

OPTIMIZATION AND AUTOMATION OF ADSORPTION PROCESSES IN WASTEWATER TREATMENT

Abstract

For humanity to survive, it is essential to bring elevated concentration of contaminants in waterbodies down to safe levels. Both traditional purifying methods and new technologies for pollutant removal have been developed and put into use to remove pollutants from wastewater. Using machine learning and optimization processes, new models for adsorption are created. Adsorption efficacy, operating circumstances, and adsorption mechanism are all included in various stages of operations. Recently, desalination and wastewater treatment have both benefited from usage of artificial intelligence. By reducing process costs and maximizing chemical use by avoiding more trial-and-error techniques, artificial intelligence improves the optimization of treatment processes. This chapter discusses issues and provides recommendations for effective application of several optimization algorithms in real-world water treatment systems. This chapter also emphasizes how process variables affect adsorption efficiency and suggests some possible directions for further research, including using mathematical models to predict theoretical adsorption efficiency and applying machine learning to adsorption processes.

Keywords: Machine learning; Artificial intelligence; Mathematical models, Wastewater treatment, Adsorption

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I. INTRODUCTION

Undesired inclusion of toxins into water directly or indirectly as a result of technological advancements in several industries, including leather tanning, textile, mining, and electroplating, results in water pollution. Most water contaminants are either poisonous or cancer-causing in nature. Consequently, their excessive content should be limited. Traditional methods for removing contaminants from wastewater include filtration, chemical precipitation, ion exchange, coagulation, flocculation, adsorption, flotation, and many others. Among these, adsorption is regarded as most effective and acceptable technique for removal of heavy metal ions and organic dyes from wastewater [1]. Adsorption is a key benefit of method because it is affordable, efficient, and simple. However, the adsorption process' effectiveness is dependent on the kinds of adsorbents utilized and other conditions. To colour a product, dyes and pigments are mostly utilized in the textile industry. The effects of colored wastewater from industry are quite detrimental to the ecosystem. These dye compounds are primarily made up of poisonous and cancer-causing azo dyes. Adsorption alone is the most effective conventional technique utilized in WWT. Adsorption is frequently used to remove pollutants, such as dyes and heavy metal ions, from wastewater. Today's adsorbents include resins, reduced graphene, biomasses, magnetic nanoparticles, and activated carbon [2, 3, 4, 5]. In dye-polluted water, colour is the first observable contaminant. Because they are linked to COD, biodegradation, and toxicity, dye effluents from the textile sector pose the most concern. Industrial effluent and wastewater that has not been completely treated pose a severe concern as well. Dye is a substance that is poisonous, cancer- and mutagenic in nature. Most artificial colored dyes have an aromatic ring structure in their molecules. Due to these factors, dyes are inert, mutagenic, and non-biodegradable. Due to its high treatment effectiveness and lack of harmful byproducts in the treatment of wastewater, the adsorption process has an advantage over other approaches. Since water makes up between 70 and 80 percent of all living things, the world would not be able to sustain life without it. Water is the only raw material that cannot be substituted since the quality of this precious resource directly affects both animal and human survival. When wastewater from these operations is dumped into natural channels, it pollutes the air, water, and soil in developing countries where population and industrial growth are increasing the need for water supplies [6]. The fabric of contemporary society is textiles.

There are several different dyes that are used as colorants in textiles, including Malachite Green (MG), Safranin (SA), Rhodamine-B (RB), Active Orange, Phenol, etc. When these industrial wastes are discharged into open streams and people drink the water, it can irritate their skin, eyes, respiratory systems, etc. These contaminants have also been reported to cause reproductive and developmental problems in both humans and animals [7, 8]. Currently, the lack of access to clean water is to blame for 80% of infections. 1.8 billion people will experience water scarcity if the current trend continues. Water contamination has caused dissolved oxygen levels to drop, which has a deleterious effect on aquatic life. So, before being used for home purposes, these effluents must be treated. It is more important than ever to use generated and recycled water for toilets, gardens, industrial cooling, and other secondary uses [9, 10, 11]. The ineffectiveness of traditional water treatment techniques like adsorption (physical), chlorination (chemical), and ozonation (biological) non eliminating pollutants prevents them from complying with international environmental requirements. The businesses now require the technological advancements in organic

pollution treatment. Concern has been raised about the stability and increased use of current textile dye compounds.

