processes

Review

A Review on Pollution Treatment in Cement Industrial Areas: From Prevention Techniques to Python-Based Monitoring and Controlling Models

Xinghan Zhu [1], Jinzhong Yang [2], Qifei Huang [3] and Tao Liu [1,*]

[1] College of Environmental Science and Engineering, Ocean University of China, Qingdao 266100, China
[2] Solid Waste Risk Management Theory Research Office, Chinese Research Academy of Environmental Sciences, Beijing 100012, China
[3] State Environmental Protection Key Laboratory of Hazardous Waste Identification and Risk Control, Chinese Research Academy of Environmental Sciences, Beijing 100012, China
* Correspondence: liutaoouc@163.com

Abstract: Anthropogenic climate change, global warming, environmental pollution, and fossil fuel depletion have been identified as critical current scenarios and future challenges. Cement plants are one of the most impressive zones, emitting 15% of the worldwide contaminations into the environment among various industries. These contaminants adversely affect human well-being, flora, and fauna. Meanwhile, the use of cement-based substances in various fields, such as civil engineering, medical applications, etc., is inevitable due to the continuous increment of population and urbanization. To cope with this challenge, numerous filtering methods, recycling techniques, and modeling approaches have been introduced. Among the various statistical, mathematical, and computational modeling solutions, Python has received tremendous attention because of the benefit of smart libraries, heterogeneous data integration, and meta-models. The Python-based models are able to optimize the raw material contents and monitor the released pollutants in cement complex outputs with intelligent predictions. Correspondingly, this paper aims to summarize the performed studies to illuminate the resultant emissions from the cement complexes, their treatment methods, and the crucial role of Python modeling toward the high-efficient production of cement via a green and eco-friendly procedure. This comprehensive review sheds light on applying smart modeling techniques rather than experimental analysis for fundamental and applied research and developing future opportunities.

Keywords: cement plant; pollution treatment; pollution monitoring; modeling; python

Citation: Zhu, X.; Yang, J.; Huang, Q.; Liu, T. A Review on Pollution Treatment in Cement Industrial Areas: From Prevention Techniques to Python-Based Monitoring and Controlling Models. *Processes* **2022**, *10*, 2682. https://doi.org/10.3390/pr10122682

Academic Editor: Carlos Sierra Fernández

Received: 18 October 2022
Accepted: 27 November 2022
Published: 13 December 2022

1. Introduction

The urbanization and industrialization of communities have led to environmental pollution and global warming concerns around the world. Among diverse polluting industries, cement complexes are one of the most critical zones under the red class [1–3]. After water, cement is ranked as the most consumed substance in developing and developed societies. Cement is used in construction, civil engineering [4,5], decorative applications [6–8], medical and dental fields [9–11], and many more. Statistics illustrated the production of about 3600 million metric tons of cement in 2021 by several countries: China, India, Vietnam, the United States, Turkey, Indonesia, Brazil, Iran, Russia, Japan, Mexico, South Korea, and Egypt [12,13]. Based on the predictions, cement consumption will reach up to 5800 million metric tons by 2050, as presented in Figure 1a [12]. Meanwhile, the CO_2 pollution emitted by these plants constitutes around 10–15% of the total CO_2 released into the environment per year among the main industries, including refineries, iron and steel, high-purity sources, and other sectors (see Figure 1b) [13]. The extraction of limestone and various production procedure of cement cause hazardous impacts on the environment and degradation of landscapes, resulting from dust pollutants and overburdened material dumping [14,15]. The cement industries generate a wide range of contaminations affecting human health directly and indirectly. The emission of the particulate materials, oxides, sulfides, and other contaminants through the output air into the environment is potentially able to affect human well-being. The released wastewater and solid wastes can pollute the soil, drinking water, and agricultural products, which impact human life indirectly. Therefore, the prediction, monitoring, and treatment of the resulting pollution from cement plants have been initiated for several years [16,17]. It is noteworthy that solar calcination has been extremely focused in developed countries in recent years to dramatically reduce CO_2 emissions. Using such progressed systems efficiently decreases the need for pollution monitoring systems while approaching the solar calcination seems to be not realistic in the near future [18].

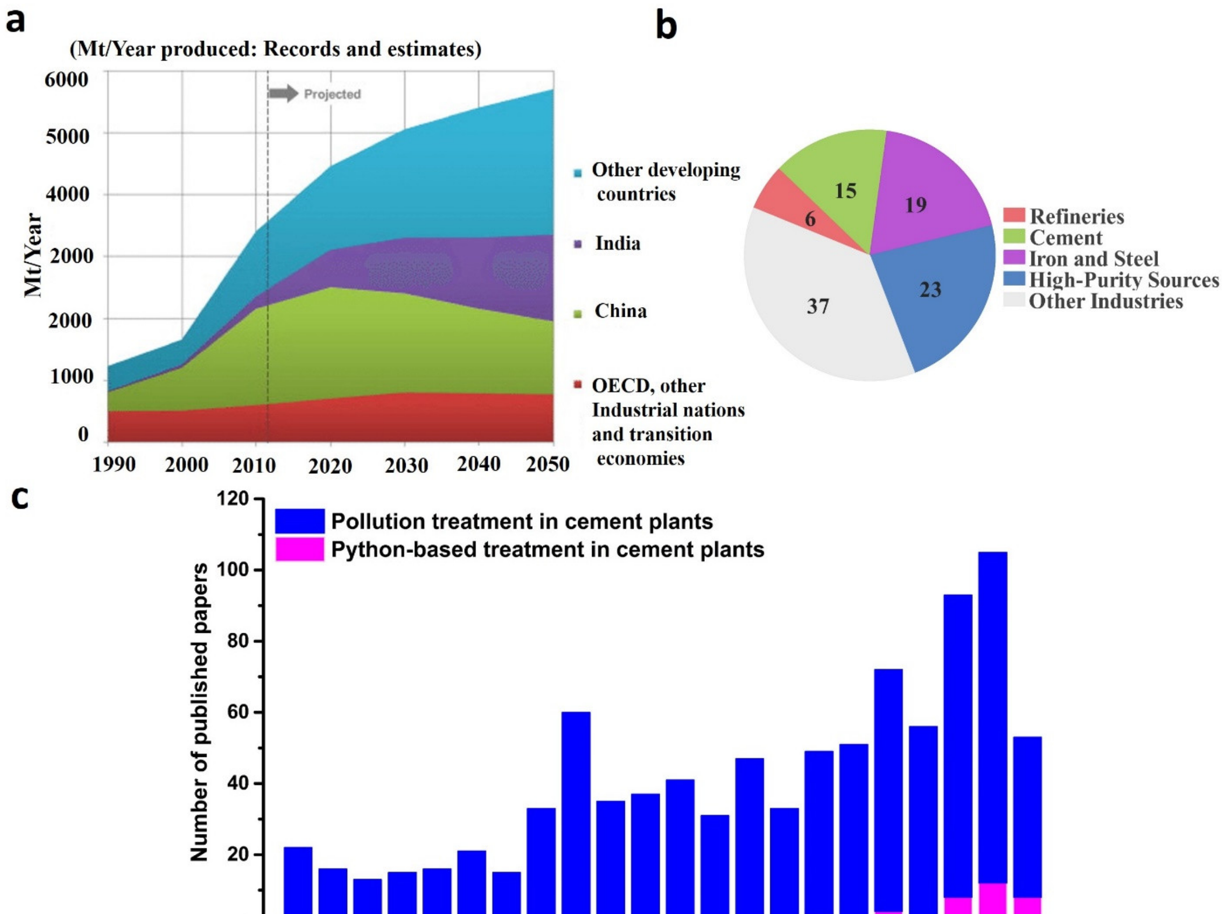

Figure 1. (**a**) Production of cement from 1990 up until now and the predicting the cement manufacturing up to 2050 (reprinted under open access license from Ref. [12]), (**b**) the emitted CO_2 pollution from various industries, (**c**) the number of Scopus-indexed papers regarding the pollution-treatment in the cement industries, and the number of Scopus-indexed published research to treat pollution in the cement industries using Python.

To evaluate the focus of researchers on treating the pollution released by the cement plants and other sectors, the studies published in the Scopus and Web of Science were assessed by the following search strings: “pollution AND cement plants”, “cement plants AND Python”, “pollution AND modelling”, and “pollution AND cement plant AND Python.” After screening the papers, the English papers published after 2000 based on the modeling techniques were included. Accordingly, several attempts have been carried out in this era using modeling investigations based upon various methods, such as experimental [19,20], mathematical [21,22], and machine learning [23–25] techniques. Software, intelligent models, and sensors are increasingly applied in today's technology-based age to monitor and control air and water quality. Streeter et al. [26] introduced the Streeter-Phelps model to monitor the water quality in the Ohio River. The research in this era has been continued till now regarding the importance of environmental issues as well as the high efficacy of the modeling toward the prediction and monitoring of contaminations. As an example, Chapra et al. [27] modified and developed the classical Streeter-Phelps model to generalize the obtained water quality data to the world's rivers. Among various introduced models, Python is extensively employed in the fields relating to environmental concerns. The open-source nature, accessibility of the online databases, and feasible readability of this modeling program potentiate advanced mathematical performance, the development of machine-learning-based models, and the prediction of environmental data. For example, Kumar et al. simulated air pollution using Python in Indian cities, showing a high accuracy for the Gaussian Naïve Bayes model [28].

Based on the above considerations, we concentrated on treating various pollutants emitted by the cement industries, using the machine learning model obtained via Python. Figure 1c shows the number of published studies on the pollution-treatment in cement complexes using various methods. In addition, employing Python-based models for improving the product quality and reducing pollution in cement industries is displayed in Figure 1c. According to the number of publications, the attention gained by the pollution-treatment from these plants has increased from year to year. In addition, the Python-related models have been progressively applied to overcome this challenge in recent years, confirming the importance of this critical issue.

