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Original Research

Assessment and Predictions of Air Traffic Noise at Mitiga International Airport in Tripoli, Libya

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Abstract

Noise generated by air traffic is one of the leading problems in urban areas in the world. That is why the measures for reducing the noise generated by air traffic are today the subject of constant improvement, extensive research, and standardization. Monitoring and predicting air traffic noise levels represent an important factor in quality control and noise management. In order to reduce the noise level in the vicinity of Mitiga International Airport (Tripoli) in Libya, the aim of this paper is to assess the noise emission levels before and after the introduction of certain measures to reduce airborne noise, as well as to predict the noise level at the analyzed area. The method of interpolation in the Geographic Information System (GIS) was used to graphically represent the spatial distribution of noise emissions in the study area, and by applying zonal statistics deviations from the allowable values for each control grid were calculated. The obtained results showed that the application of certain measures has a great impact on reducing noise levels on controlled grids. Finally, the reliability of noise level prediction was successfully assessed using the artificial neural network (ANN) method.

Keywords: noise, air traffic, noise reduction measures, GIS, ANN method

Introduction

Despite being a significant form of pollution, noise pollution continues to be overlooked in numerous modern cities across the globe [1]. However, according to Fallah-Shorshani et al. [2] in recent years the issue of noise caused by traffic is becoming increasingly concerning. Because of that it requires a comprehensive and coordinated effort from all stakeholders to effectively address it and achieve the desired outcome of acceptable noise levels in different areas of the city [3]. Also, it should be noted that ambient noise and air pollution frequently appear together since they stem from identical origins, namely traffic [4], which is even more concerning because previous studies confirmed spatial connection between noise caused by traffic and air pollution [5]. In recent years, there has been an intensive development of air traffic, which in the areas located on the routes of airlines, and especially at airport locations, has led to environmental burdens to the upper tolerable limits. Although the aviation sector brings significant economic and social benefits [6] to the state, it also affects the increase in noise pollution and local air quality, as well as climate change [7]. The further

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growth of the aviation sector is directly conditioned by its efficient response to today's major environmental challenges. The answers to these challenges must be environmentally sustainable and innovative, which is the only way to increase the competitiveness of the aviation sector in the global market [7]. The aviation sector is not fully comparable with other economic sectors, because the reduction of factors that affect environmental pollution in aviation is more difficult to achieve [8]. A full scientific understanding of the impact of aviation on the environment is an essential basis for discussing informed policy and for developing effective mitigation measures, which achieve the desired result in a cost-effective way.

Noise near airports is generated by aircraft movements, engine testing and other noise sources at airports, "en-route" aircraft flying and breaking the sound wall of supersonic aircraft [8]. The anxiety, which residents feel about a certain level of noise generated by air traffic, is greater than the anxiety caused by other means of transport [7]. Because of all the above, the fundamental goal of incorporating noise modeling in the process of evaluating environmental impact is to estimate the amount of noise that will be produced by a specific activity in the surrounding area [9]. This problem is especially pronounced when airports are located in the immediate vicinity of residential areas, hospitals and schools, as in the case of Mitiga Airport, which was the reason for conducting the research presented in this paper.

Geographic information system (GIS) has gained significant popularity and emerged as a pivotal evaluation tool in the field of ecological environment evaluation [10]. Because of that GIS was used during the research for generating noise maps [11] and graphical interpretation of the most polluted areas, based on measured noise levels (L_{den}) before and after the introduction of corrective measures and the creation of distribution maps. Graphical representation of these results in GIS is enabled by applying the Inverse Distance Weighting (IDW) interpolation technique. The IDW method is based on the assumption that the variable being mapped becomes less influential as the distance from its sampled location increases. It is particularly effective for the interpolating phenomena that exhibit a strong correlation with distance, such as air quality, water flow, and noise levels [12]. The decision to use IDW over alternative methods like Kriging was made on the assumption that IDW would result in a closer resemblance between the values of sample points and the values projected onto the cells [13]. This assumption is based on the idea that as a sample point gets closer to the cell being projected, the value of that cell would increasingly reflect the value of the sample point [13]. In contrast, Kriging estimates the intensity of unknown variables, without necessarily reducing intensity with distance [13]. Also, according to Ghojogh Nejad et al. [14], the IDW interpolation method better presents the mean values of the measured noise levels, compared to the Kriging method used to generate a map based on the maximum values of the measured noise levels. For this reason, the IDW interpolation technique was used in this study.

According to Olayode et al. [15], artificial neural networks (ANNs) can be characterized as a mathematical framework capable of conducting simulation analyses on the functional and structural components of biological neural networks. Neural networks can be described as mathematical systems that are capable of learning in a nonlinear manner [16]. Mansourkhaki et al. [17] believe that ANNs can be used more successfully comparing to traditional methods of data analysis and modeling [18]. Thanks to the latest progress in machine learning and the widespread access to enormous data collections, it is now feasible to create neural network models that can anticipate aviation noise based on the flight paths of airplanes [19]. In urban areas, traffic is the most prominent contributor to noise pollution which has a detrimental impact on human well-being, both physically and mentally, as well as work productivity [20]. Now, it is possible to create a predictive method by utilizing a range of detection devices to gather traffic data and incorporating historical traffic patterns and other significant variables [21]. Since ANN was already used in predicting air pollution [22], and it is also crucial to develop models that accurately predict the noise generated by air or road traffic [20], this was the reason why, in the final part of this paper, ANNs were used to assess the reliability of predicting noise levels generated by air traffic.

Due to all the above, the purpose of this research is to assess and reduce noise levels after the introduction of certain corrective measures to reduce the impact of noise at the specific airport Mitiga (Tripoli) in Libya, in order to present the distribution of noise levels in research and mark the most critical grids using various GIS techniques. Finally, the technique of ANNs, multilayer perceptron (MLP) was applied in order to assess the reliability of predicting the level of noise generated by air traffic, and the results were compared with the results of multiple linear regression (MLR) models to confirm the reliability of noise level prediction using ANN method.

Materials and Methods

A model for estimating, reducing and predicting noise emissions has been created in order to enable the most efficient management of this environmental pollutant. The model consists of seven steps (Fig. 1).

The first step was defining the research goal – estimating, reducing and predicting noise emissions caused by aircrafts. The second step was collecting and creating data sets – in this step noise emissions were measured at three locations within the research area, before and after the introduction of measures to reduce noise emission generated by air traffic. The third step