Total recovery of semi-conducting particles employed in reactors may be unattainable from a practical standpoint. Leaching, centrifugation, and then filtration is just a few of the processes that must be completed if the adsorbent is employed in slurry form. Although different nanomaterials have been utilized to slow down the degradation of certain dyes, their effectiveness still must be increased. Adsorption-based water treatment methods would be advantageous for underdeveloped nations. The current situation calls for efficient and cost-effective water and wastewater treatment solutions with the right nanomaterials. For this, an interdisciplinary approach from semiconductor photocatalysis, environmental chemistry, green chemistry, materials chemistry, etc. is necessary [12, 13]. Additionally, several techniques have been used to treat inorganic ions using readily available, inexpensive materials as adsorbents, such as activated carbon, coconut shell charcoal, bone charcoal, fire clay, and some natural zeolites [14, 15, 16]. However, these techniques are very specialized in nature. According to the literature, substantial application of nanomaterials in water and waste water treatment is more laboratory scale.

However, there are several obstacles in the way of their industrial usage. Further research is being done on novel nano composite materials for the adsorption processing of textile colors. However, it is uncommon to find research on theoretical efficiency prediction of nanomaterials. This review chapter discusses the current advances in using nanomaterials in adsorption by leveraging AI approaches and different optimization methods, as well as the difficulties that arise when these applications are to be deployed on an industrial scale. An effort has been made to shed light on how mathematical modelling and machine learning are used in the field of adsorption.

II. ADSORPTION PROCESS

Adsorption is the process of molecules (or ions) physically adhering to or attaching to the surface of another substance, specifically a two-dimensional surface. In this instance, the solid surface is the adsorbent and the substance that has gathered at the contact is the adsorbate. When using the adsorption system for both industrial large-scale treatments and laboratory scale applications, it is crucial to take the modes of interaction between the solid adsorbent and the wastewater into account. To collect experimental data and for industrial applications, a variety of contacting systems are available. These include batch procedures, fixed-bed-type operations, pulsed beds, moving mat filters, and fluidized beds. It is crucial to note that non-destructive adsorption employing batch systems only causes a phase change in the pollutants, creating additional issues with sludge disposal. There are two major methods (regeneration step and replacement) for dealing with used adsorbent in fluidized-bed reactors [17]. Ability of a solid material to regenerate itself if necessary is one of its key properties. In order to reduce process costs and increase the likelihood of recovering the contaminant removed from the solution, the renewal of the adsorbent may be of utmost importance. Activated carbons, ion-exchange resins (polymeric organic resins), and inorganic substances including activated alumina, silica gel, zeolites, and molecular sieves (which are technically not zeolites) are included on the list of conventional commercial adsorbents [18]. The commercial usage of adsorption has been dominated by just four general adsorbent types: activated alumina, zeolites, carbons, and silica gel. The list of unconventional adsorbents also

includes biosorbents like chitosan, natural materials like clays, industrial byproducts like red mud, activated carbons made from agricultural solid waste and industrial byproducts, and other adsorbents.

Water pollution caused by the growth of industrialisation has emerged as a serious environmental problem in the recent years. Application of different optimization-based modelling tools have gained attention for improving efficiency and assessing the performance of the adsorbent. Artificial intelligence and its importance with time due to the integration of artificial intelligence-based systems with intelligence, adaptability, and intentionality in their proposed algorithm. AI is applicable in all interdisciplinary field. They played a significant importance in optimization classification. AI tools are used in the combination with experimental design techniques such as response surface methodology (RSM) to enhance the precision of optical solution prediction. The application of AI is emerging in water treatment to overcome the complication of traditional methods [19]. Application of AI in water treatment made the process easy due to its implementation, flexibility, generalization, and design simplicity.

Commonly used AI techniques (figure 1) in water treatment includes recurrent neural network (RNN), Convoluted neural network (CNN), decision tree (DT), support vector machine (SVM), self-organizing map (SOM), artificial neural network (ANN), particle swarm optimization (PSO), random forest (RF), genetic algorithm (GA). K-nearest neighbour (k-NN), fuzzy neural network (FNN) and deep neural network (DNN). There is also hybrid system in adsorption for wastewater treatment which includes ANN-GA, MLP-ANN, ANN-PSO, PSO-GA, FFBP-ANN etc [20].