According to the critical concerns stated, we overviewed the pollution resources and their impactful treatments in the following section of this paper. Then, the defined models and simulations toward the controlling and treatment of the pollution from the cement plants focusing on Python are described and evaluated. Finally, limitations, challenges, and future remarks in this field are highlighted.

2. Overview of Pollution Emission from Cement Industries

In general, four steps are followed to manufacture cement in industries, including the extraction of the raw materials, processing of the provided substances calcining, and then clinker grinding. The essential raw materials for cement production are obtained through mining. Limestone ($CaCO_3$), alumina (Al_2O_3), silica (SiO_2), and iron (Fe) are accounted as the starting materials in such industries [28,29]. Of note, the mining stage is followed by quarrying procedures (e.g., blasting, drilling, handling, excavating, and so on) to obtain fine materials. Afterward, the prepared raw materials are mixed and ground to achieve cement with the correct chemical configuration and appropriate mechanical characteristics. In this phase, dry, wet, and semidry processes are employed. In summary, impact, drum, and paddle-equipped rapid dryers are applied to dry the raw materials before grinding. Then, water is introduced into the materials during grinding as the wet procedure, and finally, the pellet of the materials is formed by adding water into a pelletizing device. In the next step, cement clinkers are produced via a chemical reaction between the raw materials using a heating procedure, including pre-heating, calcining, and burning [30,31]. The thermal step causes the formation of spherical nodules of clinkers with diameters in the range of 0.3 to 5.0 cm. In the end, a cooling process is employed to approach high-quality materials, commonly using airflow. Notably, a final grinding process as a finish milling is applied before usage to downsize and sort the obtained particles [31,32].

During all production phases, pollutant materials are emitted to various media resulting in human health problems. These adverse effects could be transmitted to humans by direct (air inhalation) and indirect ways (distribution in soil, water, etc.). According to the literature, respiratory, gastrointestinal, lymphatic, and central nervous system impairments are the most reported health issues caused by the aforementioned pollutants [16,31,33,34]. Figure 2 describes the drawbacks of cement complexes dealing with environmental problems. To overcome the downsides, the inherent physical–chemical features of the various pollutants, their degradability properties, and many more characteristics should be accurately evaluated. The pollutant materials emitted from the cement industries are classified into five categories: solid waste, wastewater, air emission, noise pollution, and waste fuels, which are summarized in the following.

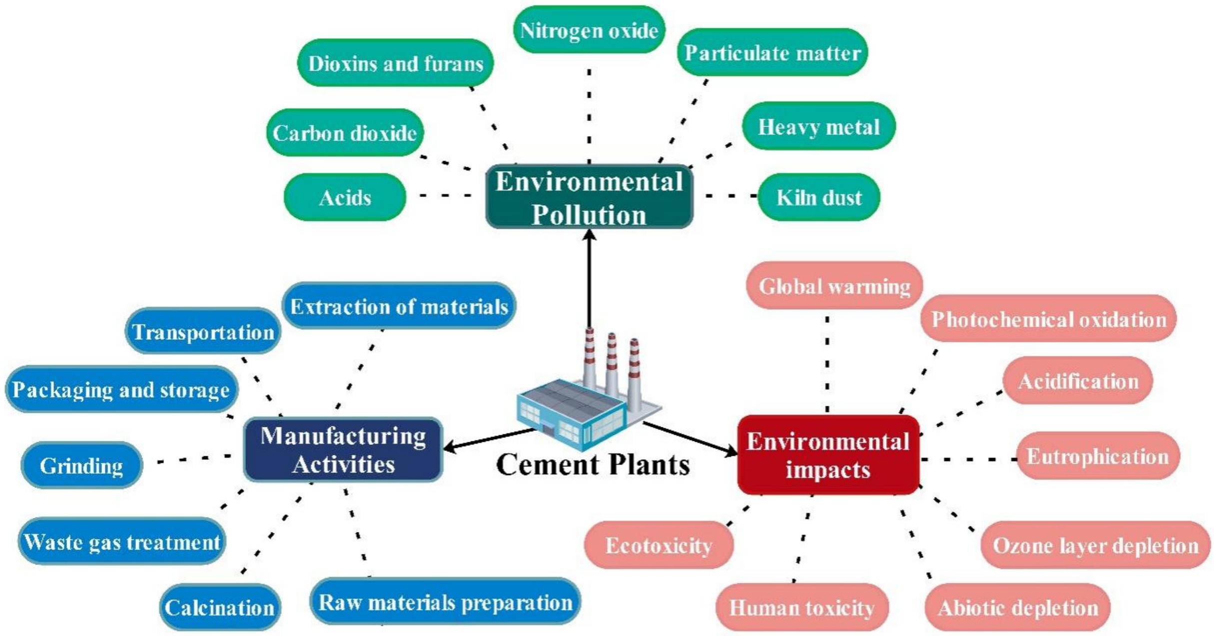

Figure 2. Potential resources of the pollution from the cement industrial zones.

2.1. Solid Waste

In various cement manufacturing, fly ash, rock spoil, and dust are generated as solid wastes. Cement bypass dust is the main solid waste in cement industries collected from the surface of the dust filter membranes. These materials contain pollutant particles with alkaline behavior (pH~11–12) and a diameter of 1 to 10 µm, known as particulate matter (PM). The size and chemical composition of the PM is driven by the weather and emission source. The formation of finer particles makes the pollutant treatment more challenging. Therefore, the PM pollutant is mainly divided into two classes of PM_{10} and $PM_{2.5}$, respectively attributed to the particles with a diameter below 10 and 2.5 µm. Because of the high volume of this pollutant, it results in most health and environmental issues. In addition, these particles can penetrate deeper into the lungs and harm human health. According to the analysis, Al_2O_3, Fe_2O_3, and MgO heavy metals comprise a significant ratio of the solid waste content [35,36]. These compounds are able to harm biotic and abiotic elements in the environment. Therefore, treating the mentioned waste components is essential to prevent their subsequent emissions into the air, water, and soil. Based on the projections, solid waste would increase up to 2.2 billion tons per year by 2025. Correspondingly, 40% of the PM emission is linked to cement manufacturing [37,38].

2.2. Wastewater

Water is applied in different sequences of cement production, such as cooling systems and washing processes. Most of the water amount used is in a non-contact form, such as processes of kiln bearing, grinding devices, thermal pipes, compressors, and finishing steps. At the same time, water is employed to feasibly grind the materials in a contact form. Additionally, the raw materials are required to be washed before processing. During the material washing, limestone and iron particles, as well as suspended solids, are entered into the water, leading to water pollution. As an eco-friendly solution, the applied washing water should be neutralized, followed by waste particle sedimentation to remove toxic materials and reuse them in the production cycle [39–42]. The quality of wastewater in cement industries is determined using four main indexes, including chemical oxygen demand (COD), biochemical oxygen demand (BOD), total suspended solids (TSS), and pH. Based on the standards, the BOD/COD ratio should be below 1 with a COD value of 250 mg/L. Therefore, reducing this ratio can help to approach a more environmentally friendly production cycle. In addition, the proper pH of the wastewater could be in the range of 6.5 to 9, and the standard TSS should be below 100 mg/L [43,44]. Compared with other pollutant materials released from cement plants, water waste has received the lowest attention due to its low consumption and environmental hazards during the production procedure. Therefore, it is not focused much in this paper due to the non-sufficient literature in this area [45].

2.3. Air Pollutant Emission

Air pollution is accounted for one of the biggest downsides of cement factories worldwide. The emission of dust, hydrogen chloride, nitrogen oxides, sulfur dioxides, greenhouse gases, ammonia, etc. during cement production into the environment causes air pollution. According to the statistics, cement plants produce 500,000 tons of SO_2, NO_x, and CO pollutants into the atmosphere per year. As an example, dust originates from packing and storage steps, transportation machines, and milling equipment. Additionally, nitrogen oxides are generated from fuel combustion in cement kilns. Moreover, the presence of sulfur in raw materials as well as the combustion of sulfur compounds in fossil fuels leads to the release of SO_2 into the atmosphere. The greenhouse gas is also entered into the air through heating the calcium carbonate, limestone preparation, and burning fuels [46,47]. Cement industries are known as the second highest industrial source of CO_2 release. The presence of these pollutants in the air causes acid rain, global warming, health problems, crop yield reduction, and decreased biodiversity. Therefore, the WHO has emphasized crabbing the emission of pollutant substances via employing efficient air treatments [48–50]. Based on the data obtained from the Chinese laboratories, 30% of PM contaminations, 10% of nitrogen oxides, and 4% of SO_2 in the atmosphere are resulted from cement plants. Various indexes have been reported to date for indicating air pollution around the cement industrial areas. The air quality index (AQI) is the most well-known parameter obtained through periodic measurements (daily, weekly, monthly, or annually) of PM, oxides, and greenhouse gases. Noteworthy, the proper AQI is highly dependent on the cement factories' area and differs from place to place. For example, the nitrogen and sulfur oxides' limit in China is assumed to be 400 and 200 mg/Nm^3, respectively, whereas the permissible exposure limit (PEL) of these pollutants in the European Union is considered 200–450 and 50–400 mg/Nm^3 [50,51].

2.4. Noise Pollution

One of the most harmful parameters in all cement plants is noise pollution. Various resources have been declared as a noise-generating factors in such areas, including gas dynamic, mechanical, and electromagnetic noises, by forming noises in the range of 68.8 to 103.3 dBA. Meanwhile, the Vietnamese Standard determined for the PEL for eight working hours is 85 dBA. Gas dynamic noises are produced by compressors, collectors, and blower equipment. Mechanical noises refer to the pollutants caused by milling and crusher devices. In addition, electric motors are the fundamental cause of electromagnetic noises. Cement industrial workers are in danger of hearing loss due to noise pollution. In addition, long-term working in these environments results in neurasthenia syndrome, which can lead to high blood pressure, memory loss, and insomnia. Therefore, noise-induced hearing loss has been introduced to evaluate the health issues of the laborers annually via using audiometric examinations [30,52,53].

