. Prior to the development of the prediction model, it is crucial to manage the fuzzy data to minimize errors. The experimental findings show that the suggested data preparation strategy can increase the model's accuracy.**

Keywords*—Noise pollution; forecasting; ARIMA; uncertainty; standard deviation

I. Introduction

One of the environmental challenges that has an impact on people's quality of life and well-being is noise pollution. Regular exposure to high levels of noise that might be damaging to people or other living beings is referred to as noise pollution [1] – [2]. Transportation noise, construction noise, manufacturing noise, and other extreme noise sources can all contribute to noise pollution [3] – [4]. Noise pollution has a long-term and short-term impact on human health, particularly hearing and mental health [5]. This causes awareness and action must be taken by the parties involved so that the effects of excessive noise do not cause emotional, mental, and physical health problems of people around the place involved.

Because diverse sounds occur on the construction site, the noise intensity might be extremely dangerous. Sound standard limits established by the Occupational Safety and Health Administration (OSHA) need ambient measurement. Noise levels at a construction site might vary based on the type of project and its stage of completion, whether indoors or outside [6] – [7]. As the stage is completed, all activities on the building site change. This demonstrates that noise levels at a given stage are not consistent; they can be low or high [8] – [9]. Early stages of a construction site project, for example, include carpenters, cement workers, steelworkers, roofers, and bricklayers. Carpenters, ventilation installers, electricians, and plumbers begin their work in the following stages at the same time as drywallers, painters, and floor and ceiling installers. Depending on the task at hand, each of these stages employs a different set of tools. This will result in a wide range of noise, some of which is hazardous if it exceeds the standard noise limit [10].

Noise pollution has developed as a major environmental issue with substantial implications that are both stressful and harmful to one's health. Efforts must be made to reduce pollution. As with noise pollution, management must determine what steps should be taken to limit emissions. Forecasting is necessary for stakeholders to make better decisions and establish data-driven initiatives. It boosts management's confidence in making critical decisions. Because forecasting has become an important aspect of the planning process, particularly strategic planning, the establishment of a noise pollution forecasting model is critical [11]. To a large extent, the accuracy of management decisions is dependent on precise forecasting. Noise pollution projections are the foundation for efficient pollution management strategies as a preventive measure [12]. Much development of forecasting models has been done with noise pollution [13, [14], [15]. Noise prediction in construction sites [12], [16]. Statistical techniques, data analysis, and data mining are also used to model forecasts for noise pollution. Statistical techniques, data analysis, and data mining are also used to model forecasts for noise pollution. The findings of the study have supported this issue although improvements are needed to study other issues that arise.

Noise pollution data may involve uncertainty due to measurement error produces during pollution exposure assessment [17]. The measurement error is characterized by instrument imprecision and spatial variability [18]. Fault during measuring instruments in the technique used in the experiment give rise to uncertainty involvement in data collection [19]. Since most of the data comes from secondary sources, it could have problems with validity, bias, and representation. These problems could all lead to data inaccuracies and inefficient forecasting models [20]. In short, the collected data or measured value contains uncertainty. When the data with uncertainty is analyzed to build a forecasting model, the uncertainty is carried through to the results, and thus reduces the model's accuracy. Handling uncertainty in data is one of the main challenges in forecasting. A widely used method to address the uncertainty lies in fuzzy theories [21]. Uncertainty involving noise pollution data has successfully used the fuzzy theory as a solution. Many studies have been produced with new solution model variants using fuzzy and hybrid concepts with other techniques [22] – [24].

Most studies in the literature focus on model development rather than data preparation. Good models, on the other hand, are often made from good data. Minimizing data collection and preparation errors can assist in the development of more accurate prediction models. Measuring the data collection accuracy is crucial to lower the chance of hidden errors in the created model. This paper proposes a systematic data preparation strategy for dealing with uncertainty during data preparation for forecasting, as measurement inaccuracy might have substantial implications for understanding noise pollution predictions. Time-series are used to store single-point data values and are best suited for classic time-series analysis techniques like autoregressive. The presence of underlying uncertainties, however, makes standard analysis ineffective in dealing with such data [25]. Considering this, addressing data uncertainties during data preparation is necessary as a stage in developing forecasting models. To solve the issues, this research introduces a new method of time series data preparation by modifying the spread of the symmetry triangular fuzzy number in the construction of autoregressive models.

