MODELING OF PM CONCENTRATIONS ON A CONSTRUCTION SITE BASED ON IOT MONITORING SYSTEM

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Abstract: *An IoT-based system framework integrating a distributed sensor network was implemented to collect real-time data at a construction site. Various sensors were utilized to gather data concerning particulate matter ($PM_{2.5}$ and PM_{10} concentrations) as well as meteorological parameters – wind speed, humidity, pressure, and temperature. The real-time measurements results provide an overview of air pollution levels at the construction site, revealing its association with earth excavation work, the primary construction activity. This connection allows for better management aimed at reducing concentrations of suspended particles. Through on-site monitoring of two pollutant concentrations, this study identified that the dust levels resulting from excavation activities were relatively high. It can be concluded that earth excavation significantly impacts air quality in the construction area. While exploring the primary factors influencing construction dust concentrations, the correlations indicate that these concentrations were not significantly associated with meteorological factors.*

To predict $PM_{2.5}$ and PM_{10} concentrations in the air using number of working machines and meteorological parameters as predictors, both Multiple linear regression (MLR) and Artificial Neural Network (ANN) models were applied. The ANN model demonstrates better alignment with the measured air concentrations compared to the MLR model. The ANN model demonstrated

an R-squared value of 0.674 for PM_{10} and 0.618 for $PM_{2.5}$, indicating a strong predictive capability.
The aim of this research, through modeling $PM_{2.5}$ and PM_{10} concentrations in the air at the construction site is to indicate importance of the topic, especially with respect to the health of the constuction site workers.
Key words: : *construction pollution; PM_{10}; $PM_{2.5}$; meteorology; prediction model.*

1. Introduction

In the light of the anticipated implications of climate change, the pursuit of sustainability has become an essential objective across various economic sectors, including the construction industry. All construction sites consistently generate substantial pollution levels over prolonged periods. Notably, the construction industry stands as a primary contributor to greenhouse gas (GHG) emissions, accounting for approximately 12% of the total global emissions. Official statistics from the Delhi Pollution Control Committee (DPCC) reveal that constructions sites are responsible for 30% of air pollution caused by dust emissions [1]. Numerous construction activities, encompassing excavation, operation of diesel engines, demolition, burning, and handling of toxic materials, collectively contribute to air pollution. The primary factor leading to air pollution concerning nitrogen and sulfur oxides during construction projects is the utilizations of heavy equipment such as excavators, loaders, bulldozers, etc. reliant on burning fossil fuels. Excavation work stands as a significant source of PM (particulate matter) pollution on construction sites. The emission of $PM_{2.5}$ at these sites arises primarily from exhaust fumes generated by diesel engines and diesel generator sets, vehicles, and heavy machinery. Additionally, the use of harmful substances like oils, glues, solvents, paints, treated woods, plastics, cleaning agents, and other hazardous chemicals widely used on construction sites also contribute to air pollution [2].

In 2015, 193 countries adopted the Sustainable Development Goals (SDGs), outlining the 2030 Agenda for Sustainable Development [3]. Notably, air pollution is specifically addressed in two SDG targets: SDG 3.9, aiming for substantial reduction in health impacts from hazardous substances, and SDG 11.6 focused on mitigating the adverse effects of cities on people. It is widely recognized that action within the energy sector plays a pivotal role in achieving the SDGs related to air pollution [4]. The majority of sulfur dioxide (SO2) and nitrogen oxide (NOX) emissions into the atmosphere are related to energy sources, accounting for approximately 85% of PM emissions. Three primary pollutants (SO2, NOx and PM) are responsible for the most significant air pollution effects, both directly and indirectly, after undergoing transformation through chemical reactions and transportation in the atmosphere. $PM_{2.5}$ is highly damaging to human health, while sulfur and NO_X (the latter are precursors of ozone) are linked to various illnesses and environmental damages [2,5].

PM (Particulate Matter) particles have a significant impact on human health, with numerous adverse effects. These fine particles, often originating from industrial processes and vehicular emissions, can penetrate deep into the respiratory system, causing respiratory diseases. Prolonged exposure to PM particles is associated with an increased risk of cardiovascular problems, such as heart attacks and strokes. Furthermore, PM pollution is linked to exacerbating pre-existing health conditions, including asthma and bronchitis. Research suggests that reducing PM emissions can lead to improved air quality and better public health outcomes [6,7,8,9, 10].

The Sustainable Development Scenario (SDS) is designed based on selected Sustainable Development Goals (SDGs) outlined by United Nations. Its objective is to harmonize three closely related yet distinct goals: ensuring universal access to affordable, reliable, and modern energy services by 2030 (SDG 7.1); significantly reducing air pollution, a major cause of high mortality and illness (SDG 3.9); and taking effective measures to combat climate change (SDG 13). [2]

In the Balkans, Serbia stands as a leader in the continually growing construction industry. In August 2022 alone, 2,562 building permits were issued. This escalating trend in construction raises the prospect of a substantial increase in greenhouse gas concentrations and other pollutants. Consequently, it becomes imperative to implement real-time monitoring of polluting gases and particulate matter (PM). This monitoring is essential to propose measures aimed at reducing the levels of these pollutants. Through gaining insights into the quantities of pollutants present and their correlation with atmospheric conditions, strategies for lowering their concentrations can be formulated. Despite the increasing significance of emissions of harmful substances in the construction industry due to rapid construction in Serbia, a real-time emission monitoring tool, crucial for aiding construction teams in avoiding excessive emissions, has not yet been implemented at construction sites in the country. The significant relevance of implementing this system and conducting such research lies in prioritizing the health of construction site employees. These workers often encounter health issues due to poor working conditions, particularly the substandard air quality at these sites. At times, the air quality deteriorates to such an extent that it poses a threat to the lives of the workers. This issue demands greater attention due to its impact on the health of the population in the immediate vicinity of the construction site. The research results offer a new prospect for predicting air quality at construction sites by considering meteorological parameters. This development holds significant value in the planning and management of operations, ensuring minimal impact on the health of workers, the surrounding population, and the environment. Such an approach to managing complex activities on the construction site represents a sustainable way of overseeing both the construction site and the project as a whole.

PM is one of the most prevalent air pollutants in the world, alongside NOx, photochemical oxidants, ozone (O3), carbon monoxide (CO), lead (Pb) and SO2 [11,12]. Recent research has focused on the effects of dust concentration at construction sites, particularly examining PM_{10} and $PM_{2.5}$ [13,14,15]. Investigations have revealed multiple factors influencing PM concentrations at these sites. The immediate surroundings of a construction site may act as a source of emissions that are transported and detected on-site, independent of on-site activities, commonly known as background emissions. In relation to meteorological factors, numerous studies have explored the correlation between meteorological parameters and the concentration of pollutants, including PM. [16, 17, 18]

However, differing perspectives exist on this subject. Some authors [16] suggest that meteorological parameters play an extremely significant role in PM concentration at construction sites. Yet, due to a lack of measured data, they were unable to formulate a model depicting the dependence of PM concentrations on meteorological parameters. According to certain authors [17], dust emissions from construction sites exhibit significant seasonal variations, a finding supported by others research [18]. This reaffirms a notable correlation between PM concentration and meteorological parameters. In studies [19,20] examining the relationship between construction activities and meteorological factors, it was established that PM shows a strong positive correlation with wind speed and relative air humidity, and a weaker association with temperature.