2.5. Emissions from Fuel Consumption

The main part of fossil fuel consumption during cement manufacturing corresponds to the need for energy and thermal treatments. In fact, thermal treatment in the calcination procedure and the kiln forming in the clinker require fuel consumption. The average fuel consumption in wet and dry kilns has been reported around 6 and 4.5 GJ/t, respectively. [54]. Coal, fuel oil, pet coke, and gas are the primary fossil fuels employed in the processes mentioned above, costing about 50% of the total expenses in cement plants. Pyro-processing is linked with 92.7% of the consumed energy while the remaining is attributed to the raw grinding (1.9%) and finishing (5.4%) phases. It is declared that the equivalent of 400 pounds of coal is essential for producing a ton of cement. Meanwhile, applying fossil fuels has been assumed as a critical resource for environmental pollution via emitting greenhouse gasses and heavy metals (e.g., mercury, lead, and cadmium) into the atmosphere. Hence, global warming issues and ecologically sustainable development suggest recycling the applied fossil fuels or substituting them with alternative ones [16,32,55,56].

Overall, the cement plants cause various pollution around the factories, as stated in this section. Nevertheless, the data has shown that the major rate of pollution is caused by dust and gas resources, which are summarized in Table 1 [52–56].

Table 1. Main pollutants from the cement plants and their major resources.

Emission Type	Specific Pollutant	Resource of the Pollution Material
Air Emission	SO_2	Raw mill and kiln stack exit
	NO_x	
	CO	
Water Pollution	Iron particles	Material washing, thermal pipes, and finishing
	Suspended solids	
	Oxygen demand	
Solid Waste	TSP	Clinker cooler, cement mill stacks exit, and outlets of dust control devices
	$PM_{2.5}$	
	PM_{10}	
Noise	Gas dynamic	Compressors and blower devices,
	Mechanic	Milling and crusher equipment
	Electromagnetic	Electric motors
Fuel Waste	Greenhouse gases	Energy supplying sections

3. Pollution Prevention Methods in the Cement Plant

According to the data announced by the companies, cement plants have been determined as one of the most polluting factories. Various strategies have been proposed so far to sustain the environment and decline waste materials: using green raw materials, impressive pollution treatment techniques, co-processing methods, and novel models for integrating the communal applied separation devices. In the following, the most dominant practical approaches for treating the resultant pollution from the cement industrial areas are presented.

Filtration membranes are key building blocks in cement factories for hindering the pollutants from air and water. The efficiency of the air pollution treatment emitted from the cement plants is impacted by both inherent contaminant features as well as the filtration media type. The size, density, and temperature of the particulate materials are significant characteristics of the pollutants [57,58].

Regarding the air filtration media, several solutions have been introduced in the studies. The first category is linked with the regular membranes consisting of a simple fabric layer that filters the air and gases. The second class of filtration media corresponds to the electrostatic precipitator (ESP). In this system, a negative or positive charge is applied to the dust particles by a corona discharge, forcing them to precipitate on the oppositely charged electrode as a result of the provided potential difference. Then, the collected particles are removed via washing or dry-eliminating techniques. The efficiency of this filtration media is determined through the ability to collect the particles on the electrode and then the potential of eradicating them, which is influenced directly by the electrode geometry, gas direction, and particles' resistivity. A prominent challenge linked with these filtering systems is the agglomeration of the pollution on the electrode surfaces and so the weakening of the electric field [59–63]. With the effective parameters and limitations in mind, Ando et al. [64] applied moving electrodes in ESP systems to enhance filtration efficiency and remove highly-resistive particles such as coal and sintering ashes. In addition, Kherbouche et al. [65] employed a novel ESP with an asymmetrical wire-to-cylinder configuration to boost the collection efficiency up to 95% with low power of consumption (0.2 W).

Bag filters are the best solution for hindering PMs, categorized as the third filtration group. During this procedure, the dust-laden air is entered into the bag filter, the fibrous network on the surface of the filtration device traps the pollutant particles, and then the clean air exits using a vigorous fan. Then, the filtration surfaces are cleaned using mechanical shakers, reverse air, or pulse jet [66,67]. For enhancement of the bag filter performance, Abhishek and Ramachandran [68] designed a novel pleated bag filter with the potential of trapping the particles to 30 mg/Nm^3. Meanwhile, the commonly used filters can restrict the solid pollutants between 50 to 150 mg/Nm^3. Furthermore, they reduced the size of bag house filters compared with the regular woven or non-woven ones.

Wet scrubbers are another procedure applied in cement plants to diminish the pollutants. In this case, the scrubbing liquid eliminates the pollutant particles by caging them in the droplets. This method mainly removes mercury elements from the dust-laden airflow [69,70]. As a water-treating procedure, settling, containment, and clarifying ponds are applied to suspend solid particles and modify the water pH [71].

Coal, coke, natural gas, and oil are the foremost communal fuel used in cement plants. However, in recent years, numerous attempts have been devoted to replacing conventional fuels with alternative fuels provided from biomass and biowastes, waste oils, refuse-derived fuels, used tires, industrial residues, and byproducts, such as the combination of non-recycled polymers and papers, wastewater sludge, etc. It is worth noting that several characteristics of the alternative fuels should be considered before the burning step, such as the fuel's state and morphology, toxicity, compatibility with the system, material ingredients, and chemical and physical characteristics [72,73].

There has also been some attention to cement industrial zones contributing to water treatment. As a solution, the water used in the cooling systems is then recycled by installing cooling towers and reusing it in preparation for raw materials and dust leaching [74].

Since the pollution emission from cement factories is a worldwide concern, researchers and manufacturers have declared a broad range of other solutions. For example, for NH_3 and urea, reducing agents are suggested to be employed in selective catalytic and non-catalytic reduction for reducing the amount of NOx in the emission output [75]. Based on the research carried out by Rahman et al. [76], the control of the oxygen content in the raw materials as well as the employed fuels has been identified as an influential parameter toward decrement of the SO_2 release. Moreover, several functional materials, such as activated carbon, could absorb the SO_2 content in the output air. They also reported that the CO and CO_2 concentrations could be suppressed by reducing the organic materials in the raw substances and the carbon ratio in the used fuel.

Regarding the noise pollution in cement factories, it is highly proposed to use management and technical control subsystems. Four aspects are introduced as a management monitoring system, including decrement in shift hours, updating machinery and equipment, regular maintenance and adjustment of the devices, and using a reasonable and proper layout for the machinery installation. Additionally, the technical control system is attributed to vibration attenuation, noise absorption and isolation, and employing soundproofing systems. In developed countries, hearing conservation programs consisting of identifying and controlling noise resources, labor training, and applying hearing protection devices are utilized to decline the difficulties of noise pollution in cement plants [52,77].

Although the mentioned techniques could potentially prevent the emission of various pollutants, current studies suggest applying modeling solutions to obtain a more eco-friendly procedure in the production cycles of different sectors through providing simultaneous monitoring and controlling systems. In the following section, the most useful prediction and control modeling techniques with a focus on Python is summarized.

4. Modeling Techniques for the Prediction and Control of Pollution Focusing on Python

To date, a wide range of statistical, mathematical, and computing models has been declared for various industrial areas, specifically cement plants. The main goal of such analysis is to boost product quality and suppress environmental pollution. The defined models generally assist in increasing the performance of the filtering media, decreasing the PM contents in the output, representing the distribution of pollutants in the environment, and so on.

As an example, the finite element method is a numerical solution for solving complex problems using one or more differentiated equation(s). In a case study, Kherbouche et al. [65] used the finite element method (using the COMSOL Multiphysics software) to model and analyze the particle's trajectory inside a novel ESP containing an asymmetrical wire-to-cylinder configuration. This model assumed all effective parameters, including the electric field, particle flow, particle charges, and charge density. The collection efficiency of the particles in size range from 1 to 1.075 μm was estimated through the defined model and the experimental analysis. The obtained data from the suggested model was in line with the experimental results. In addition, the simulation showed that the particles could even be collected in the cylinder's less intense electric field zone.

The relationship between an independent and a dependent variable could be evaluated using a single regression model. A multivariate linear regression model is another common method applied for estimating a single regression model containing two or more outcome variables. Purnomo et al. [67] applied a multivariate linear regression model to compare the efficiency and performance of the ESP and bag filter to treat dust. The results represented that the bag filter system can reduce the dust to 6 mg/m^3, while the ESP media displayed a dust emission of about 35 mg/m^3.

Fuzzy logic helps to solve a problem with multiple possible truth values. In this method, the variables' truth values could be any number between 0 and 1. Regarding this, Zermane and coworkers [78] used the fuzzy logic algorithm with the aim of continuous emission monitoring. Using this intelligent monitoring system, they could control the cooling system, compressed air, air pressure, and temperature with superior efficiency.

The Gaussian model is a probabilistic model commonly applied toward modeling pollutant dispersion, following normal statistical distribution. In 2019, Adeniran et al. [79] utilized air quality modeling tools and an air quality index to investigate the impact of cement plant activities on the dispersion of pollutant materials released into the atmosphere. The emission dispersion of air pollution parameters was investigated by AERMOD (American Meteorological Society/U.S. Environmental Protection Agency Regulatory Model) view. AERMOD, as a Gaussian-type dispersion model, has been applied in many case studies to predict air pollution dispersion. Based on the results, average daily concentrations of PM10 were in the range of 14.32 to 31.54% of the statutory limit in all the locations, whereas SO_2 and NO_X concentration values exceeded their borders in some locations. As a result, several point sources of atmospheric emissions were identified using the proposed model. Correspondingly, the comprehensive investigation and periodic evaluation of air pollution control facilities are suggested for future studies. Yazdi et al. [80] also used the steady-state dispersion AERMOD model to investigate the concentration level of PM_{10}. Based on the results, the data obtained through the model was in agreement with the experiment data. As predicted, the filler agglomeration was the most at 200 m from the factory zone. Furthermore, it was concluded that the emitted particles could be harmful to human wellbeing in locations less than 1000 m from the cement plants.

