

Application of Artificial Neural Networks in Adsorption-Based Wastewater Treatment: Modeling, Optimization, and Prediction

Sema Kaptanoğlu¹

Ali Rıza Kul²

Fatma Calayır³

Abstract

Due to industrialization and population growth, pollution observed in water resources increases the need for effective and sustainable treatment technologies day by day. Particularly, the dyes used in industries such as textiles, leather and medicine have serious risks in terms of environment and human health with toxic and permanent properties in the wastewater environment. In this context, adsorption methods; It is widely preferred thanks to their low cost, high applicability and environmentally friendly. In adsorption processes, interest in agricultural and industrial waste -based natural adsorbents has increased as an alternative to traditional active carbons.

However, the fact that adsorption depends on a large number of parameters makes it difficult to model these processes by classical methods. For this reason, artificial neural networks (ANN), which are among the calculating intelligence techniques, stand out as an important alternative thanks to their ability to model, generalize and make estimates with limited data. ANN provides successful results in issues such as estimation of adsorption efficiency, optimization of processing conditions and analysis of process performance.

In this section, the main principles of adsorption processes, isotherm and kinetic models used in detail are discussed in detail. In addition, ANN's structure, learning mechanism, environmental application examples and

1 Van Yüzüncü Yıl University, semakaptanoglu@yyu.edu.tr, 0000-0002-5614-7496

2 Van Yüzüncü Yıl University, alirizakul@yyu.edu.tr, 0000-0001-9331-775X

3 Afyonkarahisar Gazi Vocational and Technical Anatolian High School, fatma.calayir27@gmail.com, 0000-0001-7995-6045

advantages are examined extensively. In the application studies in the literature, it has been seen that ANN models have high accuracy rates for the removal of various pollutants such as methylene blue and heavy metals.

As a result, ANN -supported modeling approaches allow the development of faster, economical and reliable treatment processes by supporting experimental studies. These systems, which are supported by deep learning and hybrid structures, open the door of sustainable and innovative solutions in the field of environmental engineering.

1. Introduction

In recent years, rapid population growth and industrialization, surface and ground water resources bring environmental and soil contamination (Yıldız, 2001). Water is one of the most basic and indispensable components of the ecosystem. The phrase “Water is life” clearly demonstrates this importance not only in terms of maintaining its living life, but also in terms of having a wide range of uses (Kenda et al., 2024). However, human -based domestic and industrial activities adversely affect the water quality standards determined by international norms and cause environmental pollution (Bailey et al., 2022). Since the paint substances detected in water resources and wastewater have toxic and carcinogenic properties, it creates serious threats not only for human health, but also for all living species in the trophic chain. Such painting substances, especially in the textile industry; It is widely used in many sectors such as paper, medicine, food, leather processing and personal care products (Kanwal et al., 2023).

Different treatment techniques are used to remove dyes in waste water. These methods include precipitation, coagulation, flocculation, membrane filtration, ion change and adsorption. Limited efficiency of methods such as coagulation and flocculation, membrane separation and ion replacement techniques are high -cost and limited in terms of application reveals that these methods offer less advantages than adsorption (Katheresan et al., 2018). Adsorption is considered an effective method that stands out with its ease of application, economic and simple structure. Although commercial active carbon has been preferred in these processes, studies on the development of more economical and sustainable alternative adsorbents in recent years have increased in recent years (Özdemir, 2019).

Many studies based on adsorption are included in the literature for the removal of dyes from juicy solutions. Most of these studies, which have been conducted for many years, have been carried out using agricultural, domestic and industrial origin waste or materials. Among the natural adsorbanlar preferred orange peel (Khaled et al., 2009), Pirina (Gok and Mesutoglu,

2017), Rice Shell (Priya et al., 2022), Ucak Ash (Eren and Acar, 2004), Walnut Shell (Pang et al., 2009; Gemici and Özden, 2022).