Apart from excavation work, internal construction activities within buildings also contribute to emissions. Kinsey et al. (2004) observed that vehicles leaving construction sites can transport substantial amounts of dust and sediment to nearby roads, resulting in increased secondary dust [21]. Detailed monitoring conducted by Azarmi et al. (2014) during various construction phases, such as concrete mixing, drilling, and cutting, revealed that PM_{10}, $PM_{2.5}$, and $PM_{0.1}$ concentrations during drilling and cutting activities were up to 14 times higher than background levels [22]. Moraes et al. (2016) specifically focused on monitoring PM_{10} concentrations generated from concrete and masonry in construction activities [23]. These and similar studies underscore that specific construction phases and activities significantly impact PM concentrations [24].

The health risks, both cancer and non-cancer, related to exposure to $PM_{2.5}$ and PM_{10} were evaluated in research conducted by Sekhavati and Yengejeh (2023) at two construction sites in Lar, Iran, using the three-dimensional approach of inhalation, digestion, and dermal absorption recommended by the US Environmental Protection Agency. Their results indicated that the drilling process presented the highest non-cancer risk for workers. Suspended $PM_{2.5}$ posed an unacceptable risk level in all processes except for facility implementation. Their research has a limitation because they did not have a control group of workers who are exposed to PM [25].

IoT systems for monitoring PM particle pollution on construction sites have emerged as a valuable tool in environmental monitoring and occupational health and safety. These systems utilize a network of interconnected sensors that measure and monitor PM particle levels in real-time, providing valuable data on air quality conditions. By leveraging IoT technology, construction site managers can remotely access and analyze the collected data, enabling them to make informed decisions regarding pollution control measures and worker safety protocols. The integration of IoT systems in construction site monitoring helps identify potential sources of PM particle pollution, such as heavy machinery, demolition activities, or material handling processes. In the field of environmental monitoring, several conventional dust measurement techniques are commonly used, including gravimetric analysis, beta attenuation monitors, and optical particle counters. Gravimetric analysis, while highly accurate, involves manual sample collection and processing, which can be time-consuming and labor-intensive. Beta attenuation monitors offer continuous measurement but can be expensive and require regular maintenance. Optical particle counters provide real-time data but may suffer from accuracy issues under varying environmental conditions. Given these limitations, the adoption of IoT-based methods for dust measurement presents several advantages. IoT-based systems enable real-time data collection and remote monitoring, significantly enhancing the efficiency and responsiveness of environmental management practices. These systems also improve data accuracy through continuous and automated measurements, reducing the likelihood of human error and enabling more precise analysis. Additionally, IoT devices can be easily integrated into existing monitoring networks, providing a scalable solution that can adapt to changing environmental conditions and monitoring needs. By leveraging the benefits of IoT technology, we can overcome many of the challenges associated with conventional dust measurement techniques, leading to more effective and comprehensive environmental monitoring strategies. [25,26,27,28,29]

The IoT monitoring system used in our study comprises several interconnected components designed to provide real-time dust monitoring and data analysis. The primary components include:

-Sensors: These are deployed at various locations to measure particulate matter (PM) levels. The sensors are capable of detecting different sizes of particulate matter, such as $PM_{2.5}$ and PM_{10}. Each sensor node consists of a microcontroller, power supply (typically solar-powered), and wireless communication modules.

-Data Transmission: The collected data from the sensors is transmitted to a central server using wireless communication technologies like Wi-Fi, LoRa, or cellular networks. This ensures seamless and continuous data flow from remote monitoring sites to the central system.

-Central Server: The central server aggregates data from all sensor nodes. It uses cloud computing resources to store and process the data. Advanced data processing techniques, including machine learning algorithms, are applied to predict trends and analyze the data for anomalies.

-User Interface: The processed data is then visualized on a user-friendly interface accessible via web and mobile applications. This interface provides real-time updates, historical data analysis, and predictive insights, enabling stakeholders to make informed decisions.

The integration of IoT in dust monitoring systems offers several key advantages:

-Real-time Data Collection: IoT-enabled sensors provide continuous monitoring and real-time data collection, which is critical for timely intervention and response to elevated dust levels.

-Improved Data Accuracy: Automated data collection minimizes human error and ensures higher accuracy and consistency in measurements.

-Remote Monitoring: IoT systems facilitate remote monitoring of dust levels across multiple locations, reducing the need for physical presence and manual data collection.

-Scalability: IoT-based systems can easily scale to cover larger areas or additional monitoring sites by adding more sensor nodes, enhancing the overall monitoring network.

-Data Integration and Analysis: The ability to integrate and analyze data from various sensors using cloud computing and machine learning enables comprehensive environmental assessments and more effective dust management strategies.

By implementing IoT technology, we can significantly enhance the capabilities and efficiency of dust monitoring systems, leading to better environmental protection and public health outcomes. [26, ,27,28,29,30,31]

With the continuous monitoring and analysis of PM particle levels, IoT systems can contribute to the development of proactive measures to mitigate pollution, reduce health risks, and promote a healthier environment for workers and surrounding communities. The goal of this research is a deeper and more detailed analysis of the relationship between PM concentrations on the construction site that are emitted due to excavation work and meteorological parameters. The data analysis aimed to check the possibility of applying some models to predict PM concentrations depending on the meteorological parameters. MLR was chosen for its simplicity and interpretability, while ANN was selected for its ability to model complex, non-linear relationships. [22,23]

MLR (Multiple Linear Regression) models are simple statistical methods used for predicting PM (Particulate Matter) particles based on a linear model that combines multiple variables. In this case, the variables can include meteorological data, traffic information, and other factors that influence PM particle concentrations. ANN (Artificial Neural Network) models are more complex machine learning methods inspired by the structure of the human brain. They use a set of interconnected artificial neurons that communicate with each other to process data.

ANN models are more flexible and can learn complex relationships between input and output data, which can be useful for predicting PM particles. MLR models are based on the assumption of a linear relationship between variables, while ANN models do not restrict the form of the function that connects inputs and outputs. This means that ANN models can better model nonlinear relationships and complex patterns in the data, making them more powerful tools for predicting PM particles.

MLR models are simpler to implement and interpret, while ANN models are more complex and require more time and computational resources for training. However, ANN models can provide more accurate results and better generalization to new data, especially in cases where the relationships between variables are complex and nonlinear. Both MLR and ANN models have their advantages and are used in the field of PM particle prediction. MLR models are suitable for situations where the relationships between variables are relatively simple and linear, while ANN models excel in capturing intricate patterns and nonlinearity in the data, leading to improved predictive performance.