Overall, the modeling evaluations have been more desirable than experimental analysis in recent years due to the potential for the simulation, prediction, and monitoring of the various procedures. Python is one of the most motivating candidates in this era because of lower syntactical constructions, smart libraries in the environmental fields, etc.

Python is an open-source, free, dynamic, and high-level programming language that is widely used in different areas for various purposes, including software and web development, mathematics, unit testing, system scripting, documentation generation, threading, cryptography, XML, HTML, GUI, etc. [81]. These aims are achieved using Python on a server, connecting it to the database systems, and handling big data. This language was first created in 1991 by Guido van Rossum and has been developed daily by software developers under the support of the Python Software Foundation. It has specific features and code readability, making it popular in a few years and one of the first choices for coders to reach their goals in every field [82,83]. Among its versatile features, code readability, accessible writing, unique and simple syntax, existing inbuilt functions, expressing logical concepts shortly leading to fast coding, the codes with fewer lines compared to other languages like C++ and Java, and efficient system integration are highlighted. Moreover, Python is able to work on every platform, like Windows, Linux, and Mac. It also provides quick prototyping because it can run on an interpreter system. Accordingly, there is no need for a separate compilation and execution, and the program runs as soon as the codes are written [83,84].

A wide range of interpreters containing CPython, Pycharm, IronPython, PyPy, etc. can be employed for Python. An interpreter is a virtual machine that translates the codes written by the user into a language that the computer can understand. Python can also be integrated with C/C++ to provide scripting capabilities. Furthermore, several programming paradigms consisting of procedural, object-oriented, and practical ways can be supported by Python. Installing and learning Python is very feasible. There are two main versions of Python: version 2 and version 3, which are relatively different. Version 2 is not updated anymore except for the security but has more complete libraries than version 3. The standard library of Python is very extensive and provides lots of facilities such as Built-in Functions, Built-in Constants, Text Processing Services, and Numeric and Mathematical Modules, allowing the programmers to reach their goals easily. Along with the standard library, there are other diverse libraries to ease programming. Each library contains many precompiled codes applied based on the program's application when needed. Using the defined libraries prevents writing repeated codes and enables faster coding. Some of the more popular and applicable libraries are named: Numpy, which is responsible for large matrices and multi-dimensional data by suggesting in-built mathematical functions; TensorFlow, which Google developed by for high-level calculation; machine learning and deep learning algorithms; Matplotlib, which is suitable for plotting numerical data and figures and is favorable for data analysis; Pandas, which is a good tool for data scientists by providing several operations like Re-indexing, iterating, concatenation, and the conversion of data; PyGame, which is employed for creating video games and audio libraries; and PyTorch as the largest machine learning library which optimizes tensor computations. Due to the characteristics and philosophy mentioned above, organizations like Google, Yahoo (Maps), YouTube, Mozilla, Dropbox, Microsoft, Cisco, Spotify, and Quora use this programming language. Python has also found a practical and valuable level in various industries [85–88]. Additionally, various models can be applied in Python, including the support vector machine, linear regression, random forest, and so on. Table 2 describes and compares the common models employed in Python. The Python model approaches, aiming at treating pollution in different sectors and the cement plants, are summarized in the following sub-sections.

Table 2. The common models used in Python modelling.

Model	Description	Accuracy	Interpretation
Artificial intelligence	It developes problem solving ability, allows continuous learning, promotes creativity, and encourages social intelligence.	0.95 [0.85, 0.99]	0.88 [0.63, 0.99]
Support Vector Machine	This model can evaluate data for classification and data analysis via classification algorithms for two-category problems.	0.92 [0.77, 0.99]	0.85 [0.53, 0.99]
Linear regression	It describes the relationship between an independent variable and a dependent one.	0.85 [0.69, 0.96]	0.72 [0.51, 0.94]
Random forest regressor	Its potential is to integrate the accuracy and control overfitting through fitting and averaging a number of decision trees.	0.88 [0.69, 0.99]	0.73 [0.33, 0.99]
K-Nearest Neighbors Regression	This method approximates the relationship between independent variables via averaging in the same neibourhoods.	0.78 [0.51, 0.94]	0.69 [0.38, 0.91]
Gradient Boosted Regression	It is derived from the idea of decision tree model and can predict both continuous and categorical target variables.	0.85 [0.75, 0.96]	0.45 [0.11, 0.88]

4.1. Python Models for Pollution Treatment in Various Sectors

The environmental industry is an example where ecological data analysis using the software resources such as Python to reach scalable information has attracted attention in recent years. In this field, Anaconda is exploited by researchers as an excellent platform to distribute Python and R programming languages [89]. This platform supports different interpreters. It has 150 pre-installed packages, and over 8000 open-source packages can be available through the Anaconda repository. Scikit-learn is a desirable library for environmental data analysis applications. According to the literature, this library has been considered and utilized in most of cases, resulting from its various efficient tools, including classification, regression, clustering, and reduction of dimensionality. As an example, Kadiyala and Kumar [89] used this library to demonstrate the necessary steps, including importing data, performing investigative data analysis, selecting features (dimensionality reduction), generating regression models, and creating machine learning models. This study can be helpful for other researchers to carry out Python for their own data analysis. According to the literature, the Python model could be beneficial in treating the pollutions related to air, water, and noise, which are explained respectively.

Ma et al. [90] presented a novel Python-based software to model air pollution by employing Land use regression (LUR) models. GDAL/OGR, Statsmodels, and Scikit-learn Python libraries were employed in this software. Additionally, it was illustrated that the proposed software increased processing speed by inheriting the benefits and features of Python, especially when the concentrations of forecasting air pollutants were mapped at a high spatial resolution. The Python Tkinter module was exploited to provide a GUI for uploading the input data. GDAL, the abbreviation of Geospatial Data Abstraction Library, is an open-source library developed to perform on raster data, such as the Digital Elevation Model. The statsmodels module is also designed to build statistical models, execute statistical tests, and investigate statistical data by providing classes and functions.

This library, along with Scikit-learn, was employed for making and testing the regression equations [90]. Air pollution analysis was performed by Lella et al. using Python [91]. In this effort, a large-scale data set of the concentration of the pollutants was applied in the first stage. Then, the AQI prediction was performed employing Python by machine learning algorithms. Notably, supervised learning and regression techniques, including Linear regression and Random Forest regressor, were utilized for the prediction. Moreover, the Jupyter Notebook platform, the most used coding environment for Python based pollution prediction, was used as the editor [91].

In another case, the deep learning method was applied to predict CO_2 emissions as an air pollutant in India in the study carried out by Amarpuri and coworkers [92]. The proposed method combined the Convolution Neural Network and Long Short-Term Memory Network (CNN-LSTM). Python was also used for creating the model and several libraries, such as Tensorflow, Keras, Numpy, and Pandas. In the model, ReLU and Adam were considered the activation function and optimizer, respectively [92]. The effects of buildings' material on climate change and air pollution is the main approach of the investigation represented by Resch and colleagues [93]. In the mentioned study, Python was applied to obtain the changes' effects on global study parameters. To reach this, the SALib library was used, which is responsible for sensitivity analysis and contains various sensitivity methods, including Sobol, Morris, Fourier Amplitude Sensitivity Test, Random Balance Designs-Fourier Amplitude Sensitivity Test, Delta Moment-Independent Measure, Derivative-based Global Sensitivity Measure, Fractional Factorial Sensitivity Analysis, and High Dimensional Model Representation. Accordingly, building lifetime, time horizon, and the factors linked with the construction waste were the most sensitive.

The internet of things (IoT) for smart monitoring of the environment is a progressive field in which Python plays an important role. This intelligent control and monitoring covers pollution, air, water, and agricultural systems. To this end, the data collected by several wireless sensors using the Wireless Sensor Network (WSN) should be evaluated. Python is a valuable tool for the IoT backend development due to its readable syntax, easy learning, ability to use on Linux systems, and compatibility of MicroPython with microcontrollers. The various libraries of Python are proper for this purpose. Open CV for image and video processing and Tensorflow and Keras for artificial neural networks are among these libraries [94]. In the evaluation study performed by Pătrăşcoiu et al. [95], air quality was monitored using the related sensors. The IoT architecture contained a LoPy 4, which is a board to connect the objects and works based on Python. The commands were written in Python and used for further execution. Using LoRa radio communication technique, they could serve both acquisition (temperature, humidity, energy consumption, etc.) and actuation (engines, pumps, tanks, etc.) systems, enabling the remote monitoring of various sections.

As another application of Python in the environmental industry, Khoi et al. [96] utilized the machine learning models based on the Scikit-learn library for the water quality index prediction in the Vietnam zone, declaring the highest efficiency of 98% for the XGBoost boosting algorithm. Cascone et al. [97] developed a Python toolbox called AbspectroscoPY for water quality monitoring purposes. This toolbox was used for analyzing the time-series datasets gathered by situ spectrophotometers. AbspectroscoPY provides functions for importing, preprocessing, exploring, and analyzing the sensor data. Some Python built-in functions, including rolling for noise reduction and kdeplot for Visualizing data distribution, are employed directly in this toolbox [97]. Shah et al. [98] utilized and compared three Python models, including a decision tree, SVM, and random forest, to detect the accuracy of the noise pollution level. Accordingly, the Python model based on SVM should have the highest accuracy of 98%.