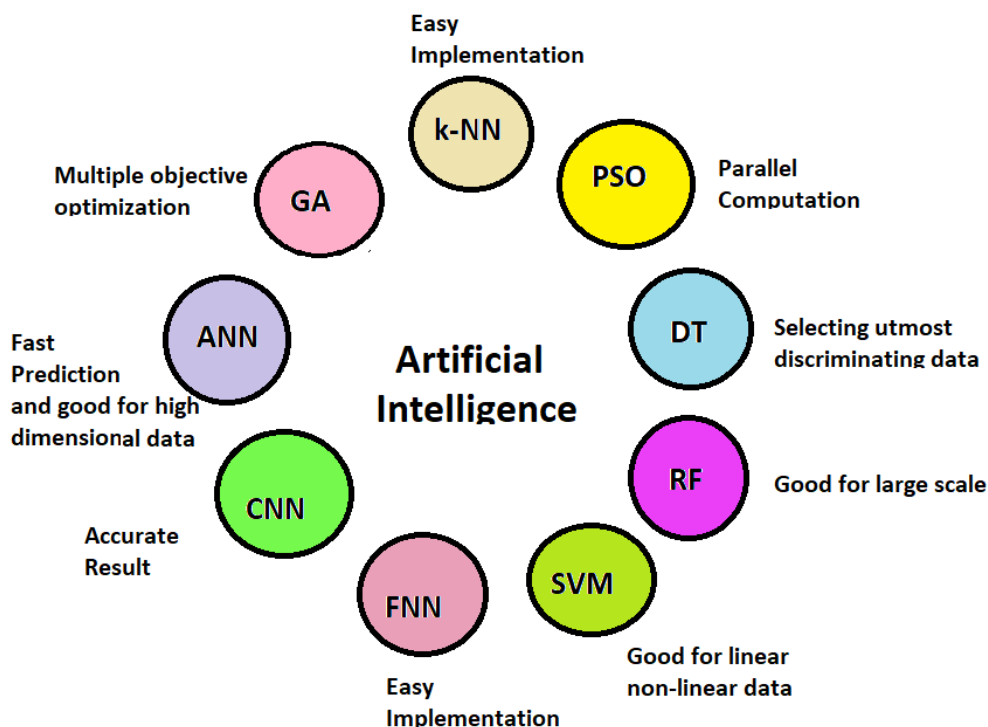


Figure 1: Applications of AI in adsorption

1. Techniques based in AI for Wastewater Treatment in Adsorption: Widely used artificial intelligence techniques for the wastewater treatment through adsorption mechanisms are mentioned below.

- **K-nearest Neighbour:** A straightforward machine learning method for regression and classification is K-nearest neighbour. K-nearest neighbour performs classification on new data points based on similarity while preserving all previously collected data [21].
- **Decision Tree:** AI professionals use it to solve their regression and clarity issues. It has a tree-like structure. The attributes or features of the data are represented by each node in the tree. The likely solution to the issue is represented by the edge. The method is more: reliable since it is simple to use and highly accurate [22].
- **Random Forest:** Problem classification and regression are done using random forest. Like a forest, there will be more decision trees, and random forest will be more reliable. By averaging their results, it reduces the overfitting of decision tree [23].
- **Artificial Neural Network:** To carry out concurrent and sophisticated computations, artificial neural network are statistical models created based on the biological human brain function. In artificial neural network, neuron serves as a node, and non-linear computations are carried out using activation functions like sigmoid and hyperbolic [24].
- **Particle Swarm Optimization:** Due to its iterative improvement of the solution connected to a particular quality measurement, particle swarm optimization is a regularly used technique for variable optimization [25]. Particle swarm optimization moves the particles through the search space while considering their position and velocity. By adjusting its velocity in accordance with the established rule, each particle searches for the ideal position inside the search space.
- **Genetic Algorithm:** Genetic algorithm is a heuristic-assisted search algorithm that operates on a population of potential solutions in a manner akin to population genetics and selection in biological processes. It used a recursive approach to iterate through several solutions until it found the optimal one. In genetic algorithm, all conceivable solutions are stored as genes that are made up of traits that resemble strings from various alphabets [26]. To solve a problem, this method is mostly used to explore a space for viable solutions and identify the best one.
- **Self-Organizing Map:** Again, one of the most used AI methods for artificial neural network models is self-organizing map. Input and output layout layers are included in self-organizing map. Map layer is the name of the last layer. Data clustering and dimensionality reduction are accomplished using self-organizing map. Self-organizing map is given a weight vector with dimensions that are like the input space [27].
- **Support Vector Machine:** Support vector machine is a renowned AI based technique used for solving classification and regression problem [28]. Fundamental idea of support vector machine is to map the input vector onto a large feature space. Different kernel functions, including radial, polynomial, and linear basic functions, are used to access the mapping. Support vector machine seeks to enhance the margin between the classes by differentiating the two classes in the feature space.
- **Recurrent Neural Network:** Like other ANNs, RNN has an additional memory-state to the neurons to share the same parameter [29]. An FFNN called an RNN transfers data from the input layer to the output layer. A long short-term memory

(LSTM) with three gates (input, output, and forget state) that calculate the hidden state is a typical type of RNN.