In this paper, an experimental design for predicting ambient noise pollution by using ARIMA is established. In the data preparation stage, improvements were made due to the presence of fuzzy data. To obtain acceptable fuzzy values before building a prediction model, a systematic data preparation approach involving the translation of fuzzy data from a non-fuzzy number to a fuzzy number is required. The development of a triangular fuzzy number (TFN) that overcomes measurement uncertainties is offered as a systematic approach. To generate a triangular fuzzy number symmetry in the noise pollution data set, this strategy uses the standard deviation method to detect the triangle spread. Focus is placed on the preparation of fuzzy data and model forecasting, both of which are critical to explore to improve prediction value and accuracy.

The remainder of the paper is divided into the following subsections. Section 2 provides the theoretical foundations of this work, which include ARIMA and the triangular fuzzy number. Section 3 provides a description of the ARIMA-fuzzy solution approach. The proposed strategy is illustrated empirically in Section 4 using data on noise pollution. A few final observations are made in Section 5 to wrap things up.

II. Related Work

The ARIMA model has three parameters, p , d , q respectively corresponding to AR, I, MA. These three parameters affect the performance of ARIMA. In the Autoregressive (AR) model, the current value of a variable is equated with the weighted sum of a set of part values and a completely random variation with the previous process and shock values. The p^{th} order autoregressive model AR(p), representing the variable y_t is generally written as follows:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + +\phi_p y_{t-p} + e_t \quad (1)$$

where c is constant, e_t is white noise (error), and y_{t-1}, $y_{t-2}, \dots, y_{t-p}$ are past series. The process at some point in time is the result variable in AR (1), and t is only related to line periods that are one period apart.

I is the number of times the differential sequence must be repeated until it reaches a stationary state. For the ARMA model to work, it must be stationary.

Meanwhile, a common strategy for modeling univariate time series is the moving average (MA) process. The output variable of the moving-average model is defined as being linearly dependent on the current and various historical values of a stochastic (imperfectly predictable) factor. The q^{th} order autoregressive model $MA(q)$, representing the variable y_t is generally written as Equation (2).

$$x_t = \mu + \phi_1 w_1 + \phi_2 w_2 + \cdots + \phi_p w_p + w_t \quad (2)$$

where μ is the mean of the series and w_t , $w_{t-1}, w_{t-2}, \dots, w_{t-q}$ are white noise (error).

A. Triangular Fuzzy Number (TFN)

The fuzzy number has been introduced to deal with imprecise numerical quantities in a practical way [26] and has commonly been used by researchers [27].

Definition 4: Let a, b, and c be real numbers with $(a < b < c)$. Then the Triangular Fuzzy Number (TFN) $A = (a, b, c)$ with membership function is as follows:

$$y = m(x) = \begin{cases} \frac{x-a}{b-a}, & x \in [a, b] \\ \frac{c-x}{c-b} & x \in [b, c] \\ 0 & x < a \; and \; x > c \end{cases} \quad (3)$$

We define TFN as Equation (4),

$$\tilde{y} = [\alpha_l, c, \alpha_r] \quad (4)$$

where c is the center, α_l is the left spread, and α_r is the right spread of the TFN. Symmetry TFN $\tilde{y}$ has the same spread where $c - \alpha_l = \alpha_r - c$, and is denoted as:

$$\tilde{y} = [c, \alpha] \quad (5)$$

α is the spread of triangular fuzzy numbers. If $\alpha = 0$, $\tilde{y}$ is a non-fuzzy number.

The information provided is utilized to create ARIMA forecasting models with data that has been processed using fuzzy methods. The data used to build the ARIMA prediction model must first be pre-processed with triangular fuzzy numbers since it contains fuzzy elements. From previous literary works, fuzzy theory has been successfully applied widely in various case areas to reduce uncertainty and inaccuracy. However, few studies have clarified the details of fuzzy data preparation, which addresses data uncertainty.