4.2. Application of Python Models in Cement Industries

Another industry in which Python can improve data analysis is cement complexes. In most cases, the product quality based on the used component is analyzed, or the properties of the manufactured cement are predicted. For both approaches, Python is employed for the assessment. In this regard, Yao et al. [99] investigated the quality of cement mixing pile production by proposing an IoT-based model and implementing it in PHP and Python. According to the results, cement mixing piles in real-time can be monitored using IoT, which can be effective for yield advantages [99]. Using the finite element numerical simulation method, Wang et al. [100] evaluated the Nonlinear Mechanical behavior of cement-based solidified sand mixture (CBSSM) affected by interphase. To this end, as the first step, the composite was geometrically modeled in Python by manipulating the Monte Carlo method. The results revealed that the macro mechanical properties of CBSSM can be improved by increasing interphase strength and stiffness [100]. To predict cement strength, Kumar et al. [101] introduced a machine learning-based method. In this technique, the cloud-based prediction model was made by defining a Levenbarg-Marquardt back-propagation-artificial neural network. The Tensor flow, Scikit-learn, and Pandas libraries of Python were applied to implement the neural network. Additionally, the Tensor flow was employed to form the neural network because of its simultaneous training and responsive construction. From the Scikit-learn package, cross-validation, feature extraction, and unsupervised learning algorithms were selected for the goal of this study. Pandas was considered for the data analysis, and dropout was used to remove the outliers in order to prevent overfitting. Based on the results, the proposed algorithm could predict the cement strength with an accuracy of about 99% [101].

Danila and Tamas [102] suggested an image processing method for estimating the parametric model of a rotary kiln to seek its thermal field for cement manufacturing. The codes to reach this goal were written in Python. It was represented that this method could give an acceptable polynomial model for the distribution of thermal power losses over the kiln's surface. Using machine learning and image processing techniques, the durability of lightweight cement composites with hydrophobic coatings modified by nanocellulose was analyzed by Barnat-Hunek et al. [103]. A scanning microscope was used to capture the images and detect textural features. The Support Vector Machine method was employed for the classification of the images. The Scikit-learn library of Python was utilized for the data preprocessing. The proposed model, with an accuracy of 82%, could help measure the amount of hydrophobization of building materials. In another study, Nayak et al. [104] assessed the fracture of metallic particulate-articulate-reinforced cementitious composites using experiments and numerical simulation. A cohesive zone model-based debonding was selected for this simulation. To predict the fracture response, the unit cells were generated where Python was engaged to implement the microstructural information, which was then imported to a finite element software. The meshing of the unit cells was also performed using Python, and periodic boundary conditions were used. Based on the obtained results, a desirable match between the experiment and computer simulation was gained.

Plattenberger et al. [105] proposed a method to display the possibility of using Calcium Silicate Carbonation to reach high-performance and low-carbon types of cement. The role of Python in this work was to visualize the map data of each manufactured sample. Viridis library was selected as the most appropriate library for this respect. This package provides the color maps with the following characteristics: colorful as possible to represent the most visible output to the user; perceptually uniform so that the color differences increases as the values get far away from each other; and robust to colorblindness meaning the two previous features hold true by transforming to the grey-scale for the people with colorblindness, and pretty. In addition, Python-based models have recently been applied to estimate and predict the pollutants from the cement plants. For example, Kurnaz et al. [106] suggested a Long-short term memory method using Python software to predict SO_2 and PM_{10} emitted into the air from the cement plants in Sakarya industrial city. Compared to the actual data, correlation values of 0.67–0.88 were obtained based on the statistical analysis performed in this study. Exceeding the PM_{10} from the legal rate was observed three times during peak production days. Table 3 summarizes various proposed models for the control and monitoring of the emissions from the cement plants.

Table 3. Monitoring of industrial pollution using various modeling techniques.

Purpose of the Study	Zone	Model and Software	References
Predicting PM_{10}	Sakarya city, Turkey	Multi-linear regression and multilayer perception neural network models and MATLAB software	2018 [107]
Modeling of $PM_{2.5}$	Tehran, Iran	Random forest model and Python software (XGBoost library)	2019 [108]
Estimation of CO, SO_2, NO_x, and PM_{10}	Bojnourd Cement plants, Iran	AUSTAL 2000 model and Arc GIS software	2019 [109]
Water pollution	Langat River, Malaysia	Support vector regression model	2019 [110]
Forecasting PM_{10}	Mexicocity, USA	Multilayer perception model enhanced with Bagging ensemble model	2020 [111]
Assessing the emitted NO_2	Auckland, Newzealand	Land use regression model and Python software	2020 [90]
Fuel consumption	Cement plant, Greece	Machine learning-based model	2021 [112]
Water pollution	Guangxi, China	Support vector regression model and MATLAB software	2021 [113]
CO_2 emission	Cement plant, India	Artificial neural network-based models	2021 [114]
Assessing the health effects of $PM_{2.5}$, PM_{10}, NO_x, and O_3	Cement plant, Pakistan	Air Q+ software	2022 [115]
Prediction of SO_2 and PM_{10}	Sakarya city, Turkey	Python software	2022 [106]
Estimation of $PM_{2.5}$ and PM_{10}	Talca, Chile	Support vector regression model and Python software	2022 [116]
Evaluating the relationship between the air pollutants and the meteorological variables	Ningxia, China	Decision tree regression model	2022 [117]
Fuel consumption	Cement plant, Iran	Support vector regression, random forest, and XGBoost models	2022 [118]
Fuel consumption	Cement plant, Spain	Neural network and genetic algorithm models	2022 [119]
Assessing the emitted CO_2, SO_2, and NO	Cement plant	Machine learning-based model and MATLAB software	2022 [120]

With a closer look at what is mentioned in this section, it can be concluded that a new approach has not been addressed as it should and, perhaps, is predicting the pollution level in the cement industry using machine learning and Python. Based on the literature, most of the performed studies toward monitoring the air pollution in various sectors have employed the Scikit-learn library and support vector machine possibly due to its desirable accuracy and interpretation. In addition, applying hybrid libraries as well as combined models has been declared as versatile methods to approach highly efficient outcomes. As the cement industry is the third-largest industrial pollution source because of the emission of sulfur dioxide, nitrogen oxide, and carbon monoxide pollutants, this line of research requires special attention. Therefore, it is highly suggested to emission monitoring units around the world to employ a remote controlling platform, in which the pollution evaluation occurs in 3 steps, including (a) collecting the pollutant data from the sensors, (b) simulating the pollution distribution around the factory by Python, and (c) observing the emissions from the factory online and making a thorough decision.

5. Conclusions and Future Remarks

Environmental pollution has continued to gain a great deal of interest worldwide, resulting from its direct and indirect adverse impacts on human health, whereas the growing rate of non-eco-friendly activities has caused the unceasing release of contaminations in industrialized and modernized societies. Cement is accounted as a key substance to satisfy construction and civil engineering, as well as dental and medical applications. Meanwhile, the whole cement production procedure emits various contaminants into the environment. Therefore, effective monitoring and treatment are mandatory to treat the resultant water, solid, and fuel wastes along with air and noise pollution. Numerous strategies have been proposed to deal with these challenges, classifying them into practical and modeling techniques. Based on novel explorations, a wide range of statistical and computational modeling has been suggested in recent years to enhance production quality as well as predict and control emission rates.

As high-performance modeling, Python has been broadly recommended in the literature. This object-oriented programming could predict and monitor the released pollutants as a result of smart and powerful libraries, readability, and powerful syntax. According to the literature, the major Python-based modeling is linked to monitoring air pollution, harmful gases, and different conditional parameters of the environment. Correspondingly, this paper reviewed and summarized various contaminations from the cement plants as well as their beneficial treatment. In addition, the role of Python as an impactful tool was highlighted and investigated to cope with the challenges mentioned above in cement complexes.

Although efficient methods have been declared to overcome the drawbacks concerning cement production, several downsides could be efficiently addressed via Python. First, it calculates the required high temperature for calcinating and thermal treatment results in fuel consumption as well as environmental pollution. The essential temperature could be optimized by modifying the precursor materials using the Python models. Second, the oxygen concentration in the raw materials and the applied fuels requires adjustment with Python with the aim of reducing air pollution. Third, it is recommended to use successful Python packages, such as seaborn or pyGAM, to monitor water quality and reduce the water waste. Fourth, it is vital to apply the practical and efficient Python models in other sectors, including Scikit-Learn, Keras, and native TensorFlow packages, in the cement plants to predict the emissions into the air. Finally, the lack of unified standards for the cement plant activities is sensed. Overall, future studies should concentrate on data collection, pollutants characterization, and the analysis of the contaminant dispersion. Afterward, the Python-based models should be developed using the accurately collected data to provide precise prediction and monitoring programs.

Author Contributions: X.Z., conceptualization, writing—original draft, investigation, resources, and methodology. T.L., conceptualization, formal analysis, writing—review and editing, project administration, and funding acquisition. J.Y., conceptualization, writing—review and editing. Q.H., writing—review and editing. All authors contributed to the article and approved the submitted version. All authors have read and agreed to the published version of the manuscript.