Modeling or simulation of a process makes it possible to make predictions about the behavior of the process without experimental practices. Nowadays, modeling methods are used for many processes in science and engineering (Ghaedi and Vafaei, 2017). Although the expense yield in adsorption processes is considered one of the basic performance indicators; Since this data requires time -consuming experimental studies, it is not possible to measure for all conditions. Therefore, it has become important to predict the relief yield (%) with the use of a limited number of variables (Ghaedi and Vafaei, 2017). However, the relationship between the input parameters and the system output is quite complex and often not linear, making it difficult to model adsorption processes by classical statistical methods. In this context, thanks to non -linear structures and capabilities of processing complex data sets containing incomplete data, calculating intelligence models offer a more flexible and effective alternative than statistical models (Karlaftis and Vlahogianni, 2011).

At this point, especially artificial neural networks (ANN), adsorption, such as multi -variable and non -linear systems as a means of effective calculation comes to the fore. Artificial neural networks are an artificial intelligence approach that has been successfully applied in many fields such as pattern recognition, estimation and classification (Haykin, 2009), inspired by the knowledge processing and learning mechanisms of the human brain (Haykin, 2009). Thanks to the ability to learn and generalize complex relationships between input and output variables, ANNs offer a strong alternative to estimating process performance based on experimental data. In adsorption processes; ANN -based approaches are widely used to model the effects of parameters such as initial concentration, contact time, pH, temperature and amount of adsorbent (Kang et al., 2013). With these methods, comprehensive predictions can be made based on limited number of experimental data, and therefore significant advantages are obtained both in terms of time and cost.

The main purpose of this section is to combine the modeling approaches developed in the intersection of these two areas by combining the adsorption method commonly used in the removal of environmental pollutants with artificial neural networks (ANN). The advantages of artificial intelligence -based prediction models are discussed extensively by drawing attention to the limitations of traditional experimental methods used in the removal of various contaminants through adsorption in aqueous environments. In

this context, ANN's theoretical infrastructure, application processes, model optimization and performance evaluation criteria are explained in detail; In addition, application areas are analyzed through the sample studies in the literature.

This section is a practical guide for researchers in the fields of environmental engineering and chemicals, focusing on artificial neural -based modeling techniques that allow the analysis of adsorption processes to be analyzed more efficiently and rapidly. It contributes to the development of sustainable environmental technologies by showing how advanced data analysis methods can be used as a supportive and complementary tool. In addition, it is aimed to promote sustainable solutions both environmentally and economically by evaluating agricultural and industrial wastes as an alternative adsorban. Thus, this section aims to give the reader a interdisciplinary perspective with both theoretical knowledge and practical examples.

2. Fundamentals of Adsorption

Adsorption is the event of keeping liquid or gas molecules on the surface due to the unsaturated areas on the solid surfaces and unstable molecular forces. This process creates a dynamic balance between the adsorption of gas or fluid to the surface and the balancing of these forces. While the molecules held on the surface are called “adsorbat, the solid substance that forms the surface is called” adsorban. Adsorption events are usually coincidental and progress in line with the decrease in free energy in the system. When the gas molecules adsorbe, they have a more limited freedom of movement than the free phase; This causes a decrease in entropy during the adsorption process (Bansal and Goyal, 2005).

Adsorption is a process that takes place as a result of the effect of unbalanced molecular forces on solid surfaces and unsaturated regions. When such surfaces come into contact with liquid or gas phases, adsorption begins. In this process, both physical and chemical interactions play an important role such as dipole moments, polarization effects, reorganization of electrons in the valence band. Adsorption is basically divided into two types: physical and chemical adsorption. In physical adsorption, adsorbat molecules are weakly attached to the surface with van der waals forces; In chemical adsorption, strong chemical bonds are formed between the adsorbate and the solid surface based on electron exchange or sharing (Bruch et al., 2023).