- **Deep Neural Network:** DNN contains multiple hidden layers along with input and output layer. DNN is commonly used for learning complex models and high dimensional data process with the inclusion of more hidden layers and neurons [30]. Compared to other ANN, DNN gives the best performance if the datasets have enough data.
- **Fuzzy Neural Network:** FNN is developed from the grouping of 2 fields, fuzzy logic, and neural network. FNN detects the parameters of a fuzzy system including fuzzy sets and fuzzy rules by varying the approximation technique from neural network [31]. It is mainly used for patternization and density estimation in a condition where no mathematical model exist for a specific problem.
- **Convolutud Neural Network:** It is the commonly used class of ANN. Here convolution used as an alternative to general matrix multiplication in at least one of their layers, known as feed forward neural network FFNN [32]. In an RNN, a type of FFNN, data is sent from the input layer to the output layer. A form of RNN that is often used is called long short-term memory (LSTM), which has three gates (input, output, and forget state) to calculate the hidden state. Applications of AI for adsorption of contaminants from aqueous solution are shown table 1.

Table 1: Applications of AI for adsorption of contaminants from aqueous solution

Pollutant	Adsorbent	AI technique	Input variable	Output Variable	Ref.
Basic red	Walnut husk	ANN	Temperature, time, initial dye concentration, Ph, dosage of the adsorbent	Removal%	[33]
EY	ZnO nanorods	ANN	Time, initial dye concentration, dosage of the adsorbent	Removal%	[34]
CY	ZnO -NR- AC nanorods	ANN	Dosage of the adsorbent, conc. and sonication time	Removal%	[35]
Congo Red	Fe ₂ O ₃ nanoparticles	ANN	Dosage of the adsorbent	Removal%	[36]
AR	Mesoporous carbon coated monolith	ANN	Dosage of the adsorbent time, Temperature, initial ion conc.	Removal%	[37]
Pb(II)	Biochar (date seed)	ANN	Dosage of the adsorbent, time, Temperature, initial ion conc.	Adsorption efficiency	[38]

Cr (II)	Clay composites	ANN	Dosage of the adsorbent time, Temperature, initial ion conc.	Biosorption efficiency	[39]
Cu(II)	Bone char	ANN	Dosage of the adsorbent time, Temperature, initial ion conc.	Removal %	[40]
Co(II)	Chitosan composites	ANN	Dosage of the adsorbent time, Temperature, initial ion conc.	Adsorption efficiency	[41]
Cd(II)	Rice straw	ANN	Dosage of the adsorbent time, Temperature, initial ion conc.	Adsorption efficiency	[42]

Hybrid techniques of AI includes 4 main techniques. GA, PSO, RNN and SVM combinations. They are used in combination with other techniques. Examples includes GA-FNN, GA-FL, SVM-SA, SVM-ASAGA, SVM-SA, PSO-WNN, PSO-ENN, ANN-GANN, GA-MLPANN, etc. All have wide application in water treatment. The network of AI is shown in the figure 2.