2. Materials and Methods

The study involved measuring the concentrations of suspended $PM_{2.5}$ and PM_{10}, in the air, along with measuring meteorological parameters (air pressure, temperature, humidity, and wind speed). This study was conducted at six construction sites in Belgrade and Novi Sad (refer to Figure 1 and Figure 2) over a total of 40 days during spring and summer of 2019, as well as the summer of 2022.

Figure 1. Location of the construction site in Belgrade, Serbia

Figure 2. Location of five construction sites in Novi Sad, Serbia

In Belgrade, two electric-powered machines were operational in the excavation areas during workdays (Monday to Saturday). Heavy excavation work was performed every day except Sunday, from 07:00 to 17:00. Identifying the origins of the polluting substances in the air was not feasible and was not the objective of this study. Nevertheless, throughout the measurement period, heavy earth excavation activities were the predominant ongoing tasks, while any other work, such as interior construction inside nearby buildings, occurred only sporadically. Consequently, we believe that the air pollution at the sites can be attributed to the heavy earthworks. Therefore, the primary focus of this study was on assessing the impact of meteorological conditions on the presence of PM in the air, considering it to originate from the heavy earth excavation works.

Both measurement devices were of the sensor type, portable, and suitable for both outdoor and indoor use. These devices were placed in the measurement station, and measurements were recorded every 5 minutes. The RS-MG111-WIFI-1 (Reinke) (Figure3a) functions as an air environment multi-element transmitter. It was employed to detect $PM_{2.5}$ and PM_{10} in the air at the measurement site. This transmitter utilizes an original imported sensor and a control chip with characteristics such as high precision, high resolution, and good stability. It was directly connected to the on-site WIFI network for convenience. Through either the free monitoring platform software or the free IoT cloud platform, it forms an online integrated air environment monitoring system widely used in heating, ventilation, and air conditioning systems. This system is intended to provide energy savings in smart homes, schools, hospitals, airports, train stations, and other such locations. Another device utilized was the CC-M12 weather station with RH&T and 4G communication (Figure 3b), serving as an anemometer to measure wind direction (WD) and wind speed (WS), as well as air temperature, air pressure, and humidity. The entire system enabled the managers of the construction site and the company to gain detailed real-time insight into air quality. This facilitated the identification of sources emitting harmful gases from three primary construction activities: earthworks, transportation, and interior works. The system included web and mobile applications that offered data visualization through maps, lists, and charts. Additionally, it provided notifications or alarms when values exceeded predefined ranges, algorithms for data processing, and the capability to export data to a CSV file. The sensors underwent calibration against an official site to validate the quality of the data, and both demonstrated an accuracy higher than 0.98. Calibration was conducted using the field collocation method, wherein a low-cost device was placed alongside a public air quality monitoring station for 15 days (the dataset contained hourly averaged values from both the device and the public monitoring station). For calibration purposes, the Least Squares Method (LSM), chosen due to its common usage and implementation simplicity, was employed [32].

The measurement device utilized at the construction sites in Novi Sad was developed by the research team as part of the project "Development of the methods, sensors, and systems for monitoring the quality of water, air, and soil – RS-III43008." This device incorporates the Alphasense OPC-N2 as the PM sensor and a mobile chip for internet connectivity with the IoT cloud platform (Figure 3c). The OPC-N2 is pre-calibrated in accordance with the European Standard EN481 for particle mass concentrations concerning PM_1, $PM_{2.5}$, and PM_{10} size fractions, which define particles regularly inhaled by humans. An important advantage of the OPC-N2 is its capability to operate for extended periods without the need for maintenance or cleaning. This is due to all sampled airborne particles passing directly through the sensor without being deposited. Additionally, external factors such as wind power and direction in the proximity of the OPC can influence the sample flow rate through the sensor. However, these variations are dynamically monitored and corrected by the OPC-N2 to ensure that particle concentrations and derived PM values remain unaffected by flow variations. The data obtained from the sensor exhibits very high accuracy and precision, particularly when the humidity is below 70%.

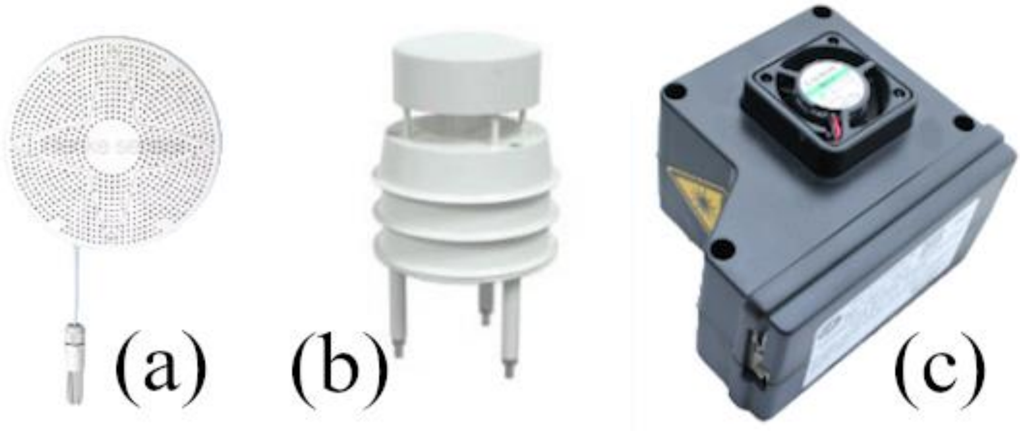

Figure 3. Measurement devices: a) RS-MG111-WIFI-1 (Reinke) device, b) CC-M12 weather station with RH&T, c) 4G communication and the Alphasense OPC-N2

In 2019, five selected construction sites in Novi Sad were monitored. Each construction site was observed continuously for five consecutive days, from Monday to Friday, under clear weather conditions with humidity lower than 70%. Monitoring occurred during earth excavation operations from 07:00 to 16:00, with sensors transmitting measurements every 5 minutes. To ensure better quality of results, diverse construction sites were chosen. The specific locations were as follows: C1 involved road reconstruction (12th to 16th of August), C2 was a small family house (19th to 23rd of August), C3 pertained to multifamily housing (15th to 19th of July), C4 was a residential and commercial building

(15th to 19th of April), and C5 was a residential complex (1st to 5th of July). Diesel-powered machines for excavation and transport were utilized on the monitored construction sites C1 to C5, involving 10, 3, 4, 6, and 12 machines, respectively, depending on the size and intensity of the work. Data analysis in this study was performed using SPSS 23.0 statistical software and Excel. Additionally, Statistica v.13 (StatSoft) software was employed for data modeling, specifically multiple linear regression (MLR) and artificial neural networks (ANN).

The MLR model was developed by fitting a linear equation to observed data. A significant advantage of this statistical method lies in its ability to illustrate relationships between variables, even though it does not indicate a causal mechanism. The MLR model played a crucial role in determining how meteorological factors influenced air pollutant concentrations. Consequently, PM concentrations were considered as a response to meteorological variables acting as predictors.