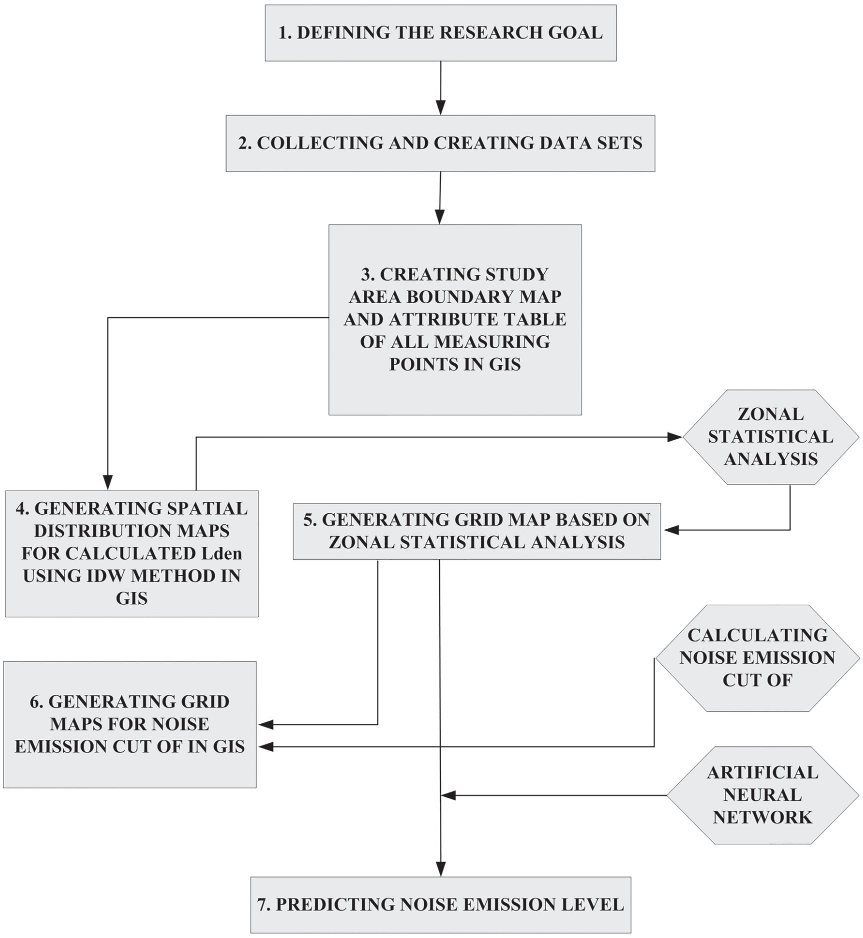

Fig. 1. Noise emission assessment and prediction model.

was creating study area boundary map and attribute table of all measured points in GIS – in this step a database was created in GIS, which contains all the necessary data on measuring points and measured noise emission (L_{day}, $L_{evening}$, L_{night} and L_{den}) before and after the application of reduction measures. The fourth step was generating spatial distribution maps for calculated L_{den} using IDW method in GIS – in this step the IDW method in GIS was used for creating interpolation maps of the research area with measuring points, in order to graphically present the distribution of noise emissions before and after the introduction of certain corrective measures. The fifth step was generating grid map based on zonal statistical analysis – in this step the investigated area was divided into 16 grids (4x4) and zonal statistics applied to the data before and after the introduction of certain measures. The sixth step was generating grid maps for noise emission cut of in GIS – the results of zonal statistics were used to calculate the noise level in each control grid before and after the application of reduction measures, based on which the mapping of grid according to the level of noise pollution was performed. Finally, the seventh step was predicting noise emission level – in this step ANNs have been used to assess the reliability of predicting noise levels in the research area.

Research Area

The area of research is Mitiga International Airport in Libya (13°16'40"E, N32°53'40"N, elevation 11 m) (Fig. 2). This airport is located in the municipality of Tripoli, the capital of Libya. The planes operating on these routes are Airbus 320, Airbus 319, Airbus 321, Airbus 332, Boing 738, Boing 734, CRJ9 and ERJ145. The runway has an asphalt surface and has a length of 3,400 m. Near the airport are Mitiga Military Hospital (13°16'08"E, 32°54'25"N, elevation 10 m) and Halim Al Saadia Elementary School (13°16'12"E, 32°53'29"N, elevation 11 m).

In the period when the noise level was measured, there were an average about 43 landings and take-offs per day. Noise level measurement was carried out in the period of June, July, August 2021, and cases of approximately the same engine power were analyzed. Phase 1 was from June 1 to July 15, 2021, and Phase 2 from July 16 to August 31, 2021. The total number of flights in the observed period is: June 1,363; July 1,364 and August 1,242.

Therefore, measurements were made continuously for 3 months, 24 hours a day (except for the school location). The measurement was carried out in the period from June 1 to August 31, 2021, because it was observed that in that period, although the traffic frequency was not the highest in 2021, it was the highest in previous years. It was not possible to perform longer-term measurements, because this research was conducted only as a part of the student's doctoral dissertation. As a result, the obtained L_{den} values are more conservative and higher than the actual ones. The noise level was measured with three sensors of the same type, which were placed at locations M1, M2 and M3 (Fig. 2).

Given that airborne noise has an impact on the health of people living near the airport, as it affects sleep disorders, cardiovascular diseases, including hypertension, altered cognitive abilities in children, preterm birth, hormonal disorders [23, 24, 25], and higher risk of metabolic syndrome [26], the research idea was to determine the noise level in the area that would include these three locations and to implement measures to reduce noise levels in accordance with the measurement results, the effect of which would be determined by a new set of noise measurements, at the same locations.

Measuring of the Noise Level

During three-month period (from June until September in 2021.) noise levels were measured at three locations near the runway threshold 10 (13°16.22'E, 32°53.75'N) (Fig. 2):

– M1 (measuring spot 1) - at Mitiga Airport, where the airport staff is about 1,500 m away from the runway threshold 10 (13°16'40"E, N32°53'40"N),
– M2 (measuring spot 2) - in the military hospital Mitiga, which is at a distance of 1,225 m from the runway threshold 10 (13°16'08"E, 32°54'25"N) and
– M3 (measuring spot 3) - Halima Al Saadia Primary School, which is 550 m from the runway threshold 10 (13°16'12"E, 32°53'29"N).

Measurement of noise levels at all three locations was done for the peak load of the airport (the largest number of take-offs and landings of aircraft that generate high noise levels). Also, the measurements were performed in two phases: (1) before the introduction of noise reduction measures and (2) after the introduction of noise reduction measures.

These measures were implemented as a test for this research, which lasted from July 16 to August 31, 2021. The airport authorities have built barriers made of brick and aluminum. All airlines that used the airport in the specified period, as well as ATC (air traffic control), participated in the introduction of the measures.

The impulse precision sound level meter B&K 2209, manufactured by Brüel & Kjær, was used to measure the noise level, and the measurement was performed during three periods, during the day (from 7 h to 19 h), in the evening (from 19 h to 23 h) and at night (from 23 h to 7 h) at the airport and hospital, while at

Fig. 2. International airport Mitiga with measuring spots.

the school location, the measurement was performed only during two periods, during the day and in the evening (the measurement was not done at night, because at the time the school was closed).

One of the goals of this paper is to determine the spatial distribution of 24-hour noise emissions (L_{den}) generated by air traffic at Mitiga Airport (Tripoli, Libya) using GIS methodology, in order to identify noise pollution levels in relation to the location of Mitiga Military Hospital and Halim Al Saadia Elementary School located near this airport. Due to the fact that noise was measured at three measuring points, during the day, evening and night, 24-hour noise emissions (L_{den}) had to be calculated using "the following formula [27, 28]:

$$L_{den} = 10\log\frac{1}{24}\left(12 \cdot 10^{0.1\cdot L_d} + 4 \cdot 10^{0.1\cdot(L_e+5)} + 8 \cdot 10^{0.1\cdot(L_n+10)}\right) \tag{1}$$

where:

– L_d is the A-weighted long-term average sound level determined over all the day periods of the year,
– L_e is the A-weighted long-term average sound level determined over all the evening periods of a year, and
– L_n is the A-weighted long-term average sound level determined over all the night periods of a year" [27, page 252].

Mihajlov and Prascevic [27] used noise indicators L_d, L_e and L_n to present daily, evening and night noise indicators (L_{day}, $L_{evening}$ and L_{night}).