Typically, expert definitions are used to define fuzzy numbers to address ambiguity. The definition of an expert, on the other hand, may be difficult to obtain and inconsistent, making it a difficult effort. Thus, in this study, a standard approach has been introduced to address uncertainties during data processing. The next section will describe the ARIMA prediction experiment that uses triangular fuzzy numbers as the data preparation method.

III. Fuzzy ARIMA Modeling

The process of cleaning and converting raw data prior to processing and analysis is known as data preparation. Reformatting data, making data adjustments, and integrating data sets to enrich data are all part of this crucial stage before processing. For data specialists or business users, data preparation may be time-consuming, but it is critical to place data in context to turn it into insights and reduce bias caused by poor data quality.

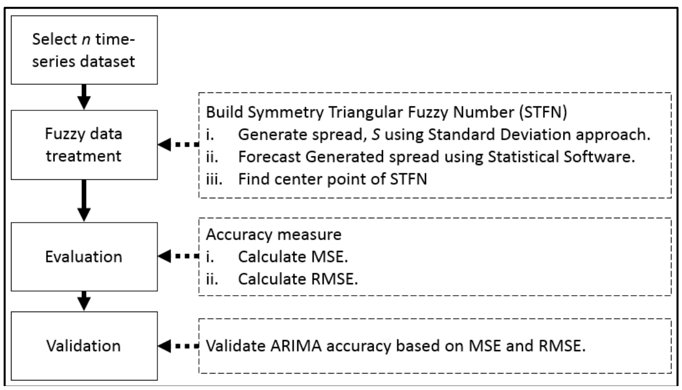

Fig. 1. Design of Experiment for ARIMA based Fuzzy Data Preparation.

The steps for building ARIMA with standard deviation-based symmetry triangular fuzzy number, Δ_s is explained as follows:

Step 1. Select times series datasets as input data. Table I shows the input data format.

TABLE I. Input Data Format

Data	1	2	…	n
Input	y_1	y_2	…	y_n

Step 2. Construct a fuzzy number of symmetrical triangles with spreads generated by the standard deviation method, Δ_s.

1) Generate spread, S: In Equation (6), a fuzzy time-series data $\tilde{y}_t^s$ at a time, t is written with symmetry triangular fuzzy number data.

$$\tilde{y}_t^s = [y_t - s, y_t, y_t + s] \tag{6}$$

where y_t is time-series data at a time, $t(t = 1,2, \dots, n)$ and Δ_s is the triangular spread based on the standard deviation of the dataset. The concept of standard deviation, which measures the spread of data, strikes at the core of this strategy.

2) Forecast generated spread using statistical software.

3) Find center value for symmetry triangular fuzzy number, $\bar{\tilde{y}}_t^s$.

The center value for the symmetry triangular fuzzy number is computed as follows:

$$\bar{\tilde{y}}_t^s = 0.5(\hat{y}_t^s + \vec{y}_t^s) \tag{7}$$

where $\bar{\tilde{y}}_t^s$ represent a center point for the triangle. $\hat{y}_t^s$ and $\vec{y}_t^s$ represent left predicted value and right predicted value, respectively. Table II shows the data format of the center point for symmetry triangular fuzzy number, $\bar{\tilde{y}}_t^s$.

TABLE II. Data Format for Center Point, $\bar{\tilde{y}}_t^s$

y_t	y_1	y_2	…	y_n
$\bar{\tilde{y}}_t^s$	$\bar{\tilde{y}}_1^s$	$\bar{\tilde{y}}_2^s$	…	$\bar{\tilde{y}}_n^s$

Step 3. Calculate the Mean Squared Error (MSE).

The results are analyzed after all of the datasets have been tested. MSE is used to evaluate the accuracy's performance. The MSE for each y_t^s is calculated using Equation (8).

$$MSE = \sum_{i=n}^{n} \frac{(y_t - \bar{\tilde{y}}_t^s)^2}{n} \tag{8}$$

where y_t is a time-series data and $\bar{\tilde{y}}_t^s$ are a predicted times series data at a time, $t(t = 1,2, \dots, n)$ and n is a sample size.