The Artificial Neural Network (ANN) stands as one of the well-known prognostic methods used when other statistical methods are not applicable. Its advantages, such as the ability to learn from examples, fault tolerance, real-time operation, and forecasting non-linear data, render it a widely utilized statistical tool. Furthermore, ANN adeptly accommodates nonlinear variables, a notable advantage compared to multivariate linear analysis based on linear variables. ANN models aim to imitate and simulate the function of neurons in the human brain through mathematical functions. The Multilayer Perception (MLP) comprises an input layer with artificial neurons corresponding to the input data, followed by one or more hidden layers housing additional artificial neurons. Each artificial neuron in the hidden layers interconnects and exchanges information with all neurons in both the previous and subsequent layers. Subsequently, the output layer includes artificial neurons known as "targets. The Coefficient of Determination (R2) served as one of the indicators used to determine whether the data provided sufficient evidence indicating that the overall models contributed enough information for predicting concentrations. Additionally, it acts as a measure of how well the prediction models fit the data. The coefficient values range from zero to one. The closer the value is to one, the more accurate and better the prediction.

The ANN model used in this study was designed to predict $PM_{2.5}$ and PM_{10} concentrations in the air at construction sites based on meteorological parameters. The model follows a typical Multilayer Perceptron (MLP) architecture. The key components of the architecture include:

- Input Layer: The input layer consists of neurons representing the input data, which in this case are the meteorological parameters: wind speed, air pressure, humidity, temperature, and the number of working machines.
- Hidden Layers: One or more hidden layers with artificial neurons that process the inputs. Each neuron in a hidden layer is connected to every neuron in the previous and next layers, allowing the model to learn complex patterns.
- Output Layer: The output layer includes neurons that provide the predicted PM_{10} and $PM_{2.5}$ concentrations.

The design choice of using an MLP is due to its capability to handle non-linear relationships and its robustness in learning from complex datasets. The Coefficient of Determination (R^2) was used to evaluate the model's performance, with higher values indicating better predictions .

The hyperparameters for the ANN model were chosen based on a combination of empirical testing and optimization techniques. The process involved:

1. Initial Selection: Preliminary hyperparameters were selected based on existing literature and prior experiments.
2. Grid Search: A grid search method was employed to explore a range of values for each hyperparameter systematically.
3. Cross-Validation: The model's performance was evaluated using cross-validation to ensure that the chosen hyperparameters generalize well to unseen data.
4. Optimization: Hyperparameters such as the number of hidden layers, the number of neurons in each layer, the learning rate, and the activation functions were fine-tuned to minimize the prediction error.

The ANN model achieved an R^2 of 0.674 for PM_{10} and 0.618 for $PM_{2.5}$, indicating a good fit for the data .

The study utilized data collected from six construction sites in Belgrade and Novi Sad over a total of 40 days during spring and summer 2019 and summer 2022. The dataset comprised measurements of $PM_{2.5}$ and PM_{10} concentrations and meteorological parameters recorded every 5 minutes during work hours. The total dataset contained 4217 valid data points due to occasional interruptions in the device's operation.

- Training Data: 2924 data points were used for training the model.
- Testing Data: 1293 data points were used for testing the model's performance.
- Validation Data: The entire dataset was used for final validation to ensure the model's robustness and accuracy.

Before feeding the data into the ANN model, several preprocessing steps were carried out:

1. Data Cleaning: Removing any incomplete or erroneous records to ensure the quality of the dataset.
2. Normalization: Scaling the input features to a standard range (e.g., 0 to 1) to ensure that the model trains effectively and converges faster.
3. Feature Engineering: Creating new features or modifying existing ones to better capture the underlying patterns in the data.

4. Splitting Data: Dividing the dataset into training, testing, and validation sets to evaluate the model's performance accurately.

These preprocessing steps were crucial for enhancing the model's predictive power and ensuring that it generalizes well to new data.

By implementing this systematic approach, the ANN model was effectively developed to predict air pollutant concentrations, providing valuable insights for managing air quality at construction sites and protecting workers' health.

The procedure for calculating the importance of independent variables in the context of ANN (Artificial Neural Network) modeling for PM (Particulate Matter) concentration prediction involves several steps.

Data Preparation: Initially, the dataset is preprocessed to handle missing values, normalize features, and split into training and testing sets. This ensures that the model receives consistent and meaningful data.

Model Training: An ANN model is trained using the training dataset. The architecture of the ANN, including the number of layers, neurons per layer, activation functions, and learning rate, is designed to best capture the relationships between independent variables and PM concentration.

Feature Importance Calculation: After training the model, the importance of each independent variable is assessed. Several methods can be used, including: Permutation Feature Importance (This method involves randomly shuffling the values of each feature and observing the decrease in model performance. A larger decrease indicates higher importance); Partial Dependence Plots (PDP) show the marginal effect of each feature on the predicted outcome, allowing visualization of the relationship between each feature and PM concentration; and SHAP (Shapley Additive exPlanations) Values thatt provide a unified measure of feature importance based on cooperative game theory, attributing the prediction to individual features.

Understanding the importance of independent variables is crucial in ANN modeling for several reasons:

- Model Interpretation: It helps in interpreting how different features contribute to the predictions, providing insights into the underlying processes affecting PM concentration.
- Model Optimization: By identifying the most influential features, the model can be optimized by focusing on these features, potentially reducing complexity and improving performance.
- Feature Selection: It aids in selecting relevant features for model training, which can enhance model efficiency and generalizability by eliminating irrelevant or redundant features.

3. Results and discussion

The measurement results for the measurement period are displayed in Figures 4-8. The data provided are for work hours. By monitoring the concentrations of polluting substances ($PM_{2.5}$, PM_{10}), two sets of data were acquired. As depicted in Figure 4, these sets of data are presented as box plots (PM_{10} and $PM_{2.5}$).

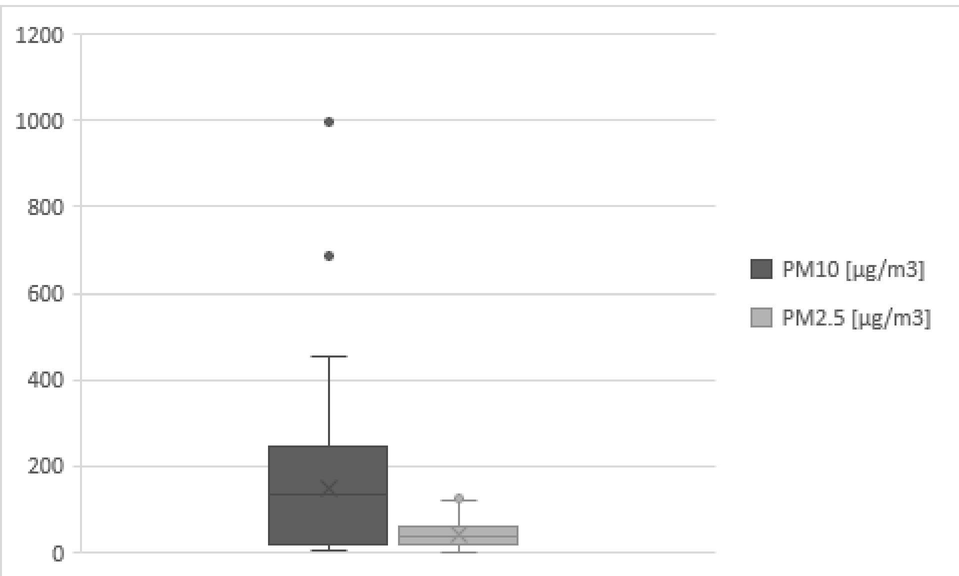

Figure 4. Mean concentration of PM_{10} and $PM_{2.5}$ in the air (minimum, 1st quartile, median and mean value, 3rd quartile, and maximum, as well as outliers are shown) at the construction site during excavation works in a period of 40 days (data from work hours).