The Guideline Development Group (GDG) of the World Health Organization (WHO) has suggested that the noise levels produced by aircraft should be reduced to levels below 45 dB L_{den} and 40 dB L_{night} during night time as it can have negative effect on health and sleep [29]. The GDG has also expressed its confidence in the fact that exposure to noise levels below 45 dB L_{den} can lead to an increased risk of annoyance [29]. We noticed that these threshold values are about 10 dB lower than the threshold values in the EU member states, so we increased the WHO limit values for L_{den} and L_{night} by 10 dB and conducted this research with a limit value of L_{den} = 55 dB and L_{night} = 50 dB.

Noise at the school location was measured only during the day and evening, because the school does not work at night, so when calculating the L_{den} value for a given location for L_{night}, a limit value of 50 dB was taken into account. The pupils are not affected by noise during the night, since the school is closed, but the people living near the school are. Since the aim of our research was to assess the noise impact on pupils who are attending school near Mitiga airport, not the people living nearby, we did not measure noise during the night at the measuring spot M3, but we assumed that it was within the limit value (50 dB), and the sensitivity analysis have shown that the results for L_{den} would not differ much in case that the values for L_{night} are equal to 0 dB. Besides, in reality outdoor noise value at night is never 0 dB. This is why we used the limit value for L_{night} = 50 dB. Although, if the noise was measured during the night period in the measuring spot M3, the values would certainly be higher than 50 dB, as well as the calculated L_{den} values**.**

It was assumed that the noise at the M3 measuring point at night would be greater than 50 dB because it is close to the runway, and the noise level measured at the M2 measuring point is the farthest from the runway before and after the introduction of noise reduction measures, was greater than 50 dB. Also, it is a well-known fact that the noise is decreasing by increasing the distance. The sensitivity analysis was done separately for the measurement results before and after the introduction of noise decrease measures. The value for the M3 measuring point at night was increased by 10 and 20% to get the value for L_{night} as closest to the mean noise value measured at the measuring point M2 at night which according to the results in Table 1 was 58.04 dB.The results have shown that in this case values for L_{night} would be 55 dB (increased by 10%), and 60 dB (increased by 20%), and the calculated mean values for L_{den} would be 70.78 dB and 71.80 dB, respectively. The same analysis was done for the measurements after the application of noise decrease measures. However, since the mean noise level at measuring point M2 at night (Table 2) in this case was 51.34 dB, it was necessary to increase noise at the M3 measuring point at night by 2.5 and 5%, thus the new values for L_{night} would be 51.25 dB (increased for 2.5%) and 52.5 dB (increased for 5%). New calculated mean L_{den} values for the M3 measuring point were 58.64 dB and 59.45 dB, respectively. As can be seen, the sensitivity analysis has shown that by increasing the L_{night} values, the L_{den} values will also be higher. However, the influence of increased L_{night} values on mean L_{den} values at the M3 measuring point will not be so big, as can be seen by comparing with the results for calculated mean L_{den} values at the M3 measuring point (Tables 1, 2).

Geographic Information System

Fig. 2 shows a map with three locations where noise was measured (measuring points M1, M2 and M3). This map was created in GIS, using the QGIS software package (version 3.6). Since GIS has a very powerful spatial analysis capabilities [30, 31], it was used to create layers that contain all the necessary information for segmenting grids based on the boundaries of the research area. The research area consisted of 4x4 grids covering an area of 5.968 square kilometers. It has also been considered dividing the area into different numbers of grids but the results were not significantly different. In order to generate noise levels per grid, the measured noise values (L_{day}, $L_{evening}$ and L_{night}) were used to calculate the 24-hour noise (L_{den}) measured at three locations and these results were then used

Table 1. Descriptive statistics of the measured noise emission caused by aircrafts before the introduction of measures.

Measuring spot	Parameter	Min	Max	Mean	Skewness	Kurtosis
M1	L_{day}	69.40	81.80	76.41	-0.150	-1.280
	$L_{evening}$	71.00	84.40	78.11	-0.030	-1.434
	L_{night}	68.30	81.00	74.82	-0.113	-1.462
	L_{den}	76.07	87.90	82.00	-0.064	-1.526
M2	L_{day}	52.90	66.20	60.21	-0.068	-1.416
	$L_{evening}$	56.80	67.50	62.10	0.057	-1.564
	L_{night}	51.00	62.50	58.04	-0.625	-1.516
	L_{den}	59.02	70.30	65.53	-0.439	-1.562
M3	L_{day}	60.00	73.20	68.72	-0.748	-1.396
	$L_{evening}$	63.90	76.40	70.85	-0.299	-1.406
	L_{night}	/	/	/	/	/
	L_{den}	63.28	75.29	70.35	-0.521	-1.432

Table 2. Descriptive statistics of the measured noise emission caused by aircrafts after the introduction of measures.

Measuring spot	Parameter	Min	Max	Mean	Skewness	Kurtosis
M1	L_{day}	54.00	57.40	55.58	0.361	-1.514
	$L_{evening}$	54.00	57.42	55.62	0.354	-1.529
	L_{night}	53.40	57.35	55.30	0.110	-1.492
	L_{den}	59.99	63.76	61.77	0.173	-1.506
M2	L_{day}	50.00	53.30	61.83	-0.280	-1.539
	$L_{evening}$	50.00	53.35	52.05	-0.445	-1.280
	L_{night}	49.00	53.25	51.34	-0.260	-1.601
	L_{den}	55.72	59.65	57.90	-0.258	-1.583
M3	L_{day}	52.00	56.40	54.26	-0.033	-1.531
	$L_{evening}$	52.00	56.45	54.29	-0.033	-1.527
	L_{night}	/	/	/	/	/
	L_{den}	56.96	58.94	57.92	0.135	-1.525

in zonal statistics in GIS. The spatial distribution of noise emission was calculated using the IDW interpolation method, and the previously calculated L_{den} values for all three measuring points. IDW interpolation method [32] was used in this study to show the spatial distribution [33] of noise emission. The IDW method generates maps that offer valuable information for monitoring purposes, even when only a small number of monitoring units are available [34]. This is one of the simplest methods based on the assumption that the value at an uncompressed point can be approximated as a weighted average of values within points within certain distances or from a given number of the nearest points (usually 10 to 30) [35]. The weights are usually inversely proportional to the distance [27], which leads to estimation in an unspecified location. Therefore, the interpolation is calculated as follows [36]:

$$F(r) = \sum_{i=1}^{m} w_i z(r_i) = \frac{\sum_{i=1}^{m} z(r_i)/|r-r_i|^p}{\sum_{j=1}^{m} 1/|r-r_j|^p} \quad (2)$$

where m represents the number of the nearest points, r location, and p represents the parameter [36].

After applying the IDW interpolation method and creating spatial distribution maps [37] of noise emission and obtained average L_{den} values per grid, using zonal statistics as table tool in GIS, deviations from the limit value in each grid were calculated, assuming that the limit value for L_{den} is 55 dB.