Step 4. Calculate the Root Mean Square Error (RMSE)

The RMSE is also calculated to help with the analysis. The RMSE for each y_t^s is calculated using Eq. 9.

$$RMSE = \sqrt{MSE = \sum_{i=n}^{n} \frac{(y_t - \bar{\tilde{y}}_t^s)^2}{n}} \tag{9}$$

where y_t is a time-series data and $\bar{\tilde{y}}_t^s$ are a predicted times series data at a time, $t(t = 1,2, \dots, n)$ and n is a sample size.

Step 5. MSE and RMSE values are used to validate ARIMA with Δ_s accuracy. The model with the least MSE and RMSE has a higher prediction accuracy.

Model building refers to the process of deciding what model to use for the context. Sometimes, existing well-supported theory or knowledge guides the choice of model, but sometimes the choice needs to be made empirically, which is based on real data. Ordinary Least Squares (OLS) is a linear regression technique utilized in this study to infer the association between a variable and an outcome, especially when other factors are present. The coefficient and constant of linear regression are calculated using OLS and used to construct a linear regression model. When employing interval data, the method for obtaining the center point is critical for the validation phase.

The ARIMA model is built with fuzzy number production from a single point value to resolve uncertainties, as indicated in the systematic methods described in this section. Because crisp reliability is insufficient to grasp data-inbuilt uncertainties, this phase is critical during the data preparation process [28] – [29].

IV. Experimental Result and Discussion

Noise data collected at the construction site were used to evaluate the performance of the methods proposed in this section. The ARIMA model of this data set is ARIMA (1.0,0). The data set used has 1000 data points and covers the period from March 1, 2020, to March 31, 2020. Data was collected using a web-based Environmental Site Monitoring (IoT) System [30]. The technology is designed to monitor ambient noise throughout the day and provide real -time sound updates. Favoriot platforms collect and store data on cloud servers.

Step 1. Select noise time-series datasets. Table III shows noise datasets.

TABLE III. Noise Datasets

Data	**1**	**2**	**…**	**999**	**1000**
Noise	74	58.8	…	81.5	80

Step 2. Build symmetry triangular fuzzy number based on Standard Deviation method, Δ_s.

1) Generate spread, S*:* The standard deviation approach (see Section 3 step 2) is used to calculate the spread of symmetry triangular fuzzy numbers, which is based on Eq (6). $(\tilde{y}_t^s, y, \vec{y}_t^s)$ represents a symmetrical triangle fuzzy number with a standard deviation-based spread. Table IV depicts the range of possible numbers of fuzzy symmetrical triangles.

TABLE IV. Symmetry Triangular Fuzzy Number Spread

n	y_1	y_2	…	y_{999}	y_{1000}
$\tilde{y}_t^s$	66.6956	51.4956	…	74.1956	72.6956
$\vec{y}_t^s$	81.3044	66.1044	…	88.8044	87.3044

2) Forecast generated spread using statistical software. The predicted result for the spread shown in Table V.

TABLE V. Predicted Result for the Spread of Symmetry Triangular Fuzzy Number

n	y_1	y_2	y_3	…	y_{23}
$\tilde{y}_t^s$	-	12.7987	12.9442	…	14.6047
$\vec{y}_t^s$	-	14.1413	14.2848	…	15.9473

3) Find the center value of symmetry triangular fuzzy number, $\bar{\tilde{y}}_t^s$ using Eq. (7). To calculate the MSE, the predicted value is transformed from the symmetry triangular fuzzy number to a single point. Table VI shows the symmetrical triangle fuzzy number's center value.

TABLE VI. Center Point Value for The Spread of Symmetry Triangular Fuzzy Number

y_t	y_1	y_2	y_3	…	y_{999}	y_{1000}
$\bar{\tilde{y}}_t^s$	-	74.5032	64.6617	…	77.6864	77.3949

Step 3. The MSE for the noise data is calculated based on Eq. (8), and then presented in Table VII.