The results indicate that $PM_{2.5}$ concentrations ranged from 1 to 125.39 µg/m3. The mean $PM_{2.5}$ concentration during work hours was 41.43 µg/m3, with a standard deviation of 27.16 µg/m3. During work hours, PM_{10} concentrations ranged from 2 to 996.73 µg/m3, with a mean concentration of 149.49 µg/m3 and a standard deviation of 124.43 µg/m3. Median Value for PM_{10} is 134.35 µg/m³ and for $PM_{2.5}$: 36.64 µg/m³. The highest concentrations of PM_{10} and $PM_{2.5}$ were measured during the night (non-work) hours, which could be attributed to the stable stratification of the atmosphere.

The analysis reveals a right-skewed distribution for both $PM_{2.5}$ and PM_{10}. The relationship between PM_{10} and $PM_{2.5}$, based on mean concentrations, was computed, showing that $PM_{2.5}$ constitutes approximately 27.7% of PM_{10}. With this calculated value, it becomes possible to indirectly estimate the emission sources. The smaller ratios indicate the dominance of coarse particles, which could be associated with natural sources of air pollution, construction activities, and so on.

As per the World Health Organization [33], $PM_{2.5}$ should not exceed an annual mean of 5 µg/m3 or a 24-hour mean of 15 µg/m3, while PM_{10} should not exceed an annual mean of 15 µg/m3 or a 24-hour mean of 45 µg/m3. Upon analyzing the average 24-hour means for $PM_{2.5}$ and PM_{10} at our construction sites, it is evident that PM pollution poses a significant health hazard, as the measured concentrations far surpass the recommended daily limits. The Republic of Serbia adopted the Law on Air Protection in 2009 to align with European Union (EU) legislation, although the EU standards are not as stringent.

Four sets of meteorological data, including wind speed, temperature, humidity, and atmospheric pressure, were collected. As depicted in Figures 5-8, these data sets are presented in box plots. The atmospheric pressure fluctuated between 999 and 1018 kPa during work hours, with an average of 1006.38 kPa and a standard deviation of 4.18 kPa. A left-skewed distribution was observed for the pressure data. The average work hours-mean humidity ranged from 18 to 91.1%, with a mean value of 39.48%. The standard deviation for humidity was recorded at 10.97%. The average work hours-mean air temperature spanned from 9 to 41.1°C, with the mean work hours-mean air temperature recorded at 26.69°C. The standard deviation for temperature was 6.07°C. Right-skewed distributions were observed for both humidity and temperature.

During work hours, the wind speed (24-hour mean) ranged from 0 to 4 m/s. The mean wind speed during work hours was calculated at 1.74 m/s, with a standard deviation of 1.36 m/s.

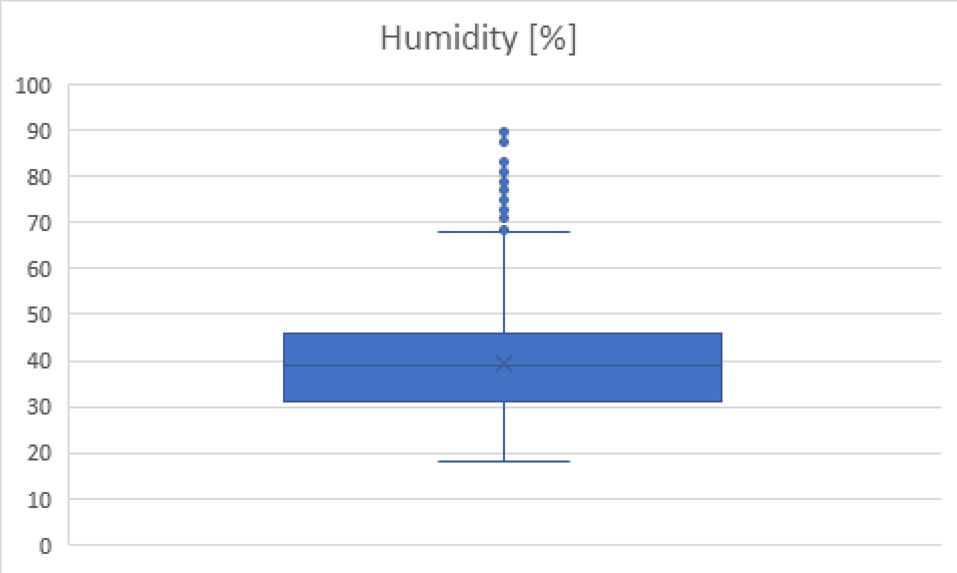

Figure 5. Atmospheric pressure (minimum, 1st quartile, median and mean value, 3rd quartile, and maximum, as well as outliers are shown) at the construction site during excavation works in a period of 40 days (data from work hours).

Figure 6. Humidity (minimum, 1st quartile, median and mean value, 3rd quartile, and maximum, as well as outliers are shown) at the construction site during excavation works in a period of 40 days (data from work hours).

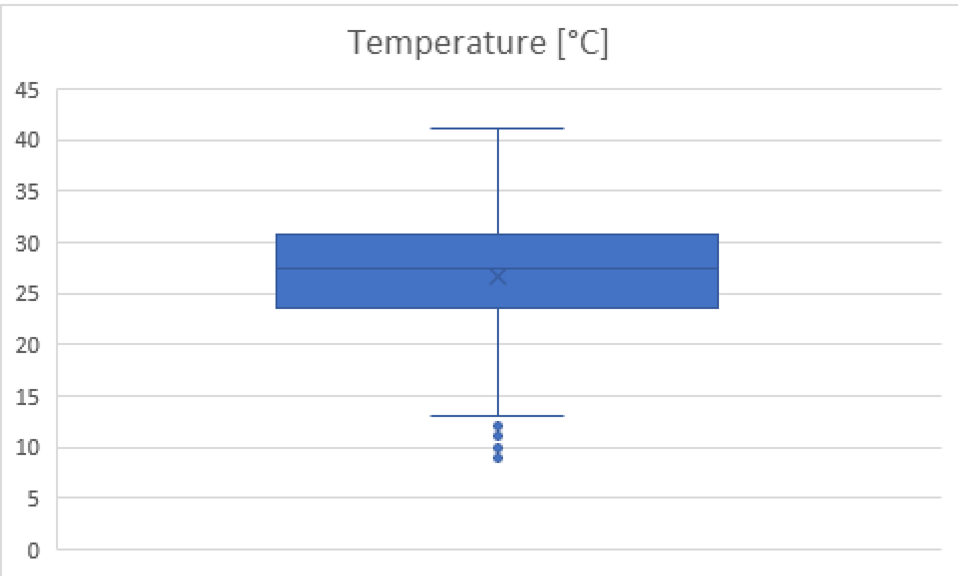

Figure 7. Temperature (minimum, 1st quartile, median and mean value, 3rd quartile, and maximum, as well as outliers are shown) at the construction site during excavation works in a period of 40 days (data from work hours)