Artificial Neural Networks

ANN technology was used to assess the reliability of noise level prediction [17]. This technique was used within the SPSS software package (version 20) and on that occasion the MLP structure of the neural network was used as one of the most commonly used ANNs. MLPs include input layer, hidden layer and output layer [38], and in this study they were used to predict variations in noise levels. Each MLP had one output (L_{day}, $L_{evening}$, L_{night}, or L_{den}) and three inputs (engine power, take-off and landing runway distance, and air traffic volume) that were used to identify differences between noise measurement locations. The training, validation and testing phases play a crucial role in the field of machine learning [39]. During the training phase, the corpus was organized in a manner that aligns with the algorithms' computational requirements. This allows the model to learn from their trial and error experiences. To ensure comprehensive training, the dataset was divided into three segments, so when defining MLPs, it was determined that 70% of the sample would be random selection for training, i.e., calibration model, 20% for testing and 10% for model validation. Ratio 70:20:10 was also used by other authors like Zhang et al. [40], Kowsher et al. [39] and Karpathy et al. [41]. As Kowsher et al. [39] stated the training segment, comprising 70% of the dataset, was utilized to train the models. The testing phase involved using the remaining 20% of the dataset as a dedicated testing set to assess the models' performance [39]. Lastly, 10% was set aside for validation, aiding the models in evaluating their own performance and facilitating iterative improvements during the training process [39]. A training dataset for an ANN can have any number of hidden layers, which can also have any number of neurons [42]. Until the sum of the square error of the training template reached the minimum, the training is performed. The MLP analysis in this research was done based on 198 samples (for training, testing and holdout) for all outputs except for L_{night} (132 samples) because the measurement was not done during the night period. To assess how well the ANN models are performing in terms of precision, the criterion used is the root mean square error (RMSE). The RMSE is calculated using the following equation [16]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{3}$$

where O_i is the observed value and P_i is the computational value. The *n* parameter represent the number of data.

Multiple Linear Regression

MLR method was also used in predicting noise pollution levels at Mitiga International airport in Tripoli, in order to compare the results achieved by ANN method with another traditional model like MLR.

The equation for multiple linear regression for *k* variables used for calculating noise pollution levels in the research was [43]:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + e_i \tag{4}$$

where the dependent variable i.e. noise pollution levels (L_{day}, $L_{evening}$, L_{night} and L_{den}) is y; coefficients of the regression evaluation are β_1, β_2 and β_k while β_0 is the y-intercept (value of y when all other parameters are set to 0); x_i values are independent variables (runway distance (RD), air traffic volume (ATV) and engine power (EP)); e_i is model error.

Results and Discussion

Descriptive statistics for all measured noise emission values (L_{day}, $L_{evening}$, L_{night} and L_{den}) at all three measurement locations are shown in Table 1 and Table 2.

In Table 1 Skewness values are negative for all noise indicators except for measuring spot M2 (for noise indicator $L_{evening}$) where it is positive and greater than zero. Negative Skewness values mean that the noise emission has a longer left tail distribution, while positive and greater than zero Skewness values mean that the noise distribution of the test area is asymmetric. All Kurtosis values (Table 1) are negative, which means that the noise emissions also have a light-tailed distribution. Additionally, it should be noted that the noise was not measured at night at the measuring spot M3 (in both cases, before and after the introduction of measures), considering that the school is closed during night hours, so the descriptive statistical analysis was not made for noise indicator L_{night}.

In Table 2 Skewness values are positive for measuring spot M1 (for all noise indicators), while negative for measuring spots M2 (for all noise indicators) and M3 (for all noise indicators except noise indicator L_{night}). The Kurtosis values are all negative.

Considering that the maximum noise emission level for all four parameters was 81 dB and higher, it was determined that it is necessary to take certain measures to reduce the noise emission levels caused by air traffic. In this sense, after the first phase of measurements, the following measures were introduced to reduce noise emissions:

- Engine power was reduced during take-off (from 92.8% and 83% to 83% and 80%, respectively);
- Engine power at landing remained at 38%, but the speed of the aircraft was reduced to the lowest possible;
- An aluminum partition has been installed at one end of the runway threshold 10, towards the hospital. The thickness of this barrier is 2 mm, the length is 750 m, and the height 2 m. The aluminum barrier is 232 m away from the hospital;
- Another, brick partition was set up towards the school, almost parallel to the runway. The thickness

of the masonry partition is 40 cm, the length is 825 m, and the height 4 m. The masonry barrier is 26 m away from the school;

– The flight procedures in the take-off phase (on departure) have been changed. On departure there are two noise abatement procedures where a stepped departure climb is being used. They are called "NADP 1" and "NADP 2" (Noise Abatement Departure Procedures). NADP 1 is used where there are noise sensitive areas close to the airport and is used to alleviate noise in an area further away, say +25 km from the start of roll on the airport runway. The restriction to two noise abatement departure procedures was agreed at the ICAO (International Civil Aviation Organization) in order to minimize confusion internationally at the appropriate procedure to use for the lessening of noise for people on the ground. Essentially the two noise abatement procedures are:
– NADP 1: Aircraft to climb to 800'+ and then reduce thrust. Keep flaps lowered in take-off mode and continue climbing as fast as possible to 3,000'. Then retract flaps, increase thrust and go on their way;
– NADP 2: Aircraft to climb to 800'+ and then reduce thrust. Withdraw flaps at that point and continue at a decreased rate of climb until 3,000' Then increase climb and thrust and go on their way.
– The NADP 1 procedure was applied in the research.

Application of GIS

After all measurements were performed both before and after the introduction of corrective measures to reduce noise levels, at all three locations, the data were entered into the GIS database for further analysis. First, based on the entered data on measured values and the application of the IDW interpolation method (Equation 2), maps of noise emission distribution were created before and after the introduction of corrective measures (Fig. 3).

It is noted that the noise level was significantly higher before the introduction of corrective measures (Fig. 3a), with the lowest noise emission values (from 59.02 dB to 70.30 dB) recorded in the military hospital (M2), while in the school area (M3) recorded values were between 63.28 dB and 75.29 dB. The highest values of noise emission were measured in the area of the airport (M1) and ranged from 76.07 dB to 87.90 dB. After the introduction of corrective measures (Fig. 3b), the noise emission values in the hospital area (M2) ranged from 55.72 dB to 59.65 dB, in the school area (M3) between 56.96 dB and 58.94 dB. The highest noise level was still in the area of the airport (M1) and ranged between 59.99 dB and 63.76 dB.

The distribution maps shown in Fig. 3 indicate that the area around Mitiga Airport and the population living in that location are still exposed to noise above 55 dB. According to Souza & Zannin [44] exposure to noise above 55 dB can reflect the health of the population living nearby [45]. Also, Baloye and Palamuleni [46] stated that noise sensitivity zones with noise level between 50 dB and 60 dB are considered risky, between 60 dB and 65 dB moderately risky, between 65 dB and 70 dB highly risky, between 70 dB and 75 dB dangerous, between 75 dB and 80 dB highly dangerous, while noise levels above 80 dB are extremely dangerous.

After creating maps of spatial distribution of noise emissions, the investigated area was divided into 16 grids and zonal statistics as table tool in GIS was applied for calculating deviations from the limit value for each grid. Then these deviations were entered into the GIS database and maps were created showing the deviations from the limit values per grid. Deviations from the limit values were calculated for L_{den} before and after the introduction of corrective measures (Fig. 4).