2.1. Adsorption Kinetics

Adsorption kinetics include models developed to explain the speed of attachment to the adsorbent surface of the adsorbate molecules and the mechanism of the process. Kinetic studies are critical to determine the controlling stages of adsorption and to ensure the optimization of the process (Foo and Hameed, 2010). The most common kinetic models are pseudo primary and pseudo second -degree kinetic models. Pseudo first -degree kinetic model assumes that the adsorption rate is proportional to the adsorbate concentration, while Pseudo suggests that the second -degree kinetic model adsorption is performed by chemical attachment and the speed is related to the capacity of adsorbent (Ho and McKay, 1999). In addition, Weber-Morris intraparticle diffusion model is used to analyze mass transfer mechanisms during the adsorption process (Weber and Morris, 1963).

Adsorption kinetics plays a critical role in understanding and modeling the stages involved in the adsorption process. The adsorption of solute molecules from a solution onto the surface of an adsorbent typically occurs through four main steps:

1. **Diffusion through the film layer:** In the initial stage, the solute diffuses from the bulk solution toward the boundary layer (film) surrounding the adsorbent. Agitation of the solution reduces the thickness of this layer, thereby accelerating diffusion. Due to the typically negligible resistance in this step under stirred conditions, it is often omitted in kinetic evaluations.
2. **Film mass diffusion (boundary layer diffusion):** During this phase, the solute traverses the stagnant film layer and reaches the external surface of the porous adsorbent. This step represents the mass transfer resistance in the liquid phase adjacent to the solid surface.
3. **Intraparticle diffusion:** Once the solute reaches the surface, it diffuses into the internal pores of the adsorbent towards the active adsorption sites. This stage is commonly regarded as the rate-limiting step in many adsorption systems, especially for porous adsorbents.
4. **Surface adsorption:** Finally, the solute molecules are retained on the internal surfaces within the pores. In the absence of agitation, the boundary layer remains static, making this step potentially rate-limiting. However, under stirred conditions, the resistance in both the first and last stages is significantly reduced, rendering their contribution to overall kinetics minimal. As a result, the second and third steps generally govern the adsorption rate.

To assess the influence of film diffusion during the early stage (typically the first 5–10 minutes), a plot of $-\log(C_t/C_0)$ versus time is constructed. The linearity of this graph, particularly its proximity to unity, provides insight into the extent to which film diffusion contributes to the adsorption process. To investigate the effect of intraparticle diffusion, a plot of $qt_{1/2}$ versus the square root of time is examined. The slope of the resulting linear portion of the graph corresponds to the rate constant for intraparticle diffusion (Balci, 2007).

Effect of the Border Layer:

$$-\log C_t/C_0 \rightarrow t$$

Here;

C_t : t Concentration (ppm),

C_0 : Starting Catches (ppm),

t: Time (dk.)

The degree of proximity of the slope obtained from the graph shows the effect of this phase.

Effect of In -Particle Diffusion:

$$q_t \rightarrow \sqrt{t}$$

Here;

q_t : Time Adsorbent quantity (mg/g)

t: time (min.)

The slope obtained from the graph gives the cruise constant (k_p).

2.1.1. Pseudo First Degree Kinetic Model

Another widely used equation to elucidate the rate-determining steps of the adsorption process is the pseudo-first-order (PFO) kinetic model, originally proposed by Lagergren (Ho and McKay, 1999). This model provides a simplified representation of first-order adsorption kinetics.

The linearized form of the pseudo-first-order kinetic equation is expressed as follows:

PFO Linear Equations (Lin and Wang, 2009),

$$\log(q_e, \exp - qt) = \log(q_e, \text{calc}) - k_1 t / 2.303; \quad \log(q_e, \exp - qt) \rightarrow t$$

Here;

$q_{e, \text{exp}}$: Experimental q_e value (mg/g).

$q_{e, \text{calc}}$: The calculated q_e value (mg/g).

q_t : The amount of adsorbed substance (mg/g),

k_{1p} : The first order pseudo kinetic constant (1/min)

t : time (min)

To assess the suitability of the adsorption process to the pseudo-first-order kinetic model, both the coefficient of determination (R^2) and the calculated adsorption capacity ($q_{e, \text{calc}}$) are evaluated. A high R^2 value, approaching 1, along with a close agreement between the calculated ($q_{e, \text{calc}}$) and experimental ($q_{e, \text{exp}}$) adsorption capacities, indicates that the process conforms well to the pseudo-first-order kinetic model.