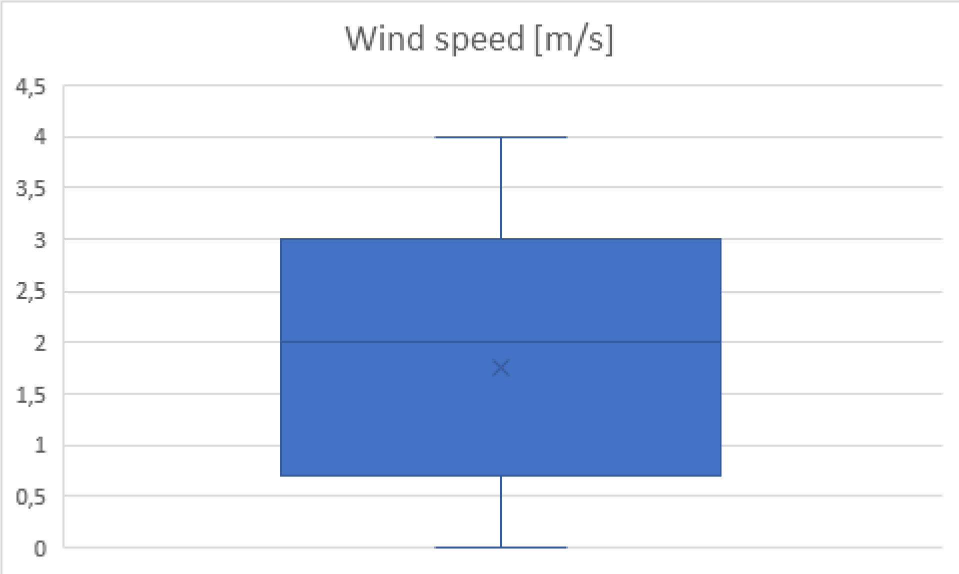

Figure 8: Wind speed at the construction site (minimum, 1st quartile, median and mean value, 3rd quartile, and maximum, as well as outliers are shown) during excavation works in a period of 40 days (data from work hours)

In Table 1, the Spearman correlation coefficients for the measured parameters are presented. The analysis suggests that the concentrations of PM_{10} and $PM_{2.5}$ did not show significant correlation with any meteorological factor. However, a very high correlation between $PM_{2.5}$ and PM_{10} was observed. This coefficient was selected considering the non-normal distribution of the data.

Table 1. Values of the Spearman correlation coefficient among the measured parameters.

	PM_{10}	**$PM_{2.5}$**	**Pressure**	**Humidity**	**Temperature**	**Wind speed**	**n**
PM_{10}	**1**	**0.99**	**-0.08**	**0.17**	**0.20**	**0.14**	**0.77**
$PM_{2.5}$		**1**	**-0.10**	**0.15**	**0.21**	**0.13**	**0.75**
Pressure			**1**	**0.76**	**-0.03**	**0.67**	**0.12**
Humidity				**1**	**-0.45**	**0.52**	**0.17**
Temperature					**1**	**0.20**	**-0.18**
Wind speed						**1**	**-0.66**
n							**1**

The absence of correlation between dust and the investigated meteorological factors could be attributed to the multifaceted nature of construction dust, influenced by numerous variables.

Construction activities, play a direct and substantial role in generating construction dust [24], overshadowing the impact of meteorological factors.

Throughout the monitoring period, the meteorological conditions remained stable, potentially mitigating the influence of these factors on construction dust. Pressure was included as a predictor due to its potential interactive effects with other variables, which can be effectively captured by the ANN model. Precipitation stands out as the primary meteorological factor affecting dust levels. Hence, it can be inferred that the emission of construction dust might not significantly align with any particular meteorological factor when these conditions remain relatively constant. This observation somewhat aligns with the findings of urban PM_{10} and $PM_{2.5}$ research [34,35].

Two prediction models were formulated using experimental data: the MLR (Multiple Linear Regression) model and the ANN (Artificial Neural Network) model. Out of the expected dataset, only 4217 valid data points were utilized due to occasional interruptions in the device's operation, such as power supply or internet connectivity disruptions during parameter measurements.

3.1. Prediction model for air pollutant concentrations: ANN-model

The ANN model for air pollutant concentrations employed 2924 data points for training, 1293 for testing, and the entire 4217 for model validation. The predictors used for PM_{10} and $PM_{2.5}$ predictions included wind speed (m/s), pressure (kPa), humidity (%), the number of working machines (-), and temperature (°C). The dependent variables were PM_{10} (μg/m3) and $PM_{2.5}$ (μg/m3), achieving an R-squared coefficient of determination of 0.674 for PM_{10} and 0.618 for $PM_{2.5}$. Detailed results are available in Table 2 and Figures 9-10.

Table 2. Model Summary (ANN)

Training	Sum of Squares Error		1016.634
	Average Overall Relative Error		.348
	Relative Error for Scale Dependents	PM10 [μg /m3]	.325
		PM2.5 [μg/m3]	.371
	Stopping Rule Used		1 consecutive step(s) with no decrease in error
	Training Time		00:00:00.171
Testing	Sum of Squares Error		428.856
	Average Overall Relative Error		.325
	Relative Error for Scale Dependents	PM10 [μg /m3]	.305
		PM2.5 [μg/m3]	.345

