# **FROM COAL TO NATURAL GAS: ANALYZING PM2.5 CONCENTRATION CHANGES CAUSED BY DISTRICT HEATING PLANT FUEL SWITCH**

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#### **---** *ABSTRACT:*

*Kragujevac is one of the biggest industrial and educational centers in the Republic of Serbia with more than 150000 citizens. For many years this city has struggled with intensive air pollution caused by particle matter (PM), consequently influencing the environment, citizens' health, and life quality. One of the biggest sources of pollution in this city is the heating plant which was powered by coal until heating season 2022/2023, and from heating season 2022/2023 it operated using natural gas. By utilizing a machine learning approach, this study analyzes how the transition of the heating plant from coal to natural gas affected the PM2.5 pollution.* 

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*Keywords: air pollution, environment, human health, life quality*

## **1. INTRODUCTION**

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Causing around 6.7 million deaths annually [1], air pollution is currently one of the biggest problems that people are facing. According to IQAir [2], the most dangerous pollutants are the particulate matter<sup>1</sup> (PM). Airborne particles (PM) can be divided into two groups based on their size: i)  $PM_{10}$  – particles with a diameter under 10 µm and ii)  $PM_{2.5}$  – particles with a diameter under 2.5  $\mu$ m. Because of their size, PM<sub>2.5</sub> can easily enter the human bloodstream through the lungs, consequently causing respiratory and cardiovascular problems, and cancer [3]. It is estimated that this pollutant causes around 4 million premature deaths annually [4].

 $PM_{2.5}$  often originates from different emission sources, simultaneously varying in chemical composition. Overall, the process of combustion of gasoline, oil, diesel fuel, or wood is the main producer of  $PM_{2.5}$  [5]. Tessum et al. [6] analyzed sources of ambient  $PM_{2.5}$  in 96 global cities. The results show that in 46%, 27%, and 10% of cities, the biggest sources of  $PM_2$ <sub>5</sub> were industry, energy transformation, and residential and commercial activities, respectively.

 $<sup>1</sup>$  Floating particles in polluted air which includes dirt, dust, smoke, and tiny drops of liquid</sup>

Kragujevac is one of the biggest administrative, educational, and industrial centers in the Republic of Serbia with more than 150000 citizens. Thus, this city was facing an air pollution crisis a few years in a row. The main sources of air pollution in the city of Kragujevac are:

- i. District heating plant;
- ii. Residential heating systems (mainly based on coal or solid biomass) in combination with low-efficiency buildings;
- iii. High-intensity traffic with an absence of ring roads;
- iv. Coal-powered power plants the closest of which is at a distance of 30 km;
- v. Highway A1 (Belgrade Niš) and other regional roads.

In the heating season 2022/2023 the district heating plant in Kragujevac underwent a fuel switch. Until (and including) the heating season 2021/2022, the heating plant operated using coal as fuel, afterward the heating plant switched to natural gas. According to Zeng et al. [7] cities that have undergone similar fuel shifts have witnessed a significant drop in air pollution. Using a machine learning approach, this study analyzed how the coal-tonatural gas transition of the heating plant influenced the air quality in the city of Kragujevac.

### **2. MATERIAL AND METHODS**

The observed citizen-installed  $PM_{2.5}$  sensor in Kragujevac measured 28 months of data (November 2021 – February 2024). Fig. 1 shows the location of the observed sensor and heating plant.



**Fig. 1.** Observed sensor and heating plant locations

The aforementioned sensor (SDS 011 Sensor developed by Nova Fitness, a spin-off of the University of Jinan, China) is part of a network of sensors installed by citizens united in efforts to improve air quality (the sensor can be accessed through https://sensor.community/en/ website).