As can be seen in Fig. 4a), before the introduction of corrective measures less than 20% deviations was on the following grids: 672 (19.94%), 771 (18.43%) and 772 (16.91%), between 20% and 25% deviations was on the grids: 471 (22.05%), 472 (21.96%), 473 (22.55%), 474 (24.32%), 571 (21.65%), 572 (21.88%), 573 (23.22%), 671 (20.02%)) and 673 (24.54%), while over 25% of the deviations were on the grids: 574 (26.28%), 674 (30.21%) and 774 (31.96%). Regarding deviations after the introduction of corrective measures (Fig. 4b), less than 6% of deviations were on the following grids: 471 (5.48%), 472 (5.19%), 473 (5.58%), 571 (5.58%), 572 (5.37%), 671 (5.68%), 672 (5.73%), 771 (5.53%) and 772 (5.22%), between 6% and 9% deviations were on the grids: 474 (6.65%), 573 (6.10%), 574 7.70%), 673 (7.33%) and 773 (7.45%), while more than 9% of the deviations were still on the grids: 674 (9.66%) and 774 (10.50%).

All deviations from the limit value of noise levels used in the research, before and after the introduction of measures to reduce noise levels caused by air traffic are shown in Table 3.

As can be seen from Table 3, after the application of certain measures to reduce noise levels caused by air traffic, a significant reduction in noise emissions was achieved, but it is also noticeable that it is necessary to introduce additional measures to keep noise levels within limits, i.e. below 55 dB.

For this reason, the following additional measures have been proposed, which can be applied in the research area:
– planting trees in the immediate vicinity of the school and military hospital,
– implementation of the so-called green roofs on both buildings,
– thicker facade of buildings and replacement of windows and doors (sound insulation), etc.
–

Application of ANNs

In order to assess the reliability of predicting the emission of the examined parameters (L_{day}, $L_{evening}$, L_{night} and L_{den}), i.e., to achieve the second goal of the research, the method of ANNs, i.e., MLP was used. Input, i.e.

independent variables of this model included: engine power (%), runway distance (m) and air traffic volume, while the dependent variables included noise emission parameters (L_{day}, $L_{evening}$, L_{night} and L_{den}).

The results of ANN analysis for all four outputs (L_{day}, $L_{evening}$, L_{night}, or L_{den}) are presented in Table 4.

The results in Table 4 show that in all cases, ie. for all four outputs (L_{day}, $L_{evening}$, L_{night}, or L_{den}) RMSE values are lower than 1 which implies a higher coefficient of determination (Figs 5-8). RMSE is a performance metric that provides information about the short-term efficiency of a model. It measures the difference between predicted values and observed values, with a lower RMSE indicating a more accurate evaluation. On the other hand, the coefficient of determination (R^2) measures the variance explained by the model, reflecting the reduction in variance when using the model. R^2 ranges from 0 to 1, with a value close to 1 indicating a model with strong predictive ability and a value close to 0 indicating a model that is not effective in analyzing the data. These performance metrics, RMSE and R^2, are reliable measures of the overall predictive accuracy of a model [47]. Accuracy metrics are commonly used in ANNs to assess the quality of predictions. Beside Mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and symmetric mean absolute percentage error (SMAPE), RMSE is widely used accuracy metrics in various fields such as weather forecasting, medical, and engineering [48]. RMSE, specifically, measures the average magnitude

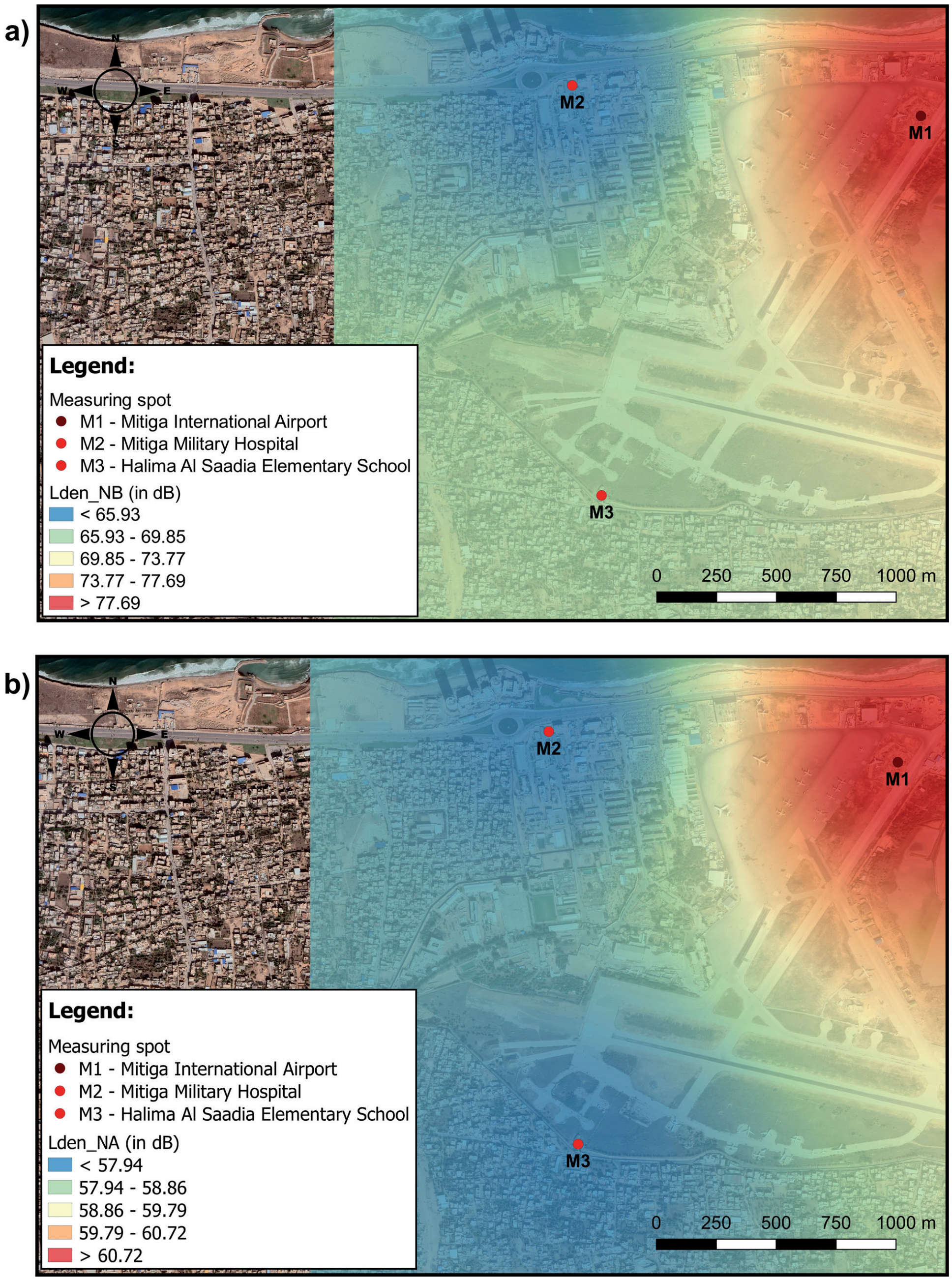

Fig. 3. L_{den} distribution maps: a) noise before corrective measures (L_{den}_NB) and b) noise after corrective measures (L_{den}_NA).