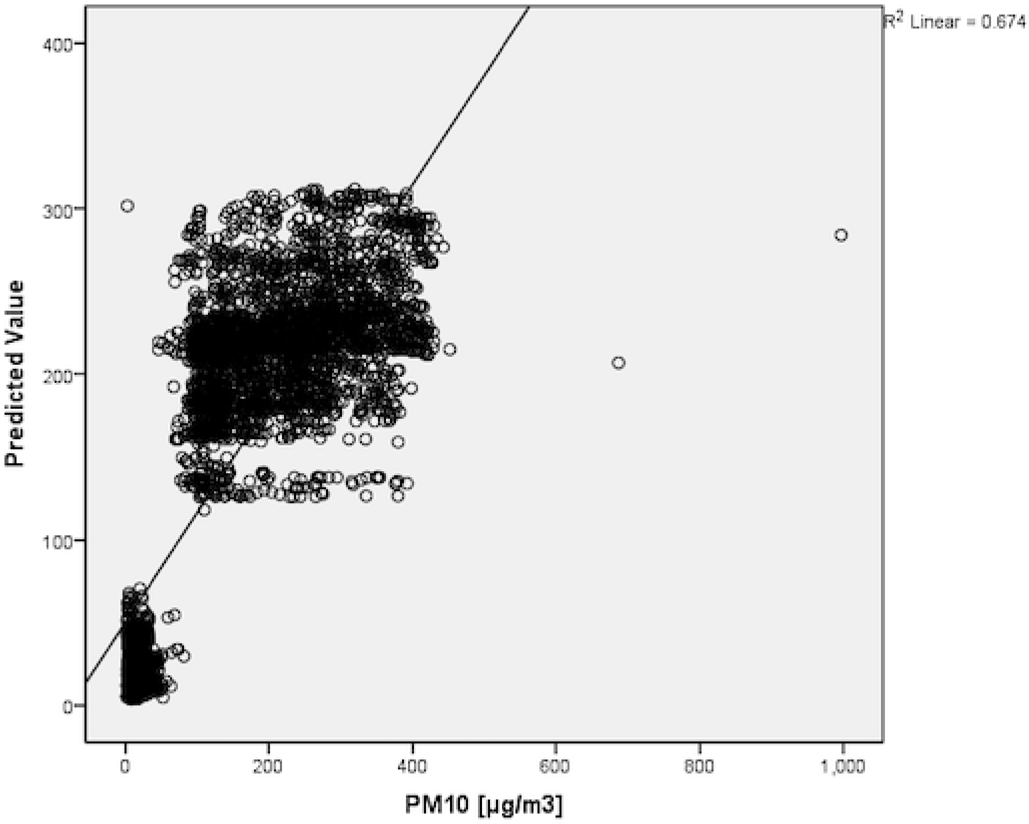

Figure 9. ANN model results for PM_{10} concentrations

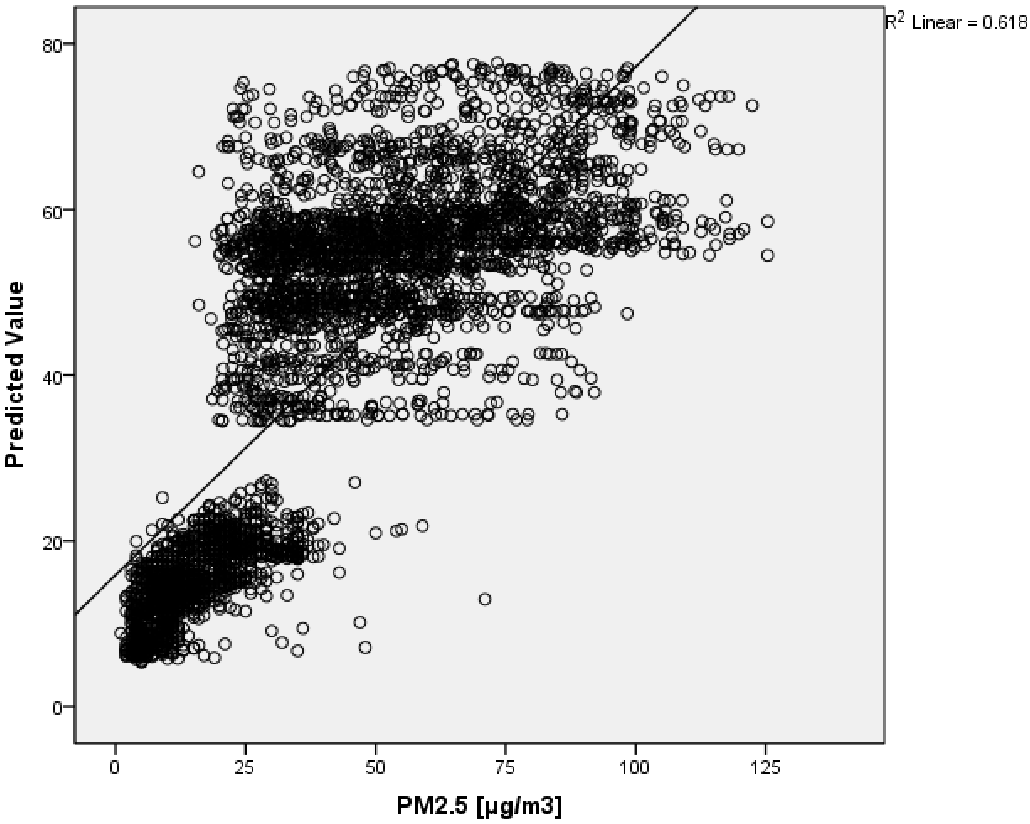

Figure 10. ANN model results for $PM_{2.5}$ concentrations

The significance and importance of independent variables are provided in Table 3.

Table 3. Independent Variables Importance

	Importance	Normalized Importance
Pressure [kPa]	.120	28.7%
Humidity [%]	.226	53.8%
Temperature [°C]	.157	37.4%
Wind velocity [m/s]	.076	18.2%
n	.420	100.0%

3.2. Prediction model for air pollutant concentrations: MLR-model

The predictors used in the MLR model for PM_{10} prediction were wind speed (m/s), pressure (kPa), humidity (%), the number of working machines (-), and temperature (°C). The dependent variable considered was PM_{10} (μg/m3). The model results for PM_{10} can be found in Tables 4-5 and Figure 11.

Table 4. Model Summary (Multiple R-coefficient of correlation, R Square-coefficient of determinantion, Std.Error-standard error of the estimate) for PM_{10} prediction.

Regression Statistics	
Multiple R	0.748730592
R Square	0.560597499
Adjusted R Square	0.560075767
Standard Error	82.54164473
Observations	4217

Table 5. Model Coefficients (t-t-statistics; Sig.-significance) for PM_{10} prediction

	Coefficients	Standard Error	t Stat	P-value
Intercept	-1208.232086	379.4818659	-3.183899403	0.001463644
Pressure [kPa]	1.362261636	0.373474952	3.647531459	0.000267976
Humidity [%]	-1.765589857	0.131690214	-13.40714551	3.62094E-40
Temperature [°C]	-3.070970825	0.267667702	-11.47307201	5.01113E-30
Wind velocity [m/s]	33.69620012	1.147378619	29.36798679	1.2465E-172
n	15.23008381	0.419976282	36.26415217	7.6464E-251

Similarly, for the model used in predicting $PM_{2.5}$, the predictors encompassed wind speed (m/s), pressure (kPa), humidity (%), the number of working machines (-), and temperature (°C), with $PM_{2.5}$ (µg/m3) as the dependent variable. The model results for $PM_{2.5}$ are provided in Tables 6-7.

Table 6. Model Summary (Multiple R-coefficient of correlation, R Square-coefficient of determinantion, Std.Error-standard error of the estimate) for $PM_{2.5}$ prediction.