TABLE VII. MSE for Noise Data

Data	$ARIMA$	$ARIMA_{\Delta_S}$
Training	33.8190	19.6161
Testing	33.8194	17.0045

Step 4. The RMSE for the noise data is calculated based on Eq. (8), and then presented in Table VIII.

TABLE VIII. RMSE for Noise Data

Data	**ARIMA**	$ARIMA_{\Delta s}$
Training	5.8154	4.4401
Testing	5.8154	4.1339

Step 5. Validate ARIMA with Δ_s accuracy based on MSE and RSME.

The MSE and RMSE results are compared to verify the correctness of the prediction error. This proposed method is also compared to traditional autoregressive (AR), autoregressive with standard deviation based (AR_{Δ_s}), and conventional autoregressive moving average methods ($ARIMA$). Table IX summarizes the MSEs for the noise data.

The MSE and RMSE results are compared to ensure that the prediction error is correct. Traditional autoregressive (AR), autoregressive with standard deviation based (AR_{Δ_s}), and conventional autoregressive moving average methods are also compared to this proposed method ($ARIMA$). The MSEs for the noise pollution data are shown in Table IX.

TABLE IX. Summary of MSE

Data	$AR(1)$	$AR(1)_{\Delta s}$	$ARIMA$	$ARIMA_{\Delta s}$
Training	52.3412	33.8197	*33.8190	33.8194
Testing	173.2402	18.1800	19.6161	**17.0045

***** Smallest MSE for Training
****** Smallest MSE for Testing

The results in Table IX show good enforcement when compared to the typical strategy. The proposed technique can achieve higher accuracy than traditional AR and conventional ARIMA. In the AR model, the proposed technique drove the MSE from 173.2402 to 18.10, and in the ARIMA model, it pushed the MSE from 19.6161 to 17.0045. To improve the outcome, the RMSE approach was also used. The RMSEs for the noise pollution data are summarized in Table X.

TABLE X. Summary of RMSE

Data	$AR(1)$	$AR(1)_{\Delta s}$	$ARIMA$	$ARIMA_{\Delta s}$
Training	7.2347	5.8155	*5.8154	*5.8154
Testing	13.1949	4.2744	4.4401	**4.1339

* Smallest MSE for Training
** Smallest MSE for Testing

The outcomes in Table X surpass those in Table IX and are consistent with the standard model. The AR model's MSE may be increased from 13.1949 to 4.2744, and the ARIMA model's MSE can be increased from 4.4401 to 4.1339 using this strategy. The MSE and RMSE decrease as the results improve.

It has been demonstrated that symmetric triangular fuzzy numbers can be created using standard deviations. As shown in Tables IX and X, MSE and RMSE for ARIMA with standard deviation based are superior to other techniques. Eqs (9) and (10) show the prediction model.

$$AR(1) = ARIMA(1) = 26.59 + 0.70y_{t-1} \tag{9}$$

$$AR(1)_{\Delta_s} = ARIMA(1)_{\Delta_s} = (24.02, 29.17) + 0.65y_{t-1} \tag{10}$$

V. Conclusion

Data preparation is critical and is a necessary step before developing forecasting models. Hence, data processing is required, and it must be carried out using proper procedures to manage data errors. Furthermore, data preparation is critical for producing high-quality data. This is done by organising and reformatting the data set and ensuring the high quality of the data used in the study. A strong forecasting model can only be built with high-quality input data; hence this is an essential prerequisite. In addition, the provision of data may help relevant parties to make better business decisions. This is because fast, effective and high-quality business decisions are produced when high-quality data is handled, examined and processed more quickly and efficiently.

To address the uncertainties in the data, we describe a technique for creating symmetric triangular fuzzy integers with standard deviation. It offers a simple and easy-to-implement solution. This experiment compares the results of the suggested approach using a few different methods. The effectiveness of the suggested method has been described and evaluated against the current method. The experimental results demonstrate that this proposed strategy using symmetric triangular fuzzy numbers outperforms the others in terms of predicted accuracy. In short, symmetric triangular fuzzy numbers are one of the other approaches to improve time series forecasting outcomes, particularly in this experiment with noise pollution.