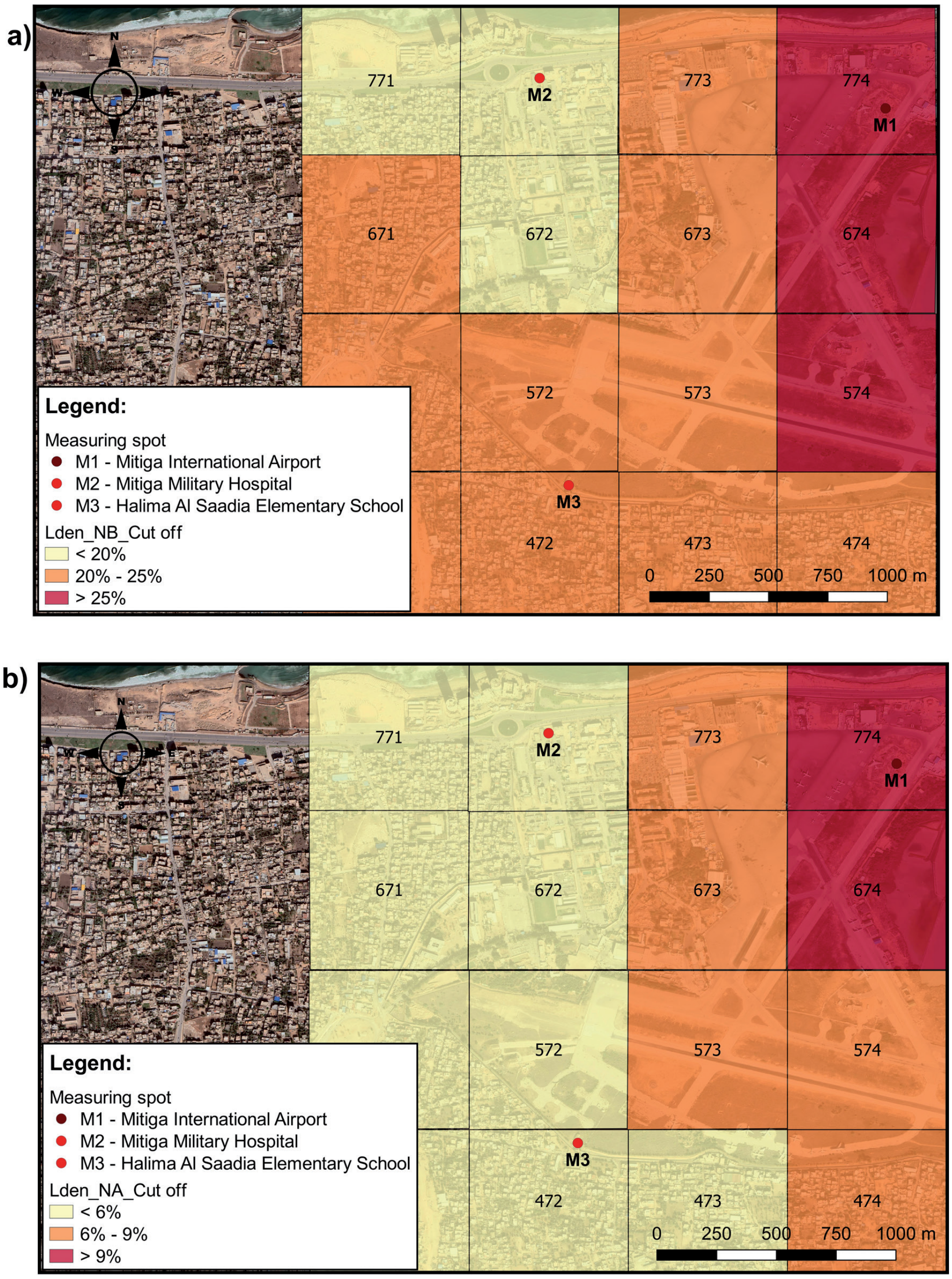

Fig. 4. L_{den} cut of scheme: a) noise before corrective measures (L_{den}_NB_cut off) and b) noise after corrective measures (L_{den}_NA_cut off).

of error between predicted and actual values. It can be visualized as the average vertical distance from the actual value to the corresponding predicted value on a fitted line. In simple terms, RMSE is the square root of MSE. Similar to MSE, the range of RMSE is from 0 to positive infinity, and a smaller RMSE value indicates a higher accuracy of the prediction model. However, unlike MSE, the units of RMSE are the same as the original units, making it more easily interpretable [48].

The assessment of the reliability of the prediction using MLP showed that changes in noise emission during the day (L_{day}) in the study area resulted in a coefficient of determination of 0.996 (Fig. 5a). As can be seen on Fig. 5a, the distinction between the actual values and the predicted values was in range of -2.04 to +1.32 dB. Significance analysis (Fig. 5b) showed that air traffic volume has the greatest impact on predicting L_{day} variations.

The assessment of the reliability of the prediction of noise levels in the evening ($L_{evening}$) resulted in a coefficient of determination of 0.997 (Fig. 6a) and that the difference between the actual values and the predicted values was in range of -1.55 to +1.40 dB, while the significance analysis (Fig. 6b) showed that air traffic volume has the greatest impact on predicting $L_{evening}$ variations.

The assessment of the reliability of the prediction of noise levels at night (L_{night}) resulted in a coefficient of

Table 3. Deviations of Lden from the limit values, before and after the introduction of corrective measures.

Grid no.	Noise cut of before corrective measures (%)		Noise cut of after corrective measures (%)		Limit
	(in %)	(in dB)	(in %)	(in dB)	
471	22.05	15.56	5.48	3.19	55
472	21.96	15.48	5.19	3.01	55
473	22.55	16.01	5.58	3.25	55
474	24.32	17.67	6.65	3.92	55
571	21.65	15.20	5.58	3.25	55
572	21.88	15.40	5.37	3.12	55
573	23.22	16.63	6.10	3.57	55
574	26.28	19.61	7.70	4.59	55
671	20.02	13.77	5.68	3.31	55
672	19.94	13.70	5.73	3.34	55
673	24.54	17.89	7.33	4.35	55
674	30.23	23.83	9.66	5.88	55
771	18.43	12.43	5.53	3.22	55
772	16.91	11.19	5.22	3.03	55
773	24.04	17.41	7.45	4.43	55
774	31.96	25.83	10.50	6.45	55

determination of 0.997 (Fig. 7a), and that the distinction between the actual values and the predicted values was in range of -1.34 to +1.24 dB, while analysis of importance (Fig. 7b), as with other examined parameters showed that air traffic volume has the greatest influence on predicting L_{night} variations.

Finally, a 24-hour noise emission prediction reliability assessment (L_{den}) was performed, which showed that the coefficient of determination was 0.998 (Fig. 8a), and that the difference between the observed and predicted values was in rang of -1.56 to +0.92 dB. The air traffic volume had the greatest impact on noise pollution, as Hamida et al., [49] also stated in their study. This was confirmed by a significance analysis (Fig. 8b).

Therefore, it can be concluded that the air traffic volume and the engine power have the greatest impact, while the distance from the runway has the least impact on the variations of the analyzed noise emission parameters. Also, as Mansourkhaki et al. [17] stated that the high coefficients of determination for all dependent variables (in this case L_{day}, $L_{evening}$, L_{night} and L_{den}) confirms the reliability of the ANNs in predicting noise pollution caused by air traffic.

Considering that ANN analysis results have indicated lower values of RMSE (Table 4) it can be concluded that the model used in this part of research is good for prediction of dependent variables (L_{day}, $L_{evening}$, L_{night} and L_{den}).