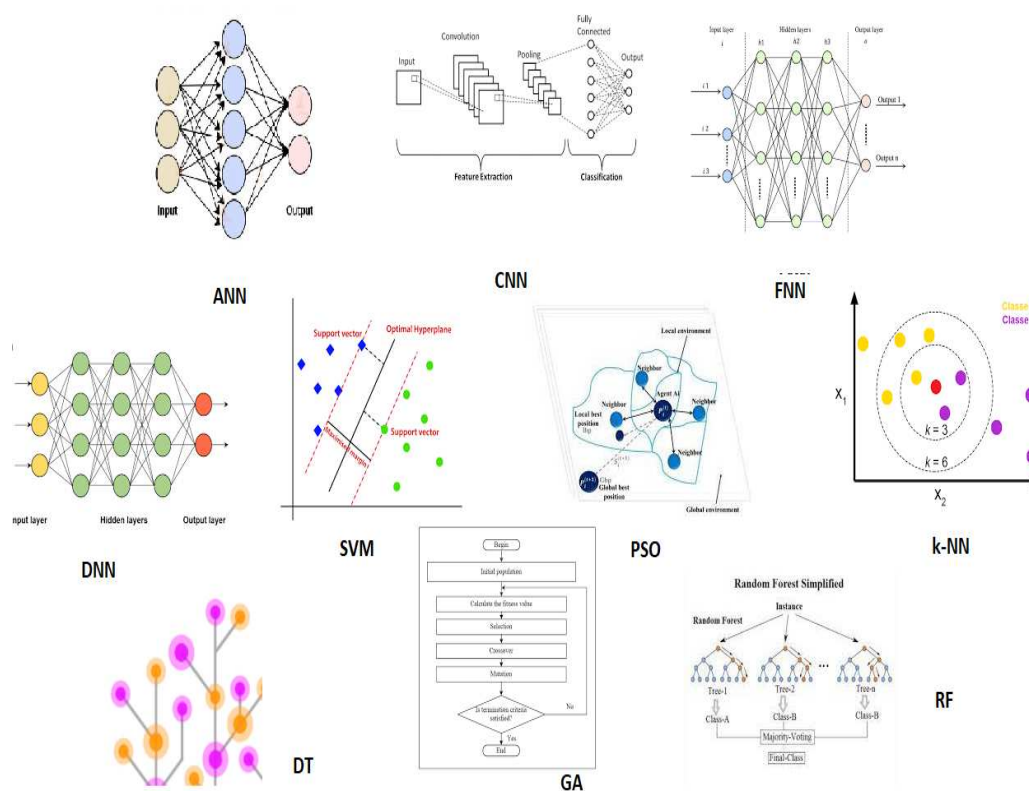


Figure 2: Network of AI in the adsorption of water treatment

III. MECHANISM OF ADSORPTION

Pollution is an undesirable change physical, chemical and biological properties of air, water, soil which have a detrimental effect on the living things. Adsorption is considered very effective for WWT. Adsorption is a surface phenomenon where adsorbate bind to a solid surface from its gaseous or liquid surroundings. Physisorption and chemisorption are considered as the main energy of interaction between the adsorbate and the adsorbent. Physisorption is associated with weak Van der Waals forces a long with dipole-dipole and hydrogen bonding developed between the adsorbent and the adsorbate [43]. Physisorption is reversible, non-selective and related with small change in enthalpy. Chemisorption dealt with irreversible and higher heat change [44]. To analyze the mechanism of adsorption many factors must be studied such as kinetic, isothermal, and thermodynamic. Types of adsorptions and its mechanism is explained based on the type of adsorbent and the adsorbate, structure, sources, and the forces of attraction. It is mainly divided in to two.

- 1. Chemisorption:** Mechanism involved in chemisorption dealt with the ionic exchange mechanism, electrostatic mechanism, oxidation/reduction mechanism etc. This mechanism can work separately or together in chemisorption. In chemisorption energy is liberated during the adsorption of the dyes hence it is an exothermic reaction., and the enthalpy is negative. It slows down the movement of the pollutant when get absorbed on the surface of the adsorbent. It also decreases the entropy of the system and the process is spontaneous in nature.
- 2. Physisorption:** Physisorption occurs between the adsorbent and the adsorbate via van der Waals forces. In physisorption adsorbent surface lacks functional groups as compared with chemisorption. As a result, adsorbent tries to physically attach to the adsorbent surface through weak van der Waals forces. Physisorption mechanism mainly depends on the pressure and temperature of the adsorption medium [45]. Therefore, the ratio of adsorption and desorption are very fast. In physisorption, adsorption process is mainly depended up on the concentration and structure of the adsorption.

IV. FACTORS INFLUENCING THE ADSORPTION PROCESS

Different parameters affect the efficiency of adsorption process. These parameters are optimized for the better result and to avoid the number of experiments. It also helps to reject the unwanted cost and the excess trials. Such factors are dosage of the adsorbents, pH, initial concentration, time, temperature, stirring speed etc.

- 1. Dosage of the adsorbent:** One of the main factors to control the absorption capacity of the adsorbent is the optimization of the amount of the adsorbent for the adsorption of the dye [46]. If other factors stay the same, it is claimed that the removal efficiency rises as the amount of adsorption increases. Like how the surface area of the adsorbent and active exchangeable adsorption sites increase, so does the dye removal efficiency. Because there were vacant adsorbent sites once agglomeration formed, adsorption effectiveness decreased.