Acknowledgment

This research was supported by the Ministry of Higher Education (MoHE) through the Fundamental Research Grant Scheme (FRGS/1/2019/ICT02/UTHM/02/7) Vot K208. This research work is also supported by the Ministry of Education, R.O.C., under the grants of TEEP@AsiaPlus. The work of this paper is also supported by the Ministry of Science and Technology under Grant No. MOST 109-2221-E-035-063-MY2.

References

[1] Mohamed, A. M. O., Paleologos, E. K., & Howari, F. M. "Noise pollution and its impact on human health and the environment," In Pollution assessment for sustainable practices in applied sciences and engineering, 2021, (pp. 975-1026). Butterworth-Heinemann.

[2] Morillas, J. M. B., Gozalo, G. R., González, D. M., Moraga, P. A., & Vílchez-Gómez, R. "Noise pollution and urban planning," Current Pollution Reports, vol. 4, no. 3, pp. 208-219, 2018.

[3] Patel, D. B., & Solanki, H. K. A. "Effects of Noise Pollution on Human Health," Research and Reviews: Journal of Environmental Sciences, vol. 3, no. 1, pp. 1-5. 2021.

[4] Farooqi, Z. U. R., Sabir, M., Latif, J., Aslam, Z., Ahmad, H. R., Ahmad, I., ... & Ilić, P. "Assessment of noise pollution and its effects on human health in industrial hub of Pakistan," Environmental Science and Pollution Research, vol. 27, no. 3, pp. 2819-2828, 2020.

[5] Hasan, S. W., & Jamal, M. A. "Noise Pollution, Effect of Noise on Behaviour of Animals and Human Health," Texas Journal of Medical Science, vol. 1, no. 1, pp. 71-75, 2021.

[6] Ning, X., Qi, J., Wu, C., & Wang, W. "Reducing noise pollution by planning construction site layout via a multi-objective optimization model," Journal of cleaner production, vol. 222, pp. 218-230, 2019.

[7] Subramaniam, M., Hassan, M. Z., Sadali, M. F., Ibrahim, I., Daud, M. Y., Aziz, S. A., ... & Sarip, S. "Evaluation and analysis of noise pollution in the manufacturing industry," In Journal of Physics: Conference Series, vol. 1150, no. 1, pp. 012019, 2019.

[8] Feng, C. Y., Noh, N. I. F. M., and Al Mansob, R. "Study on The Factors and Effects of Noise Pollution at Construction Site in Klang Valley," Journal of Advanced Research in Applied Sciences and Engineering Technology, 20(1), pp. 18-26, 2020.

[9] Mir, M., Nasirzadeh, F., Lee, S., Cabrera, D., & Mills, A. "Construction noise management: A systematic review and directions for future research," Applied Acoustics, vol. 197, pp. 108936, 2022.

[10] OSHA Region III. (2001). "Enforcement of the Occupational Noise Exposure Standards," 29 CFR 1910.95, 1926.52, and 1926.101, Inspection Procedures and Interpretive Guidance.

[11] Mohammed, M. U., Badamasi, M. M., Usman, F., Zango, Z. U., Dennis, J. O., Aljameel, A. A. I., ... & Hussein, T. M. "Towards Urban Sustainability: Developing Noise Prediction Model in an Informal Setting," Applied Sciences, vol. 12, no. 18, pp. 9071, 2022.

[12] Kwon, N., Lee, J., Park, M., Yoon, I., and Ahn, Y. "Performance evaluation of distance measurement methods for construction noise prediction using case-based reasoning," Sustainability, vol. 11, no. 3, pp. 871, 2019.

[13] Lu, H., & Wang, T. "An Automobile Noise Prediction Model Based on Extension Data Mining Algorithm," Rev. d'Intelligence Artif., vol. 33, no. 5, pp. 341-347, 2019.

[14] Sharma, A., Vijay, R., Bodhe, G. L., and Malik, L. G. "An adaptive neuro-fuzzy interface system model for traffic classification and noise prediction," Soft Computing, vol. 22, no. 6, pp. 1891-1902, 2018.