Application of MLR

Finally, MLR analysis was used for determining coefficients of determination also for all four dependent variables (L_{day}, $L_{evening}$, L_{night} and L_{den}). The independent variables used in this part of the research were the same as the ones used in ANNs (runway distance (RD), air traffic volume (ATV) and engine power (EP)).

After applying MLR method (Equation 4) for predicting dependent variables, the developed noise prediction model is given in Equations (5-8).

$$L_{day} = 11.289 - 0.007 \cdot RD + 0.093 \cdot ATV + 0.044 \cdot EP \quad (5)$$

$$L_{evening} = 9.752 - 0.005 \cdot RD + 0.091 \cdot ATV + 0.051 \cdot EP \quad (6)$$

$$L_{night} = 12.253 - 0.006 \cdot RD + 0.086 \cdot ATV + 0.046 \cdot EP \quad (7)$$

$$L_{den} = 18.095 - 0.006 \cdot RD + 0.088 \cdot ATV + 0.048 \cdot EP \quad (8)$$

According to Table 5, the correlation between independent variables (runway distance (RD), air traffic volume (ATV) and engine power (EP)) and dependent variables (L_{day}, $L_{evening}$, L_{night} and L_{den}) are 0.952, 0.951, 0.949 and 0.952, respectively. The R Squared for the regression models for dependant variables (L_{day}, $L_{evening}$, L_{night} and L_{den}) are 0.906, 0.904, 0.901 and 0.906, respectively. This results indicate that 90.6% of the L_{day} values, 90.4% of the $L_{evening}$ values, 90.1% of the L_{night} values and 90.6% of the L_{den} values can be explained

Table 4. The results of ANN models.

ANN for L_{day}	Training	138 samples	Sum of Squares Error	0.260	RMSE (training)	0.043
			Relative Error	0.004		
			Training time	0:00:00.05		
	Testing	36 samples	Sum of Squares Error	0.078	RMSE (testing)	0.047
			Relative Error	0.005		
	Holdout	24 samples	Relative Error	0.006	/	/
ANN for $L_{evening}$	Training	143 samples	Sum of Squares Error	0.206	RMSE (training)	0.038
			Relative Error	0.003		
			Training time	0:00:00.05		
	Testing	38 samples	Sum of Squares Error	0.046	RMSE (testing)	0.035
			Relative Error	0.003		
	Holdout	17 samples	Relative Error	0.001	/	/
ANN for L_{night}	Training	95 samples	Sum of Squares Error	0.120	RMSE (training)	0.036
			Relative Error	0.003		
			Training time	0:00:00.02		
	Testing	21 samples	Sum of Squares Error	0.035	RMSE (testing)	0.041
			Relative Error	0.003		
	Holdout	16 samples	Relative Error	0.004	/	/
ANN for L_{den}	Training	124 samples	Sum of Squares Error	0.096	RMSE (training)	0.028
			Relative Error	0.002		
			Training time	0:00:00.05		
	Testing	44 samples	Sum of Squares Error	0.083	RMSE (testing)	0.043
			Relative Error	0.005		
	Holdout	30 samples	Relative Error	0.002	/	/

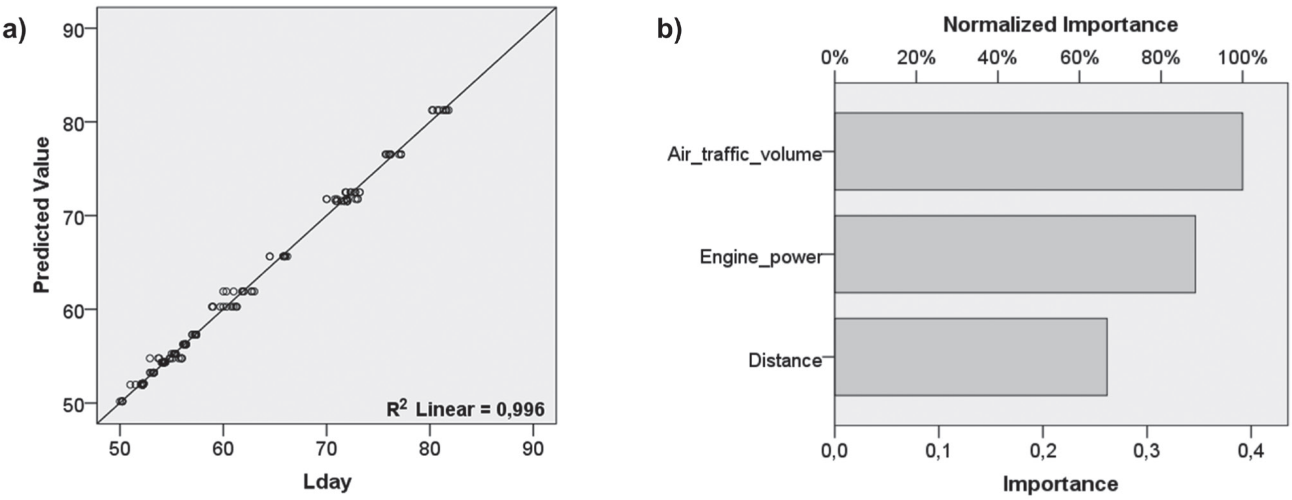

Fig. 5. Graphical representation of a) actual compared to predicted L_{day} emission values and b) importance analysis.

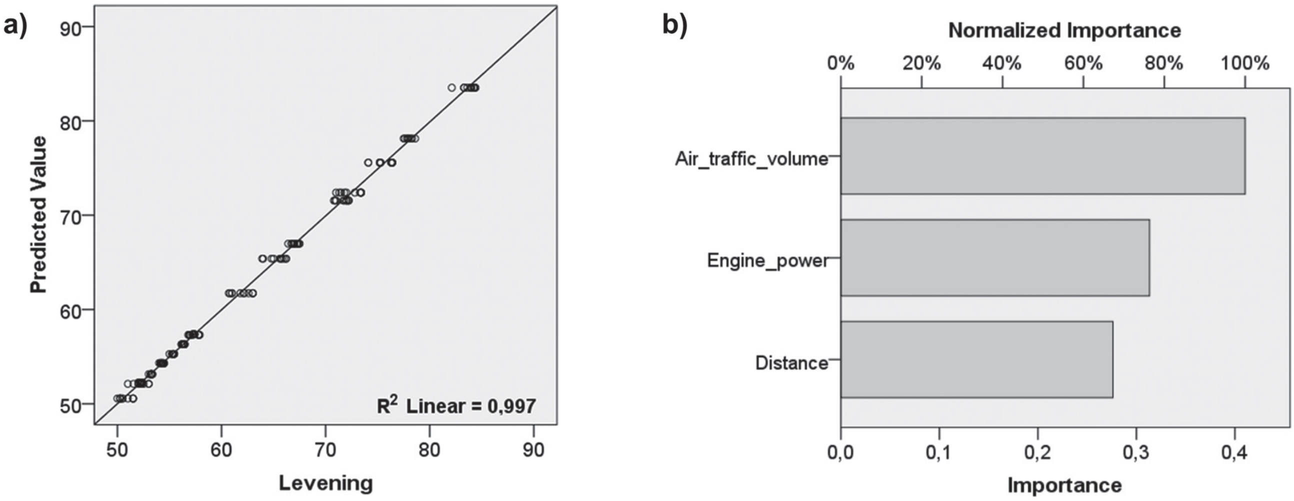

Fig. 6. Graphic representation of a) actual compared to predicted $L_{evening}$ emission values and b) importance analysis.