Funding: This research was financially supported by the General program of NSFC 42277139, National Natural Science Foundation of China (NSFC) (U2006213), Open laboratory fund (BHKF2021Z03).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Adeyanju, E.; Okeke, C.A. Exposure effect to cement dust pollution: A mini review. *SN Appl. Sci.* **2019**, *1*, 1572. [CrossRef]
2. Farrag, F.A. The Role of SPOT Satellite Images in Mapping Air Pollution Caused by Cement Factories. *Int. Arch. Photogramm. Remote Sens.* **2000**, *33*, 46–53.
3. Box, L. Determination of the elemental contents in soils around Diamond Cement Factory, Aflao. *Res. J. Environ. Earth Sci.* **2011**, *3*, 46–50.
4. Zhang, L.; Su, M.; Wang, Y. Development of the use of sulfo- and ferroaluminate cements in China. *Adv. Cem. Res.* **1999**, *11*, 15–21. [CrossRef]
5. Lungu, I.; Taranu, G.; Hohan, R.; Plesu, G. Efficient use of green cements in structural elements for civil engineering applications. In Proceedings of the 3rd International Conference on Advanced Materials and Systems, ICAMS, Bucharest, Romania, 26–28 October 2010.
6. Liska, M.; Wilson, A.; Bensted, J. Special Cements. In *Lea's Chemistry of Cement and Concrete*, 5th ed.; Hewlett, P.C., Liska, M., Eds.; Butterworth-Heinemann: Oxford, UK, 2019; p. 618.
7. Gots, V.; Gelevera, A.; Petropavlovsky, O.; Rogozina, N.; Smeshko, V. (Eds.) Influence of whitening additives on the properties of decorative slag-alkaline cements. In Proceedings of the IOP Conference Series: Materials Science and Engineering, Kharkiv, Ukraine, 21–22 May 2020; IOP Publishing: Bristol, UK, 2020.
8. Vorobchuk, V.; Matveeva, M.; Peshkov, A. (Eds.) Decorative concrete on white cement: Resource provision, technology, properties and cost-effectiveness. In *MATEC Web of Conferences*; EDP Sciences: Les Ulis, France, 2018.
9. Smith, D.C. Medical and dental applications of cements. *J. Biomed. Mater. Res.* **1971**, *5*, 189–205. [CrossRef] [PubMed]
10. Hatton, P.; Hurrell-Gillingham, K.; Brook, I. Biocompatibility of glass-ionomer bone cements. *J. Dent.* **2006**, *34*, 598–601. [CrossRef]
11. Dorozhkin, S.V. Calcium orthophosphate cements for biomedical application. *J. Mater. Sci.* **2008**, *43*, 3028–3057. [CrossRef]
12. Salman, D.M. An assessment to the oligopoly cement industry in Egypt: Is it a curse or a blessing? *Int. J. Green Econ.* **2017**, *11*, 41–61. [CrossRef]
13. Hägg, M.-B.; Lindbråthen, A.; He, X.; Nodeland, S.; Cantero, T. Pilot demonstration-reporting on CO_2 capture from a cement plant using hollow fiber process. *Energy Procedia* **2017**, *114*, 6150–6165. [CrossRef]
14. Al Biajawi, M.I.; Embong, R.; Muthusamy, K.; Ismail, N.; Obianyo, I.I. Recycled coal bottom ash as sustainable materials for cement replacement in cementitious Composites: A review. *Constr. Build. Mater.* **2022**, *338*, 127624. [CrossRef]
15. Kuter, N. Reclamation of degraded landscapes due to opencast mining. In *Advances in Landscape Architecture*; IntechOpen: London, UK, 2013.
16. Ciobanu, C.; Tudor, P.; Istrate, I.-A.; Voicu, G. Assessment of Environmental Pollution in Cement Plant Areas in Romania by Co-Processing Waste in Clinker Kilns. *Energies* **2022**, *15*, 2656. [CrossRef]
17. Cai, C.; Devassy, R.P.; El-Sherbiny, M.M.; Agusti, S. Cement and oil refining industries as the predominant sources of trace metal pollution in the Red Sea: A systematic study of element concentrations in the Red Sea zooplankton. *Mar. Pollut. Bull.* **2021**, *174*, 113221. [CrossRef] [PubMed]
18. Haneklaus, N.; Zheng, Y.; Allelein, H.-J. Stop Smoking—Tube-In-Tube Helical System for Flameless Calcination of Minerals. *Processes* **2017**, *5*, 67. [CrossRef]
19. Caselles, L.D.; Roosz, C.; Hot, J.; Blotevogel, S.; Cyr, M. Immobilization of molybdenum by alternative cementitious binders and synthetic C-S-H: An experimental and numerical study. *Sci. Total Environ.* **2021**, *789*, 148069. [CrossRef] [PubMed]
20. Subramanian, S.; Arumairaj, P.; Subramani, T. Experimental and modelling study of clay stabilized with bottom ash-eco sand slurry pile. *Géoméch. Eng.* **2017**, *12*, 523–539. [CrossRef]
21. Ariyaratne, W.K.H.; Manjula, E.V.P.J.; Melaaen, M.C.; Tokheim, L.A. Kiln Process Impact of Alternative Solid Fuel Combustion in the Cement Kiln Main Burner—Mathematical Modelling and Full-Scale Experiment. In *Advanced Materials Research*; Trans Tech Publications Ltd.: Wollerau, Switzerland, 2014.
22. Sharipov, D.; Muradov, F.; Akhmedov, D. Numerical modeling method for short-term air quality forecast in industrial regions. *Appl. Math. E-Notes* **2019**, *19*, 575–584.
23. Qi, C.; Wu, M.; Zheng, J.; Chen, Q.; Chai, L. Rapid identification of reactivity for the efficient recycling of coal fly ash: Hybrid machine learning modeling and interpretation. *J. Clean. Prod.* **2022**, *343*, 130958. [CrossRef]
24. Shamsabadi, E.A.; Roshan, N.; Hadigheh, S.A.; Nehdi, M.L.; Khodabakhshian, A.; Ghalehnovi, M. Machine learning-based compressive strength modelling of concrete incorporating waste marble powder. *Constr. Build. Mater.* **2022**, *324*, 126592. [CrossRef]
25. Amin, M.N.; Ahmad, W.; Khan, K.; Ahmad, A.; Nazar, S.; Alabdullah, A.A. Use of Artificial Intelligence for Predicting Parameters of Sustainable Concrete and Raw Ingredient Effects and Interactions. *Materials* **2022**, *15*, 5207. [CrossRef]
26. Streeter, H.W. Studies of the pollution and natural purification of the Ohio River, Part III, Factors concerned in the phenomena of oxidation and reaeration. *Public Health Bull.* **1925**, *146*, 1–80.
27. Chapra, S.C.; Camacho, L.A.; McBride, G.B. Impact of Global Warming on Dissolved Oxygen and BOD Assimilative Capacity of the World's Rivers: Modeling Analysis. *Water* **2021**, *13*, 2408. [CrossRef]
28. Kumar, K.; Pande, B.P. Air pollution prediction with machine learning: A case study of Indian cities. *Int. J. Environ. Sci. Technol.* **2022**, 1–16. [CrossRef] [PubMed]

29. Schneider, M.; Romer, M.; Tschudin, M.; Bolio, H. Sustainable cement production—Present and future. *Cem. Concr. Res.* **2011**, *41*, 642–650. [CrossRef]
30. Chen, C.; Habert, G.; Bouzidi, Y.; Jullien, A. Environmental impact of cement production: Detail of the different processes and cement plant variability evaluation. *J. Clean. Prod.* **2010**, *18*, 478–485. [CrossRef]
31. Habert, G.; Billard, C.; Rossi, P.; Chen, C.; Roussel, N. Cement production technology improvement compared to factor 4 objectives. *Cem. Concr. Res.* **2010**, *40*, 820–826. [CrossRef]
32. Mohamad, N.; Muthusamy, K.; Embong, R.; Kusbiantoro, A.; Hashim, M.H. Environmental impact of cement production and Solutions: A review. *Mater. Today: Proc.* **2021**, *48*, 741–746. [CrossRef]
33. Fennell, P.S.; Davis, S.J.; Mohammed, A. Decarbonizing cement production. *Joule* **2021**, *5*, 1305–1311. [CrossRef]
34. Etim, M.-A.; Babaremu, K.; Lazarus, J.; Omole, D. Health Risk and Environmental Assessment of Cement Production in Nigeria. *Atmosphere* **2021**, *12*, 1111. [CrossRef]
35. Rithuparna, R.; Jittin, V.; Bahurudeen, A. Influence of different processing methods on the recycling potential of agro-waste ashes for sustainable cement production: A review. *J. Clean. Prod.* **2021**, *316*, 128242. [CrossRef]
36. Kleib, J.; Aouad, G.; Abriak, N.-E.; Benzerzour, M. Production of Portland cement clinker from French Municipal Solid Waste Incineration Bottom Ash. *Case Stud. Constr. Mater.* **2021**, *15*, e00629. [CrossRef]
37. Usón, A.A.; López-Sabirón, A.M.; Ferreira, G.; Sastresa, E.L. Uses of alternative fuels and raw materials in the cement industry as sustainable waste management options. *Renew. Sustain. Energy Rev.* **2013**, *23*, 242–260. [CrossRef]
38. Kosajan, V.; Wen, Z.; Zheng, K.; Fei, F.; Wang, Z.; Tian, H. Municipal solid waste (MSW) co-processing in cement kiln to relieve China's Msw treatment capacity pressure. *Resour. Conserv. Recycl.* **2021**, *167*, 105384. [CrossRef]
39. Nanda, S.; Berruti, F. Municipal solid waste management and landfilling technologies: A review. *Environ. Chem. Lett.* **2020**, *19*, 1433–1456. [CrossRef]
40. Berner, U. Evolution of pore water chemistry during degradation of cement in a radioactive waste repository environment. *Waste Manag.* **1992**, *12*, 201–219. [CrossRef]
41. Batchelor, B. Overview of waste stabilization with cement. *Waste Manag.* **2006**, *26*, 689–698. [CrossRef]
42. Zamorani, E. Deeds and misdeeds of cement composites in waste management. *Cem. Concr. Res.* **1992**, *22*, 359–367. [CrossRef]
43. Coppola, L.; Bellezze, T.; Belli, A.; Bignozzi, M.C.; Bolzoni, F.M.; Brenna, A.; Cabrini, M.; Candamano, S.; Cappai, M.; Caputo, D.; et al. Binders alternative to Portland cement and waste management for sustainable construction—Part 1. *J. Appl. Biomater. Funct. Mater.* **2018**, *16*, 186–202. [CrossRef]
44. Faisal, G.H.; Jaeel, A.J.; Al-Gasham, T.S. BOD and COD reduction using porous concrete pavements. *Case Stud. Constr. Mater.* **2020**, *13*, e00396. [CrossRef]
45. Hasaballah, A.F.; Hegazy, T.; Ibrahim, M.; El-Emam, D.A. Cement kiln dust as an alternative technique for wastewater treatment. *Ain Shams Eng. J.* **2021**, *12*, 4201–4209. [CrossRef]
46. Perera, K.; Ranathunga, R.; Keshani, Y.; Asanka, K.; Prabhamini, T.; Piyathilaka, K.; Arachchige, U.S. Cement Industry in Sri Lanka. *J. Res. Technol. Eng.* **2020**, *1*, 16–27.
47. Brown, D.; Sadiq, R.; Hewage, K. An overview of air emission intensities and environmental performance of grey cement manufacturing in Canada. *Clean Technol. Environ. Policy* **2014**, *16*, 1119–1131. [CrossRef]
48. Zhang, Y.; Cao, S.-X.; Shao, S.; Chen, Y.; Liu, S.-L.; Zhang, S.-S. Aspen Plus-based simulation of a cement calciner and optimization analysis of air pollutants emission. *Clean Technol. Environ. Policy* **2010**, *13*, 459–468. [CrossRef]
49. Calvo, V.L.V.; Giner-Santonja, G.; Alonso-Fariñas, B.; Aguado, J.M. The effect of the European Industrial Emissions Directive on the air emission limit values set by competent authorities in the permitting procedure: The case of the Spanish cement industry. *Sci. Total Environ.* **2021**, *773*, 145491. [CrossRef]
50. Das, P.; Mandal, I.; Debanshi, S.; Mahato, S.; Talukdar, S.; Giri, B.; Pal, S. Short term unwinding lockdown effects on air pollution. *J. Clean. Prod.* **2021**, *296*, 126514. [CrossRef]
51. Ciobanu, C.; Istrate, I.A.; Tudor, P.; Voicu, G. Dust Emission Monitoring in Cement Plant Mills: A Case Study in Romania. *Int. J. Environ. Res. Public Health* **2021**, *18*, 9096. [CrossRef]
52. Karimi Ghoozlou, R.; Ahmadi, A.; Abbaspour, M.; Abbaszadeh, N. Assessment of Environmental Pollutant Particles PM10 and PM2. 5 with Air Quality Index Method (Case Study: Tehran Industrial Cement Complex). *J. Environ. Sci. Technol.* **2021**, *23*, 155–167.
53. Thai, T.; Kučera, P.; Bernatik, A. Noise Pollution and Its Correlations with Occupational Noise-Induced Hearing Loss in Cement Plants in Vietnam. *Int. J. Environ. Res. Public Health* **2021**, *18*, 4229. [CrossRef]
54. Guide, E.C.B. *Cement Clinker Production*; Natural Resources Canada–Office of Energy Efficiency: Ottawa, ON, Canada, 2001.
55. Raina, A.K.; Soni, A.K.; Vajre, R.; Sangode, A.G. Impact of topography on attenuation of noise from a cement plant in a hilly terrain. *Sci. Total Environ.* **2022**, *835*, 155532. [CrossRef]
56. Khan, M.H.; Havukainen, J.; Horttanainen, M. Impact of utilizing solid recovered fuel on the global warming potential of cement production and waste management system: A life cycle assessment approach. *Waste Manag. Res. J. Sustain. Circ. Econ.* **2020**, *39*, 561–572. [CrossRef]
57. Ishak, S.A.; Hashim, H. Low carbon measures for cement plant–A review. *J. Clean. Prod.* **2015**, *103*, 260–274. [CrossRef]