Measurements were divided into two datasets, DS1: November 2021 – March 2022, and DS2: April 2022 – February 2024. Dataset DS1 contains measurements for the heating season 2021/2022 when the heating plant was powered by coal, while dataset DS2 contains measurements for the heating seasons 2022/2023 and 2023/2024 when the heating plant was powered by natural gas. This study is based on the machine learning approach, the idea was to use the dataset DS2 to train a predictive model adjusted to the current scenario – a heating plant powered by natural gas. Afterward, the trained model was fed with parameters for the heating season  $2021/2022$  to estimate the hourly  $PM_{2.5}$ concentrations for the scenario that in the heating season  $2021/2022$  the heating plant operated on natural gas instead of coal. Finally, to analyze the effect of the heating plant transition from coal to natural gas, the actual and estimated hourly  $PM_{2.5}$  concentrations for the heating season 2021/2022 were compared. Fig. 2 shows the framework of this research.



**Fig. 2.** The framework of the research

A variety of factors generally influence airborne  $PM_{2.5}$  concentrations. Hernandez et al. [8] analyzed the effect of outdoor temperature on  $PM_{2.5}$  concentrations and they induced that with lower temperatures the concentrations rise due to intense consumption of fuels needed for heating. Relative humidity is a factor that strongly correlates to  $PM_{2.5}$ concentrations [9]. According to X Li et al. [10] high atmospheric pressures cause downward airflow, consequently increasing particle concentrations. Wind speed is another climatic factor with a significant influence on airborne  $PM_{2.5}$  concentrations. Wang and Ogawa stated that the correlation between  $PM_{2.5}$  concentration and wind speed is negative when the wind speed is under  $3 \text{ m/s}$ , but positive when it is above  $3 \text{ m/s}$  [11]. Table 1 shows the content of observed datasets.

Data type	<b>Parameter</b>	Unit	<b>Source</b>
Dependent variable	PM <sub>2.5</sub> concentration	$\mu$ g/m <sup>3</sup>	sensor.community archive [12]
Temporal data	Month		
	Hour	h	
Climate data	Outdoor temperature	$^{\circ}C$	Nasa data access viewer [13]
	Relative humidity	%	
	Atmospheric pressure	kPa	
	Wind speed	m/s	

**Table 1.** Content of observed datasets

### **3. PREDICTIVE MODEL**

According to the reviewed literature, the chosen parameters influencing the airborne PM2.5 concentrations are month, hour, outdoor temperature, relative humidity, wind speed, and atmospheric pressure. Graphical interpretation of the developed predictive model is shown in Fig. 3.



**Fig. 3.** Graphical interpretation of the developed predictive model

Before model training, the dataset was preprocessed. This includes filling in the missing data and synchronizing the concentration and climate data on an hourly level. Afterward, the preprocessed dataset was divided into a training dataset (80% of data) and a testing dataset (20% of data). The model was trained using the CatBoost algorithm. According to Hancock and Khoshgoftaar [14] CatBoost is a tree-based algorithm that can be used for regression and classification. Additionally, this algorithm showed good predictive performance in the case of  $PM_{2.5}$  concentration predictions [15][16].

In the case of this study, CatBoost performed well, resulting in an  $\mathbb{R}^2$  score of 0.817 and a mean absolute error (MAE) of 4.877  $\mu$ g/m<sup>3</sup>. Fig. 4 represents an actual versus predicted scatter diagram.



**Fig. 4.** Actual versus predicted scatter diagram

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#### **4. RESULTS**

Fig. 5 contains hourly PM<sub>2.5</sub> concentrations for the heating season 2021/2022.



Based on the given figure it can be stated that:

- Citizens of Kragujevac were exposed to highly polluted air in the heating season 2021/2022;
- For around 668 hours the concentration of  $PM_{2.5}$  exceeded 45  $\mu$ g/m<sup>3</sup>, for 96 hours it exceeded 100  $\mu$ g/m<sup>3</sup>, and for 16 hours it exceeded 150  $\mu$ g/m<sup>3</sup>.
- Average concentration of PM<sub>2.5</sub> for heating season 2021/2022 was 29  $\mu$ g/m<sup>3</sup>.