2.1.2. Pseudo Second Degree Kinetic Model

The pseudo-second-order (PSO) kinetic model, developed by Ho in 1995, demonstrates that the adsorption process depends on both time and adsorption capacity, while being independent of the amount of adsorbent used (Balci, 2014).

The nonlinear form of the pseudo-second-order kinetic equation is expressed as follows (Behnamfard and Salarirad, 2009):

$$q_t = k_{2p} q_e^2 t / (1 + q_e k_{2p} t)$$

As a result of linearization of this correlation, the following relations are reached (Behnamfard and Salarirad, 2009).

$$t/q_t = 1/k_{2p} q_{e, \text{calc}} + t/q_{e, \text{calc}} \quad t/q_t \rightarrow t \quad q_{e, \text{calc}} = e_{\text{gim}}^{-1}, \\ k_{2p} = (e_{\text{gim}}^2) / \text{kesme noktası}$$

Here;

k_{2p} : The amount of substance attached by adsorbent at the moment (mg/g),

$q_{e, \text{calc}}$: Calculated q_e value (mg/g),

$q_{e, \text{exp}}$: experimental q_e value (mg/g),

t : Time (min).

2.1.3. Weber-Morris Intraparticle Diffusion Model

This model was developed to evaluate the influence of diffusion on the adsorption process. As previously discussed, the adsorption mechanism

typically involves four distinct steps, among which the third step is known as intraparticle diffusion (ID). In this model, if the plotted line exhibits a high degree of linearity, it indicates that intraparticle diffusion is the rate-limiting step in the adsorption process (Weber and Morris, 1963).

The linear equation representing the intraparticle diffusion model can be expressed as follows (Behnamfard and Salarirad, 2009):

$$q_t = k_p t^{0.5} + C$$

In this context, k_p represents the intraparticle diffusion rate constant ($\text{mg, g}^{-1} \text{ min}^{-1/2}$), while C denotes the boundary layer thickness. When q_t values are plotted against the square root of time ($t^{0.5}$), the slope of the resulting linear equation corresponds to k_p , and the intercept indicates the value of C . The magnitude of C provides insight into the thickness of the boundary layer, whereas the slope (m) reflects the rate constant (Waranusantigul et al., 2003).

2.2. Adsorption Isotherm

Adsorption isotherms are mathematical models showing the distribution of adsorbate surface depending on the equilibrium concentration of adsorption capacity and adsorbate. These isotherms provide information about the type and surface properties of adsorption. The most commonly used models are Langmuir and Freundlich isotherm. Langmuir isothermia assumes that the surface is homogeneous and monolayer adsorption occurs; In this model, adsorption is accepted as a fixed number and equal energy surface area (Langmuir, 1916). Freundlich isothermia is applied on heterogeneous surfaces and in multi-layered adsorption and fits flexible in experimental data (Chattoraj and Freundlich, 1906). In addition, isotherm models such as cautious and dubinin-Radushkevich provide more detailed information about the thermodynamic and energy changes of adsorption (Temkin and Pyzhev, 1940; Dubinin, 1947).

2.2.1. Langmuir Isotherm

Assumes monolayer adsorption, the surface is considered to be homogeneous (Langmuir, 1916).

Langmuir izoterm

The expression of the Langmuir model is as follows;

$$q_e = \frac{q_m K L C_e}{1 + K L C_e}$$

By linearization of this equation, the following correlation is obtained;

$$\frac{C_e}{q_e} = \frac{1}{K_L q_m} + \frac{C_e}{q_m}$$

In the equation;

K_L : Langmuir constant (L/mg),

q_m : Maximum adsorption capacity of the adsorbent (mg/g),

C_e : The concentration of the substance remaining in the solution at the time of balance (ppm)

q_e : It refers to the amount of substance (mg/g) attached to the adsorbent surface at the time of balance.