- 2. pH of Medium:** Primary factor affecting the adsorbent's ability to absorb material is pH. Influences in pH can alter the properties of the adsorbent surface, which changes how much the ionized dye molecules undergo electrostatic changes. Considering the surface charge on the adsorbent, zero-point charge aids in determining the proper pH for the best absorption. The adsorbent surface's electrokinetic property is also measured using zero-point charge. The surface functional group of the adsorbent deprotonated and gained negative charge if the pH was higher than the point of zero charge. It will support the cationic dye industry. Like this, anionic dye adsorption is encouraged at pH values lower than Pzc because the surface functional group has protonated [47].
- 3. Contact Time:** Amount of time that the adsorbent and adsorbate are in touch with one another influences how well the pollutants are bound and when they are best absorbed. With more vacant surface-active adsorbing sites available, initial stage removal efficiency rises. As a result, there are fewer surface-active adsorbing sites, which reduces the number of adsorption sites, forcing molecules to go deeper into pores. Adsorption thus approaches equilibrium.
- 4. Initial Dye Concentration:** Relationship between the initial dye concentration and the availability of adsorbing sites on the adsorbent's surface determines how much adsorption occurs. The variation in the initial dye concentration has a significant impact on the adsorption and desorption efficiency.
- 5. Temperature:** An essential component of adsorption efficiency is the effect of temperature on adsorption. The feasibility of the adsorption process changes depending on how high the temperature is raised. It alters the reaction's nature, making it exothermic or endothermic.

V. DESORPTION

Adsorbate and adsorbent recovery as well as the adsorption mechanism are explained by desorption studies. Desorption studies were conducted to regenerate the used adsorbent because doing so makes the treatment procedure more cost-effective [48]. There are significant volumes of frequently dangerous by-products and waste produced because batch adsorption is not a destructive approach and the adsorbents utilised go through a phase shift. Due to their characteristics, these solids can be recycled, allowing for the recovery of the adsorbent and frequently the contaminant. As the desorption depends on the adsorbent, the adsorbate (various types of dyes with ionic nature), and the adsorption process, the process of adsorbent renewal is a challenging undertaking. Examining the adsorbent's reusability is crucial in adsorption-desorption investigations. Adsorbent needs to be cleaned and regenerate in between dye removals so that it can be used again and the water treatment may be repeated. The number of adsorption-desorption cycles that the adsorbent may successfully use to remove dye compounds is expressed by the term 'adsorbent lifetime'. Therefore, it is the responsibility of researchers who study the desorption process to share knowledge about the reproductive cycles. Different desorption techniques are used, and a wide variety of eluents are used to renew the used adsorbents, some of which are described below.

One of the most crucial economic factors could be the ability to reuse adsorbent. The decrease may generally be brought on by adsorption degradation throughout cycles of adsorption and desorption.

VI. APPLICATION OF RESPONSE SURFACE METHODOLOGY FOR MODELLING AND ANALYSIS OF WATER AND WASTEWATER TREATMENT PROCESSES

Several water and wastewater treatment systems have been modelled and optimized using the response surface methodology (RSM). RSM is a group of mathematical and statistical methods for creating models, analyzing the impacts of various variables, and determining the values of the process variables that result in ideal response values [49]. The most recent data on RSM's application to various water and wastewater treatment procedures are reviewed in this chapter. This is followed by a description of the theoretical underpinnings and procedures for implementation. Its use in advanced oxidation processes, adsorption, electrochemical processes, disinfection, and coagulation-flocculation is evaluated considering recent studies. The methodology's shortcomings are brought to light. Also highlighted are initiatives to enhance the RSM by its integration with other modelling methodologies.

- 1. Steps in RSM:** In RSM, mathematical models created utilizing experimental design data define the relationships between the independent variables (factors) and the dependent variables (responses). In addition to being used for process optimization, these models are utilized to analyse how independent variables interact with one another and with the answers. A 3-D plot and 2-D outlines are typically used to illustrate the results. Statistical experimental design, linear regression modelling, and optimization techniques must be used when using the RSM [50, 51]. When using RSM as an optimization method, there are several stages and steps involved. These include (i) choosing the independent variables and their ranges, (ii) choosing an experimental design and performing the experiments, (iii) creating a linear regression model equation based on the experimental results, (iv) assessing the suitability of the model, and (v) displaying the model graphically and achieving the best conditions. choosing independent variables, A system's response might be impacted by a lot of independent variables (factors). Screening studies are required to determine the variables with large effects because it is economically not feasible to incorporate all these factors in the experimental design. The most common method for identifying these variables is to use two-level factorial designs or the one-factor-at-a-time method in studies. (Since it has an impact on the model equation's accuracy, choosing the right range (level) for these parameters over which the variables are to be tested is also crucial. Selecting a tighter range for the factors requires prior knowledge of the system or process being researched.
- 2. Experimental Design in RSM:** Experiments can be carried out using a variety of designs. Regarding the number of runs and experimental points chosen, these designs are different from one another. Box-Behnken design (BBD), central composite design, and full three-level factorial design are a few of the frequently used experimental designs (CCD) [52]. The components of a full three-level factorial design are varied at three levels, 1, 0, and 1, which stand for minimum, mean, and maximum values, respectively. There must be $3k$ experiments, where k is the total number of independent variables. For