58. Majchrzycka, K.; Okrasa, M.; Jachowicz, A.; Szulc, J.; Gutarowska, B. Microbial Growth on Dust-Loaded Filtering Materials Used for the Protection of Respiratory Tract as a Factor Affecting Filtration Efficiency. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1902. [CrossRef] [PubMed]
59. Guo, R.; Love, E. Fuzzy set-valued and grey filtering statistical inferences on a system operating data. *J. Qual. Maint. Eng.* **2005**, *11*, 267–278. [CrossRef]
60. Gebert, R.; Rinschler, C.; Polizzi, C.; Harig, U.; Pranghofer, G.; Miller, S. A new filter system, combining a fabric filter and electrostatic precipitator for effective pollution control behind cement kilns. In Proceedings of the Cement Industry Technical Conference, 2003 Conference Record IEEE-IAS/PCA, Dallas, TX, USA, 4–9 May 2003; IEEE: Piscataway, NJ, USA, 2003.
61. Lazik, P.-R.; University of Stuttgart; Garrecht, H. Wood ashes from electrostatic filter as a replacement for the fly ashes in concrete. *J. Constr. Mater.* **2021**, *2*, 2–6. [CrossRef]
62. Miller, M.M.; Callaghan, R.M. Lime kiln dust as a potential raw material in Portland cement manufacturing. *US Geol. Surv. Open-File Rep.* **2004**, *2004*, 1336.
63. Fantom, I.; Cottingham, C.; Should, I. Replace my Electrostatic Precipitator (ESP) with a Fabric Filter (FF)? *Filtr. -Coalville* **2005**, *5*, 277.
64. Ando, H.; Shiromaru, N.; Mochizuki, Y. Recent technology of moving electrode electrostatic precipitator. *Int. J. Plasma Environ. Sci. Technol.* **2011**, *5*, 130–134.
65. Kherbouche, F.; Benmimoun, Y.; Tilmatine, A.; Zouaghi, A.; Zouzou, N. Study of a new electrostatic precipitator with asymmetrical wire-to-cylinder configuration for cement particles collection. *J. Electrost.* **2016**, *83*, 7–15. [CrossRef]
66. Bhargava, A. Design of bag filter for the control of dust emissions for a cement plant. *Int. J. Sci. Dev. Res. IJSDR* **2016**, *1*, 249–251.
67. Purnomo, C.W.; Budhijanto, W.; Alfisyah, M. Improvement of cement plant dust emission by bag filter system. In *IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, 2018.
68. Abishek, P.; Ramachandran, P. Design of pleated bag filter system for particulate emission control in cement industry. *Int. Res. J. Eng. Technol. (IRJET)* **2015**, *2*, 763–768.
69. Ngala, G.; Tela, B.; Highina, B. Mercury Removal in Cement Industry Using Venturi Type Wet Scrubber. *Int. J. Eng. Technol. Res.* **2014**, *2*, 48–54.
70. Tela, B.; Ngala, G.; Abubakar, A. Separation of Gas Particle Using Venturi-Type Wet Scrubber in Ashaka Cement Factory PLC. *Int. J. Res. Mech. Eng.* **2014**, *2*, 91–98.
71. Sharma, K.; Jain, U.; Singhal, A. Treatment of Waste Generated from Cement Industry and Their Treatment—A Review. 2012. Available online: http://dl.lib.mrt.ac.lk/handle/123/8889 (accessed on 18 October 2022).
72. Chatziaras, N.; Psomopoulos, C.S.; Themelis, N.J. Use of waste derived fuels in cement industry: A review. *Manag. Environ. Qual. Int. J.* **2016**, *27*, 178–193. [CrossRef]
73. Tsiligiannis, A.; Tsiliyannis, C. Oil refinery sludge and renewable fuel blends as energy sources for the cement industry. *Renew. Energy* **2020**, *157*, 55–70. [CrossRef]
74. Gomes, S.D.C.; Zhou, J.L.; Li, W.; Long, G. Progress in manufacture and properties of construction materials incorporating water treatment sludge: A review. *Resour. Conserv. Recycl.* **2019**, *145*, 148–159. [CrossRef]
75. Kim, J.-H.; Kim, J.-H.; Kim, H.-S.; Kim, H.-J.; Kang, S.-H.; Ryu, J.-H.; Shim, S.-S. Reduction of NOx Emission from the Cement Industry in South Korea: A Review. *Atmosphere* **2022**, *13*, 121. [CrossRef]
76. Rahman, A. Utilization of Waste Products as Alternative Fuels for Cement Industry. Ph.D. Thesis, CQUniversity, Rockhampton, Australia, 2016.
77. Orkomi, A.A.; Tavakoli, B.; Noorpoor, A. Noise pollution analysis in Tehran cement plant. *J. Occup. Health Epidemiol.* **2013**, *2*, 44–53. [CrossRef]
78. Zermane, H.; Mouss, H.; Oulmi, T.; Hemal, S. Fuzzy-based process control system of a bagfilter in cement manufacturing plant. In Proceedings of the 2017 6th International Conference on Systems and Control (ICSC), Batna, Algeria, 7–9 May 2017.
79. Adeniran, J.A.; Yusuf, R.O.; Fakinle, B.S.; Sonibare, J.A. Air quality assessment and modelling of pollutants emission from a major cement plant complex in Nigeria. *Atmos. Pollut. Res.* **2019**, *10*, 257–266. [CrossRef]
80. Yazdi, N.; Arhami, M.; Ketabchy, M.; Delavarrafeei, M. Modeling of cement factory air pollution dispersion by AERMOD. In Proceedings of the A&WMA's 109th Annual Conference & Exhibition Paper, New Orleans, LA, USA, 20–23 June 2016.
81. Lutz, M. *Programming Python*; O'Reilly Media, Inc.: Sebastopol, CA, USA, 2001.
82. Hao, J.; Ho, T.K. Machine Learning Made Easy: A Review of *Scikit-learn* Package in Python Programming Language. *J. Educ. Behav. Stat.* **2019**, *44*, 348–361. [CrossRef]
83. Hussain, Z.; Khan, M.S. Introducing Python programming for engineering scholars. *Int. J. Comput. Sci. Netw. Secur.* **2018**, *18*, 26–33.
84. Ding, L.; Ahmed, S.; Shapiro, A. A Python package for multi-stage stochastic programming. *Optim. Online* **2019**, 1–42. Available online: https://optimization-online.org/?p=15797 (accessed on 18 October 2022).
85. Kumar, R.; Carroll, C.; Hartikainen, A.; Martin, O. ArviZ a unified library for exploratory analysis of Bayesian models in Python. *J. Open Source Softw.* **2019**, *4*, 1143–1147. [CrossRef]
86. Lemenkova, P. Testing Linear Regressions by StatsModel Library of Python for Oceanological Data Interpretation. *Aquat. Sci. Eng.* **2019**, *34*, 51–60. [CrossRef]