After training and evaluating the predictive model on dataset DS2 containing heating seasons 2022/2023 and 2023/2024 when the heating plant operated using natural gas, the model was fed with data containing influencing parameters (Fig. 3) for the heating season  $2021/2022$  to estimate the PM<sub>2.5</sub> concentrations for the imaginary scenario if the heating plant worked on natural gas instead of coal. Estimated hourly concentrations for the heating season 2021/2022 are shown in Fig. 6.

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Fig. 6. Estimated hourly PM<sub>2.5</sub> concentrations for heating season 2021/2022

According to Fig. 6, it can be stated that:

- Estimated values are indicating a significant increase in air quality;
- For around 474 hours the concentration of  $PM_{2.5}$  exceeded 45  $\mu$ g/m<sup>3</sup>, for 2 hours only it exceeded 100  $\mu$ g/m<sup>3</sup>, and there were no moments when the concentration exceeded  $150 \text{ µg/m}^3$ .
- On average,  $PM_{2.5}$  concentrations are around 10% lower. Yet, during peak hours (when the concentrations are higher than  $75 \mu g/m^3$ ) the estimated improvement in air quality is 50%.

To better understand the interdependence of the population's exposure to emissions in the city and the reading from the sensor, it is necessary to take into account the direction of the wind (whether it moves from the heating plant to the sensor or vice versa, or in some other direction). In this sense, we can say that the mentioned estimated progress in air quality of 10% is certainly lower than the one that was realistically achieved. The reason is the position and distance of the sensor from the heating plant. Furthermore, it is to be expected that the actual improvement of air quality is greater than that estimated in this study, and this especially refers to the improvement that will be experienced by citizens living in locations located within 2 km of the heating plant, i.e., those located closer to the heating plant than the location of the sensor (Figure 1). Overall, it can be concluded that the transition of the heating plant from coal to natural gas had a significant influence on air quality in the city of Kragujevac. The differences are noticeable through a lower number of highly polluted hours and lower seasonal average  $PM_{2.5}$  concentration. Fig. 7 shows the graphical comparison of actual and estimated hourly concentrations for the heating season 2021/2022.



**Fig. 7.** Actual versus estimated hourly concentrations for the heating season 2021/2022

#### **3. CONCLUSION**

Kragujevac, one of the biggest cities in the Republic of Serbia, has been facing an air pollution problem for decades. In 2022, the heating plant in Kragujevac underwent a significant modification – a transition from coal to natural gas. Until (including) the heating season 2021/2022, the heating plant was powered by coal, afterward, it was powered by natural gas.

As shown in recent literature, a significant change in air quality happened in cities that have undergone similar transitions. This paper aimed to quantify the improvement in air quality in the city of Kragujevac that occurred after that fuel switch. To achieve this, the research utilized a machine-learning approach. Namely, the dataset combining PM2.5 concentration and climate hourly information for the heating seasons 2022/2023 and 2023/2024 was used to train a predictive model based on the CatBoost regression algorithm. After training and evaluating the predictive model, it was fed with hourly climate data for the heating season  $2021/2022$  to estimate the hourly  $PM_{2.5}$  concentrations for the imaginary scenario where the heating plant was powered by natural gas instead of coal. Afterward, actual and estimated hourly  $PM_{2.5}$  concentrations were compared. The comparison showed that the coal-to-natural gas transition had significant effects on air quality. Namely, the number of hours exceeding the concentration of 45  $\mu g/m^3$  decreased from 668 to 464, exceeding 100 μg/m<sup>3</sup> decreased from 96 to 2, and there were no moments when the concentration exceeded 150  $\mu$ g/m<sup>3</sup> in comparison to 16 hours for the situation "before" the switch to natural gas. Additionally, the average  $PM_{2.5}$  concentration decreased from 29 to 26  $\mu$ g/m<sup>3</sup>.

#### **4. ACKNOWLEDGMENT**

The authors acknowledge the Ministry of Science, Technological Development and Innovation of the Republic of Serbia for the support through Contract No. 451-03- 65/2024-03/ 200107.

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