more than two independent variables, the full three-level factorial design requires a relatively high number of tests, hence other designs are typically utilized. The two-level factorial design and incomplete block are combined to create the Box-Behnken design, which was first proposed by Box and Behnken in 1960. Due to the smaller number of runs required compared to complete factorial design, BBD is typically quite effective. Given that the vertices of the cubic region do not contain any experimental points, the Box-Behnken design may be helpful when testing at these locations is too expensive or impractical for other practical reasons [53]. The phrase $2k(k-1)cp$, where cp is the number of replicates at the central point and k is the number of factors, controls the number of experiments. In 1951, Box and Wilson proposed central composite design as an alternative to full-level factorial design. A central point, a central composite design, and a separate design with experimental points located at a distance from the center make up a central composite design. From the equation $2k + 2kcp$, where cp is the number of replicates at the central point, the number of experimental runs may be computed. Typically, 14 of k is used as the value of. Up until five or six elements, the central composite design has very high efficiency, but after that, it starts to decline quickly. If all the tests can be run concurrently (i.e., all at once) rather than sequentially (i.e., one after the other), CCD can be used for optimization with a high number of parameters. Despite being documented in the literature, designs like the Doehlert uniform shell design, Box-Draper saturated designs, and D-optimal designs are rarely employed in the field of water and wastewater treatment since central composite design and Box-Behnken design are more straightforward and reliable [54, 55, 56, 57, 58, 59, 60, 61]. Doehlert designs cannot be rotated, although central composite designs can. Factorial and axial points are included in central composite designs, which aid in experimentation's sequential strategy. The two-level design can be augmented with axial runs to create a central composite design if curvature is crucial. Because Box-Behnken designs are affordable, they are common in industrial research.

3. **Application of RSM in Wastewater Treatment:** RSM is a very effective method since it creates a response surface model that predicts a response based on a combination of factor levels in addition to identifying the ideal operating conditions to maximize a system's performance. It also provides information on the relative importance, impact, and interplay of various factors. It has led to their usage in modelling a range of water and wastewater treatment systems and processes as shown in table 2.

Table 2: Application of RSM in Wastewater Treatment

RSM Design	Applications	Independent Variable	Response	Ref.
BBD	Adsorption of Basic red dye	pH, temperature, initial ion concentration	Amount of dye adsorbed	[62]
CCD	Adsorption of Rh-B dye	pH, dosage of the adsorbent temperature, time	Amount of dye adsorbed	[63]

CCD	Adsorption of Cd(II)	pH, dosage of the adsorbent initial ion concentration	Amount of dye adsorbed	[64]
BBD	Adsorption of Rh-6G dye	pH, dosage of the adsorbent initial ion concentration	Amount of dye adsorbed	[65]
PBD	Adsorption of Rh-B dye	Dosage of the adsorbent, pH, temperature, time, and initial concentration	Amount of dye adsorbed	[66]
PBD	Adsorption of MB dye	Dosage of the adsorbent, pH, temperature, time, and initial concentration	Amount of dye adsorbed	[67]
BBD	Adsorption of Cu(II)	pH, temperature, and initial concentration	Amount of dye adsorbed	[68]

VII. CHALLENGES

Compared to traditional mathematical modelling, AI techniques have several benefits. It can be used to lower the expenses associated with experimentation and forecast how different water treatment processes will perform. Broad use of these procedures in actual water treatment has been hampered by a few drawbacks. Main problem with AI tools like ANNs is their poor repeatability, which is caused by random weight and bias and may lead to a locally optimal solution. To forecast the effectiveness of pollutant removal throughout adsorption process, different AI tools might be combined. For reaching high accuracy and prediction, deep learning and deep ANNs are viable solutions. However, experimental training, testing, locating local minima, and overfitting all require a considerable amount of data shall help to achieve. In some cases, process performance that AI systems forecast may differ from actual results. For instance, a sudden change in water quality or operating parameters may cause AI technologies to make incorrect predictions. It is necessary to make efforts to improve predictive capabilities of AI tools so that they may be used in a variety of situations and can handle abrupt changes in input variables. Using a lesser set of data and existing literature, AI tools have shown amazing performance when modelling batch adsorption process. The use of AI tools in real wastewater treatment with a wide variety of data has yet to be investigated.