[15] Awan, F. M., Minerva, R., and Crespi, N. "Using Noise Pollution Data for Traffic Prediction in Smart Cities: Experiments Based on LSTM Recurrent Neural Networks," IEEE Sensors Journal, vol. 21, no. 18, pp. 20722-20729, 2021

[16] Buxton, R. T., McKenna, M. F., Mennitt, D., Fristrup, K., Crooks, K., Angeloni, L., and Wittemyer, G. "Noise pollution is pervasive in US protected areas," Science, vol. 356, no. 6337, pp. 531-533, 2017.

[17] Nemes, A., Mester, G., and Mester, T. "A Soft Computing Method for Efficient Modelling of Smart Cities Noise Pollution," Interdisciplinary Description of Complex Systems: INDECS, vol. 16, no. 3-A, pp. 302-312, 2018.

[18] Murphy, E., Faulkner, J. P., & Douglas, O. "Current state-of-the-art and new directions in strategic environmental noise mapping," Current pollution reports, vol. 6, no. 2, pp. 54-64, 2020.

[19] Lagonigro, R., Martori, J. C., & Apparicio, P. "Environmental noise inequity in the city of Barcelona. Transportation Research Part D: Transport and Environment, vol. 63, pp. 309-319, 2018.

[20] Ghaderi, M., Javadikia, H., Naderloo, L., Mostafaei, M., and Rabbani, H. (2019). "Analysis of noise pollution emitted by stationary MF285 tractor using different mixtures of biodiesel, bioethanol, and diesel through artificial intelligence," Environmental Science and Pollution Research, vol. 26, no. 21, pp. 21682-21692, 2019.

[21] L. A. Zadeh, "Fuzzy Sets," Inf. Control, no. 8, pp. 338–353, 1965.

[22] De, S. K., Swain, B. K., Goswami, S., and Das, M. "Adaptive noise risk modelling: fuzzy logic approach," Systems Science & Control Engineering, vol. 5, no.1, pp. 129-141, 2017.

[23] Saleh, A., Rosnelly, R., Puspita, K., and Sanjaya, A. (2017, August). "A comparison of Mamdani and Sugeno method," for optimization prediction of traffic noise levels. In 2017 5th International Conference on Cyber and IT Service Management (CITSM) (pp. 1-4). IEEE.

[24] Singh, D., Upadhyay, R., Pannu, H. S., and Leray, D. "Development of an adaptive neuro fuzzy inference system based vehicular traffic noise prediction model," Journal of Ambient Intelligence and Humanized Computing, vol. 12, no. 2, pp. 2685-2701, 2021.

[25] Bray, S., Caggiani, L., and Ottomanelli, M. "Measuring transport systems efficiency under uncertainty by fuzzy sets theory-based Data Envelopment Analysis: theoretical and practical comparison with traditional DEA model," Transportation Research Procedia, 5, pp. 186-200, 2015.

[26] Pisz, I., Chwastyk, A., and Łapuńka, I. "Assessing the profitability of investment projects using ordered fuzzy numbers," LogForum, vol. 15, no. 3, pp. 377-389, 2019.

[27] Triangular Fuzzy Numbers.

[28] Lah, M. S. C., Arbaiy, N., and Lin, P. C. "Stock Index Modelling Using Arima with Standard Deviation Based Triangular Fuzzy Numbers," Journal of Critical Reviews, vol. 7, no. 8, pp. 1264-1268, 2020.

[29] Lin, P. C., Lah, M. S. C., and Arbaiy, N. "An Architecture of Air Pollution Alert System based on ARIMA Model," Solid State Technology, 63(3), pp. 881-892, 2020.

[30] Arbaiy, N., Sapuan, S. A., Lah, M. S. C., Othman, M. H. H., and Lin, P. C. "The Construction Site Ambient Noise Monitoring System with Internet of Things (IoT)," Comput. Res. Prog. Appl. Sci. Eng. CRPASE, vol. 5, no. 4, pp. 118-121, 2019.