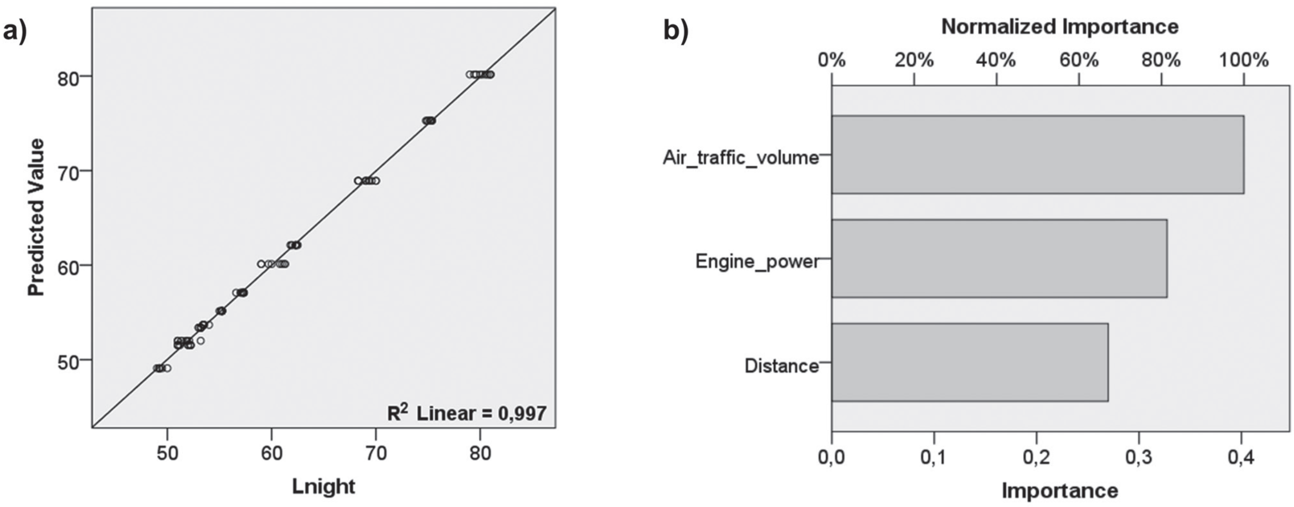

Fig. 7. Graphic representation of a) actual compared to predicted L_{night} emission values and b) importance analysis.

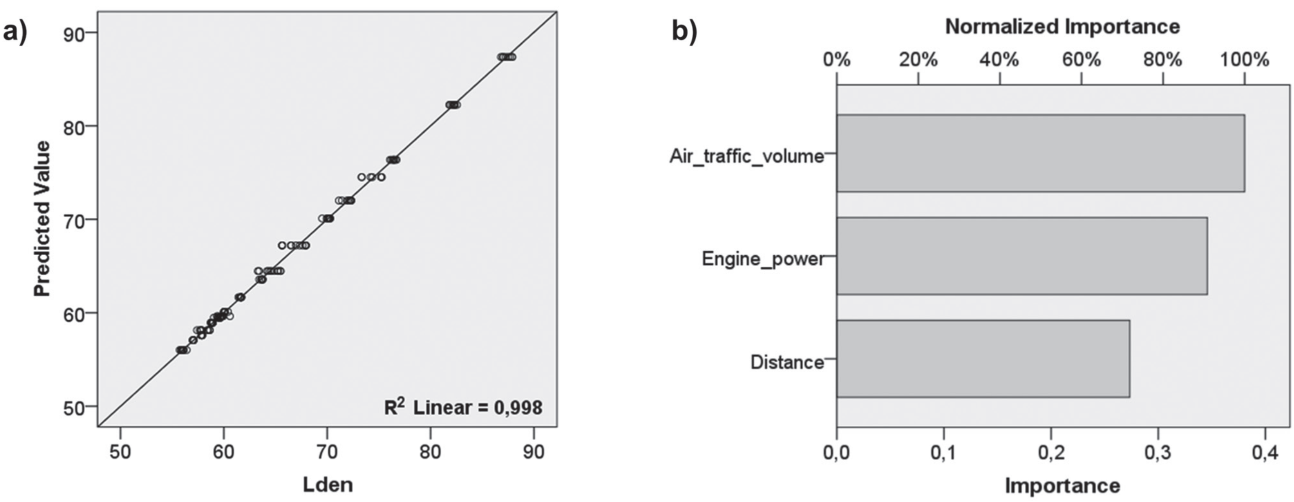

Fig. 8. Graphic representation of a) actual compared to predicted L_{den} emission values and b) importance analysis.

Table 5. The results of Multiple Linear Regression Analysis.

Multi linear regression statistics	Results for L_{day}	Results for $L_{evening}$	Results for L_{night}	Results for L_{den}
Multiple R	0.952	0.951	0.949	0.952
R Square	0.906	0.904	0.901	0.906
RMSE	3.521	3.534	3.390	3.366
Level of Significance	0.000	0.000	0.000	0.000

by the independent variables. RMSE values for L_{day}, $L_{evening}$, L_{night} and L_{den} are 3.521, 3.534, 3.390 and 3.366, respectively. Also the level of significance was less than 0.05 in all four cases, which means that all independent variable coefficients are statistically significantly different from zero.

If we take into consideration the results of the conducted ANN analysis and MLR (the values of R^2 and RMSE) it can be concluded that ANN model used in the research offers better results, as Yusof et al. [50] and Kuznetsov et al. [16] also stated in their research.

Conclusions

The results of IDW interpolation method in GIS showed that before the introduction of measures to reduce noise levels caused by air traffic on some grids it was necessary to reduce noise levels by over 30%, while the introduction of measures reduced noise levels, but still on some grids a reduction of over 9% is needed. However, it can be concluded that the application of measures to reduce noise levels in the study area has been successful, but not sufficiently to reach a noise level below the limit values and therefore additional measures to reduce noise should be introduced.

The application of ANNs in the prediction of noise variations has shown that the MLP technique can be successfully used in achieving this goal. The results of this analysis can also be used in the implementation of adequate measures to reduce noise levels. The reliability of–the ANNs in predicting noise pollution caused by air traffic was confirmed by higher coefficients of determination and lower RMSE values than the ones achieved by MLR method. However, it is important to point out that additional parameters (the speed of the aircraft during takeoff and landing, wind direction, etc.) may also be included in the analysis, which would probably affect the result of the analysis using MLP technique, or some other traditional model such MLR, but in this way, data would certainly be obtained that would facilitate decision-making on the choice of corrective measures.

Since the research the research was limited both by time and technical possibilities to perform measurements at more measuring points, in future research, within the project carried out by the airport authorities, it is planned that the measuring points are located in the direction of the extended runway, where the highest measured noise values will certainly be. This will certainly make the noise distribution different. Also, it is planned to measure noise east and west of the airport in the vicinity of residential areas, to study the impact of noise on the population living in the vicinity of the airport.

Finally, the system of preferential runways can be introduced in the future. This would make it possible to schedule the use of the runways according to the time of day, as well as according to the days of the week, which would achieve an additional reduction of the noise level in certain periods. It is also possible to introduce a flight ban for aircraft that are not noise certified for night flights. However, these are suggestions for further research.

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Conflict of Interest

The authors declare no conflict of interest.

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