Selection and availability of data are another significant obstacle for AI-based water treatment. By building datasets for system optimization and prediction, water utilities are acquired to generate, collect, process, assess, and analyze data. A random data selection relates to some downsides, special consideration must be given when choosing training data for AI systems. But for experimental design techniques (i.e., RSM) to produce an appropriate response, a sizable input dataset is typically needed. It is possible to anticipate removal of pollutants more correctly by feeding AI models operational data from actual water treatment facilities. Artificial intelligence technology has potential to be a game-changer for environmentally friendly wastewater treatment by significantly lowering operating costs. In addition to forecasting effectiveness of water treatment process, AI techniques can be used to integrate entire process, starting with water discharge, transportation, sludge management, environmental implications, economy, legislation, and many more. Successful application of AI approaches in water treatment area requires data collecting from various water treatment processes. To maintain the integrity of data, nevertheless, great care should be used while collection. Data reporting should include a complete list of all relevant details, including data sources, location, process environment, and dataset ontology. Researchers, students, and engineers will benefit from this information as they reuse data in numerous experimental domains for predictions in the future. Water sector can use AI to streamline and control water monitoring and management. To solve issues with water management and treatment, including water quality, leak detection, and process optimization, new AI-based algorithms must be developed. Prediction accuracy can be improved using hybrid AI algorithms, which lowers operating and energy costs. Optimal strategies for use in actual treatment processes should be recommended using a benchmark or framework that compares various AI-based stand-alone and hybrid water treatment techniques. Similarly, RSM based optimization helps to increase the adsorption by decreasing the number of trials.

VIII. CONCLUSIONS AND FUTURE ASPECTS

Among various water treatment technologies, photocatalysis by semiconductor nano metal oxide and biosorbents offers a greater advantage and are promising from point of view of modern environmental remediation technologies. Some of nano metal oxides not only act as adsorbents but also act as photocatalysts. Recent literature shows heterogeneous photocatalytic systems, nano composites have shown their good efficiency in photo degrading dyes present in textile effluents. Many of these studies have focused on optimization of process parameters, kinetic studies and degradation mechanism, adsorption studies which are very important for water treatment process to ensure sustainable operation. Continued efforts to explore new low cost photocatalysts composition in this area of research is very important to attain sustainable and practical solutions to existing and forthcoming environmental threats. As limited literature is available to cater to industry with respect to photocatalytic- reactor design, modeling, and scalability; more focused efforts are required by researchers with input of industry. Pilot scale and industrial scale studies are rarely seen in open literature, which should open the eyes of both researchers and practicing effluent treatment professionals. Future studies carried out in this direction can become guidelines for the both researching and industrial community to find solutions to environmental threat of various dyes that are being added to water streams. This chapter detailed about major AI techniques and RSM optimization methods employed in water treatment for uptake of different pollutants. Numerous single and hybrid AI models have successfully predicted efficiency of different adsorbents for removal of organic dyes, metal ions, drugs, and

pharmaceuticals from aqueous solution. More studies in pilot level experiments helps to address the limitations faced while applying AI tools. Regardless of those challenges, AI techniques proved that these tools have a bright future in the domain of wastewater treatment.

ABBREVIATIONS

WWT	Waste water treatment
MG	Malachite green
MB	Methylene Blue
RO	Reactive Orange
AI	Artificial Intelligence
ANN	Artificial Neural Network
DT	Decision Tree
MLP	Multi-Layer Perceptron
ANFIS	Adaptive Network based Fuzzy Inference System
RSM	Response Surface Methodology
RBF	Radial Basis Function
CNN	Convolved Neural Network
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
RF	Random Forest
KNNs	k-Nearest Neighbor
SVM	Support Vector Machine
RNN	Recurrent Neural Network
SOM	Self-Organizing Map
FNN	Fuzzy Neural Network
DNN	Deep Neural Network
RBFN	Radial Basis Function Network
GP	Genetic Programming
GA-RSM	Genetic Algorithm-Response Surface Model
GA-RBANN	Genetic Algorithm -Radial Basis Function Artificial Neural Network
GA-FNN	Genetic Algorithm -Feedforward Neural Network
GA-FL	Genetic Algorithm -Fuzzy Logic
PSO-ENN	Particle Swarm Optimization-Elman Neural Network
RSM	Response surface methodology
BBD	Box-Behnken Design
CCD	Central Composite Design
PBD	Plackett-Burman Design

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