Regression Statistics	
Multiple R	0.709117986
R Square	0.502848317
Adjusted R Square	0.502258016
Standard Error	19.16767605
Observations	4217

Table 7. Model Coefficients (t-t-statistics; Sig.-significance) for $PM_{2.5}$ prediction

	Coefficients	Standard Error	t Stat	P-value
Intercept	207.5146954	88.12261369	2.354840451	0.018576308
Pressure [kPa]	0.177363086	0.086727699	-2.045056992	0.040911271
Humidity [%]	-0.16602179	0.030580871	-5.428942558	5.98806E-08
Temperature [°C]	-0.407000931	0.062157325	-6.547915845	6.53527E-11
Wind velocity [m/s]	7.283477184	0.266442252	27.33604427	1.3412E-151
n	3.27352605	0.097526156	33.56562159	4.3098E-219

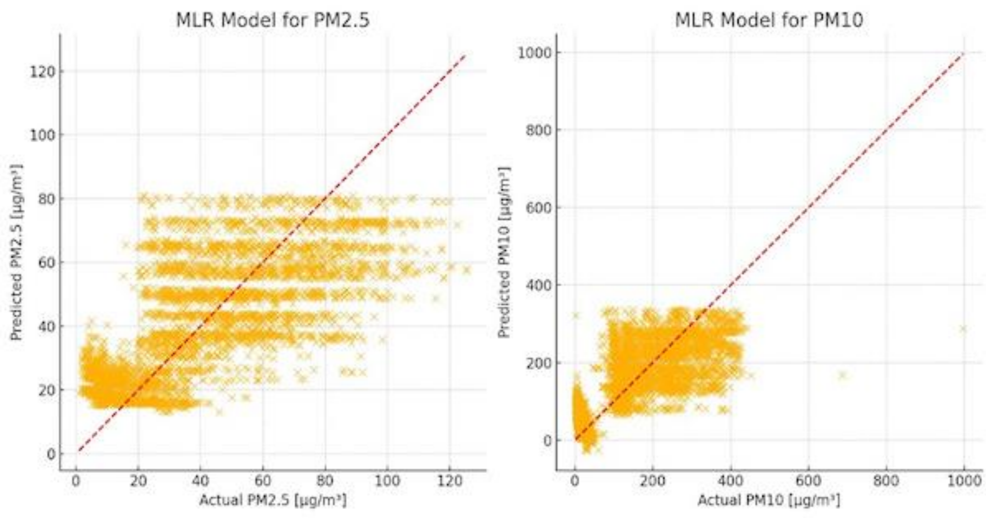

Figure 11. MLR model results for $PM_{2.5}$ and PM_{10} concentrations

Upon examination of the applied models (Tables 2-7) and Figures 9-11, it was observed that, based on the R-squared values, the ANN model demonstrated a higher level of agreement with measured air pollutant concentrations compared to the MLR model.

The implementation of predictive models for particulate matter (PM) concentrations can significantly enhance the operational efficiency and safety of construction sites. Construction site managers can leverage real-time data and predictions from these models to make informed decisions that optimize site operations and improve air quality. Key strategies for practical implementation include:

Real-time Monitoring and Alerts: By integrating sensors and predictive models, construction site managers can receive real-time alerts on PM concentration levels. This enables immediate action to mitigate high PM levels, such as adjusting work schedules or using dust suppression techniques.

Operational Adjustments: Predictive models can identify periods of high PM concentration, allowing managers to plan high-dust activities during times when PM levels are predicted to be lower. This can include rescheduling heavy machinery use or adjusting the timing of demolition activities.

Health and Safety Measures: With predictive data, managers can implement targeted measures to protect worker health. This includes providing personal protective equipment (PPE) during periods of high PM concentration and establishing safe zones with lower PM levels for worker breaks.

Environmental Compliance: Predictive models assist in maintaining compliance with environmental regulations by providing evidence-based data on PM levels. This data can be used to demonstrate adherence to air quality standards and reduce the risk of regulatory fines.

Stakeholder Communication: Real-time data and predictions can be shared with stakeholders, including workers, community members, and regulatory bodies, to foster transparency and trust. Informing stakeholders about the measures taken to control PM levels can enhance community relations and worker satisfaction. [36,37,38]

The presented work focuses on using an IoT-based system integrated with an Artificial Neural Network (ANN) model to monitor and predict $PM_{2.5}$ and PM_{10} concentrations at construction sites. The study involves real-time data collection using various sensors and employs ANN for better prediction accuracy compared to traditional methods like Multiple Linear Regression (MLR).

Novelty of the Presented Work Is in:

1. Specific Application: The novelty lies in applying these techniques specifically to construction sites, which have different pollution dynamics compared to surface mines.
2. Comprehensive Approach: Our work not only predicts PM concentrations but also emphasizes the impact of meteorological parameters on these predictions.
3. Real-time Data Integration: The integration of IoT systems for continuous, real-time monitoring at construction sites is a significant advancement, as previous studies often rely on periodic or batch data collection.
4. Model Comparison: By comparing the performance of ANN with MLR, this study provides insights into the benefits of using more sophisticated machine learning models for better prediction accuracy.

In conclusion, while similar studies exist, the specific focus on construction sites, the comprehensive integration of meteorological data, and the detailed model performance comparison contribute to the novelty and significance of this research.

For comparison with recent research as (Tripathi et al., 2024), it is clear that this research also employs IoT and machine learning techniques for dust monitoring but focuses on surface mine sites. Similar to our study, it uses a network of IoT sensors for real-time data collection. However, it integrates advanced machine learning models such as Support Vector Machines (SVM) and Random Forests (RF) for prediction. The study reports high prediction accuracy, highlighting the effectiveness of combining IoT with machine learning for environmental monitoring. [39]

4. Conclusion

Meteorological data and construction pollutant concentrations in the air were collected to determine the main factors affecting construction site dust concentrations, which could provide a basis for reducing the impact of dust generated by construction activities on the construction area.

On-site monitoring of a construction site in Belgrade and Novi Sad showed the dust concentration during construction activities is relatively high. The work hour mean PM_{10} concentration in the air on-site was 149.49 μg/m^3, and the work hour mean $PM_{2.5}$ concentration was 41.43 μg/m^3. Analyzing the workhour data for $PM_{2.5}$ and PM_{10} concentrations in the air, it can be concluded that PM presents great health hazard due to the concentrations being far higher than the prescribed daily limits. Regarding the main factors affecting construction dust concentrations, the results show these concentrations were not significantly correlated with any single meteorological factor, although these factors changed during the study, but concentrations were significantly correlated with number of working machines. Considering the very low correlation between the PM concentrations and meteorological parameters, MLR and ANN models were applied for prediction purposes. The ANN model demonstrated a stronger agreement with measured air pollutant concentrations compared to the MLR model.

As conclusion, we suggest future research directions by integrating additional environmental factors. This includes incorporating elements such as noise, vibration, and chemical pollutants. By expanding the scope of environmental monitoring to include these factors, future research can provide a more comprehensive analysis of environmental impacts. This approach aims to deliver more detailed and accurate data, facilitating informed decision-making for the preservation and enhancement of environmental conditions.

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