87. Eaton, D.A.R. Toytree: A minimalist tree visualization and manipulation library for Python. *Methods Ecol. Evol.* **2019**, *11*, 187–191. [CrossRef]
88. Fredericks, S.; Parrish, K.; Sayre, D.; Zhu, Q. PyXtal: A Python library for crystal structure generation and symmetry analysis. *Comput. Phys. Commun.* **2020**, *261*, 107810. [CrossRef]
89. Kadiyala, A.; Kumar, A. Applications of Python to evaluate environmental data science problems. *Environ. Prog. Sustain. Energy* **2017**, *36*, 1580–1586. [CrossRef]
90. Ma, X.; Longley, I.; Salmond, J.; Gao, J. PyLUR: Efficient software for land use regression modeling the spatial distribution of air pollutants using GDAL/OGR library in Python. *Front. Environ. Sci. Eng.* **2020**, *14*, 1–14. [CrossRef]
91. Lella, D.B.; Jogu, V.; Ballu, H. Analysing Air Pollution Through Maps & Tools and Predicting Aqi Using Python. *Int. Res. J. Mod. Eng. Technol. Sci.* **2022**, *4*, 1996–2004.
92. Amarpuri, L.; Yadav, N.; Kumar, G.; Agrawal, S. Prediction of CO_2 emissions using deep learning hybrid approach: A Case Study in Indian Context. In Proceedings of the 2019 Twelfth International Conference on Contemporary Computing (IC3), Noida, India, 8–9 August 2019.
93. Resch, E.; Andresen, I.; Cherubini, F.; Brattebø, H. Estimating dynamic climate change effects of material use in buildings—Timing, uncertainty, and emission sources. *Build. Environ.* **2021**, *187*, 107399. [CrossRef]
94. Haji, S.H.; Sallow, A.B. IoT for smart environment monitoring based on Python: A review. *Asian J. Res. Comput. Sci.* **2021**, *9*, 57–70. [CrossRef]
95. Pătrăşcoiu, N.; Rus, C.; Roşulescu, C.; Negru, N. System for Monitoring the Parameters of Pollution Factors in Industrial Areas with Application in the Jiu Valley Area. *Ann. Univ. Petrosani Electr. Eng.* **2020**, *21*, 30–43.
96. Khoi, D.N.; Quan, N.T.; Linh, D.Q.; Nhi, P.T.T.; Thuy, N.T.D. Using Machine Learning Models for Predicting the Water Quality Index in the La Buong River, Vietnam. *Water* **2022**, *14*, 1552. [CrossRef]
97. Cascone, C.; Murphy, K.R.; Markensten, H.; Kern, J.S.; Schleich, C.; Keucken, A.; Köhler, S.J. AbspectroscoPY, a Python toolbox for absorbance-based sensor data in water quality monitoring. *Environ. Sci. Water Res. Technol.* **2022**, *8*, 836–848. [CrossRef]
98. Shah, S.k.; Tariq, Z.; Lee, J.; Lee, Y. Real-time machine learning for air quality and environmental noise detection. In *IEEE International Conference on Big Data*; IEEE: Piscataway, NJ, USA, 2020.
99. Yao, Y. Internet of Things in the Quality Control of Cement Mixing Pile Construction. *J. Cases Inf. Technol. (JCIT)* **2022**, *24*, 1–22. [CrossRef]
100. Wang, F.; Hu, Y.-G.; Liu, L.; Deng, Y.; Gu, S. Interphase Effect on the Macro Nonlinear Mechanical Behavior of Cement-Based Solidified Sand Mixture. *Materials* **2022**, *15*, 1972. [CrossRef] [PubMed]
101. Kumar, N.; Naranje, V.; Salunkhe, S. Cement strength prediction using cloud-based machine learning techniques. *J. Struct. Integr. Maint.* **2020**, *5*, 244–251. [CrossRef]
102. Danila, A.; Tamas, F.L. The thermal field analysis of the rotary kiln for the cement plants by means of the image processing techniques. *IOP Conf. Series: Mater. Sci. Eng.* **2020**, *789*, 012016. [CrossRef]
103. Barnat-Hunek, D.; Omiotek, Z.; Szafraniec, M.; Dzierżak, R. An integrated texture analysis and machine learning approach for durability assessment of lightweight cement composites with hydrophobic coatings modified by nanocellulose. *Measurement* **2021**, *179*, 109538. [CrossRef]
104. Nayak, S.; Krishnan, N.A.; Das, S. Fracture response of metallic particulate-reinforced cementitious composites: Insights from experiments and multiscale numerical simulations. *Cem. Concr. Compos.* **2019**, *97*, 154–165. [CrossRef]
105. Plattenberger, D.A.; Opila, E.J.; Shahsavari, R.; Clarens, A.F. Feasibility of Using Calcium Silicate Carbonation to Synthesize High-Performance and Low-Carbon Cements. *ACS Sustain. Chem. Eng.* **2020**, *8*, 5431–5436. [CrossRef]
106. Kurnaz, G.; Demir, A.S. Prediction of SO2 and PM10 air pollutants using a deep learning-based recurrent neural network: Case of industrial city Sakarya. *Urban Clim.* **2021**, *41*, 101051. [CrossRef]
107. Ceylan, Z.; Bulkan, S. Forecasting PM10 levels using ANN and MLR: A case study for Sakarya City. *Glob. Nest J.* **2018**, *20*, 281–290.
108. Zamani Joharestani, M.; Cao, C.; Ni, X.; Bashir, B.; Talebiesfandarani, S. PM2. 5 prediction based on random forest, XGBoost, and deep learning using multisource remote sensing data. *Atmosphere* **2019**, *10*, 373. [CrossRef]
109. Atamaleki, A.; Zarandi, S.M.; Fakhri, Y.; Mehrizi, E.A.; Hesam, G.; Faramarzi, M.; Darbandi, M. Estimation of air pollutants emission (PM10, CO, SO2 and NOx) during development of the industry using AUSTAL 2000 model: A new method for sustainable development. *MethodsX* **2019**, *6*, 1581–1590. [CrossRef] [PubMed]
110. Yaha, A.S.; Ahmad, A.N.; Othman, F.B.; Ibrahim, R.K.; Afan, H.A.; El-shafie, A.; Fai, C.M.; Hossain, M.S.; Ehteram, M.; Elshafie, A. Water Quality Prediction Model Based Support Vector Machine Model for Ungauged River Catchment under Dual Scenarios. *Water* **2019**, *11*, 1231. [CrossRef]
111. Aceves-Fernández, M.A.; Domínguez-Guevara, R.; Pedraza-Ortega, J.C.; Vargas-Soto, J.E. Evaluation of Key Parameters Using Deep Convolutional Neural Networks for Airborne Pollution (PM10) Prediction. *Discret. Dyn. Nat. Soc.* **2020**, *2020*, 2792481. [CrossRef]
112. Chatzilenas, C.; Gentimis, T.; Dalamagas, T.; Kokossis, A.C.; Katsiaboulas, A.; Marinos, I. Machine learning applications and process intelligence for cement industries. In *Computer Aided Chemical Engineering*; Elsevier: Amsterdam, The Netherlands, 2021; Volume 50, pp. 711–716. [CrossRef]
113. Wang, Y.; Xue, S.; Ding, J. Research on water pollution prediction of township enterprises based on support vector regression machine. In *E3S Web of Conferences*; EDP Sciences: Les Ulis, France, 2021; Volume 228, p. 02014.

114. Sharma, P.; Rao, M.V.R.; Mohapatra, B.N.; Saxena, A. Development of suitable machine learning model for a cement plant calciner. *Int. J. Eng. Appl. Sci. Technol.* **2021**, *6*, 194–198. [CrossRef]
115. Nasir, A.H.; Nawaz, R.; Haider, R.; Irshad, M.A. Modeling Air Pollution Health Risk for Environmental Management of an Internationally Important Site: The Salt Range (Kallar Kahar), Pakistan. *Atmosphere* **2022**, *13*, 100. [CrossRef]
116. Carreño, G.; López-Cortés, X.A.; Marchant, C. Machine Learning Models to Predict Critical Episodes of Environmental Pollution for PM2.5 and PM10 in Talca, Chile. *Mathematics* **2022**, *10*, 373. [CrossRef]
117. Ding, W.; Qie, X. Prediction of Air Pollutant Concentrations via RANDOM Forest Regressor Coupled with Uncertainty Analysis—A Case Study in Ningxia. *Atmosphere* **2022**, *13*, 960. [CrossRef]
118. Fatahi, R.; Nasiri, H.; Dadfar, E.; Chelgani, S.C. Modeling of energy consumption factors for an industrial cement vertical roller mill by SHAP-XGBoost: A "conscious lab" approach. *Sci. Rep.* **2022**, *12*, 7543. [CrossRef]
119. Guzman, M.P.; Rubia, B.N.; Peris, P.M.; Alfallaluque, R. Methodoligac development for the optimization of electricity cost in cement factories: The use of artificial intelligence in process variables. *Electr. Eng.* **2022**, *104*, 1681–1696. [CrossRef]
120. Jadoon, U.K.; Ahmad, I.; Noor, T.; Kano, M.; Caliskan, H.; Ahsan, M. An intelligent sensing system for estimation of efficiency of carbon-capturing unit in a cement plant. *J. Clean. Prod.* **2022**, *377*, 134359. [CrossRef]