A linear equation can be obtained by plotting C_e/q_e versus C_e . From this plot, the intercept provides the value of $1/K_L q_m$, while the slope corresponds to $1/q_m$.

The Langmuir isotherm model can also be evaluated using the dimensionless separation factor (R_L), which offers insight into the favorability of the adsorption process. An R_L value between 0 and 1 indicates favorable adsorption, whereas a value greater than 1 suggests that the adsorption is unfavorable and the Langmuir model is not applicable.

$$R_L = 1/(1 + bC_0)$$

C_0 : Starting concentration (mg/g).

2.2.2. Freundlich Isotherm

Suitable for heterogeneous surfaces and multi-layered adsorption (Chattoraj and Freundlich, 1906).

The mathematical expression of Freundlich isotherm is as follows;

$$q_e = K_F C_e^{1/n}$$

q_e : The amount of substances adsorbed on unit adsorbent (mg/g)

C_e : Heavy metal concentration remaining in the solution after adsorption (ppm)

K_F : A definite sign of adsorption. It shows the power of the relationship between adsorbent and adsorbate [(mg/g) (L/mg) $1/n$].

A high value of K_p obtained from the calculations, indicates a strong affinity between the adsorbent and the adsorbate.

The value of n typically falls between 1 and 10, and such a range suggests that favorable adsorption has occurred. The reciprocal value $1/n$ is expected to lie between 0 and 1, depending on n . A value of $1/n$ approaching zero implies a highly heterogeneous surface.

To linearize the Freundlich isotherm equation, the logarithm of both sides is taken, resulting in the following linear form:

$$\log q_e = \log K_F + \frac{1}{n} \log C_e$$

By plotting $\log q_e$ versus $\log C_e$, the Freundlich constants K_F and n can be determined. In this graph, the intercept corresponds to $\log K_F$ while the slope gives the value of $1/n$. These constants provide valuable insight into the nature of the adsorption process (Berkem and Baykut, 1980; Sarıkaya, 2007; Kayacan, 2007).

2.2.3. Temkin Isotherm

It takes into account that adsorption temperature has changed (Temkin and Pyzhev, 1940):

$$q_e = \left(\frac{RT}{b} \right) (\ln K_T C_e)$$

In equality;

q_e : The amount of substance adsorbent by adsorbent at the time of equilibrium (mg/g),

b : The Temkin constant (KJ/mol), which provides information about adsorption temperature,

R: Ideal gas constant (8.314 J/mol),

T: Temperature (K),

K_T : Temkin isotherm constant (L/mg)

When we make the Temkin isotherm model equation linear, the following equation is obtained.

$$q_e = B \ln K_T + B \ln C_e$$

2.3. Factors Affecting Adsorption

Adsorption efficiency is determined as a result of the interaction of many factors and each of these factors plays an important role in the activity of the process. First, the physical and chemical properties of adsorbent directly affect the adsorption capacity. The high surface area and the large pore volume facilitate the access of adsorbate molecules to the adsorbent surface and provide more binding area. Furthermore, functional groups on the surface of the adsorbent are critical in chemical attachment mechanisms and allow specific interactions with certain pollutants (Ahmad et al., 2012).

Secondly, operational conditions shape the efficiency of the adsorption process. The pH can change the adsorption capacity by affecting electrostatic interactions between adsorbent and adsorbate. The temperature may affect both adsorption kinetics and surface properties of adsorbent; In some cases, adsorption can be an endothermic, sometimes an exothermic process. While the contact time determines the time required for adsorption to achieve balance, the dose of adsorbent increases the total surface area where pollutants can be connected (Babel and Kurniawan, 2003).

Thirdly, the pollutant properties also determine the adsorption performance. The molecular dimension determines how easily adsorbate can penetrate into the pores; The residence time affects the time of the pollutant's water stay and thus the chance of adsorption. Furthermore, the initial concentration of the pollutant determines how fast the attachment points on the adsorbent surface will reach saturation (Ahmad et al., 2012).

2.4. Materials Used in Adsorption

The adsorbents used in adsorption applications are quite diverse. Among the natural materials, materials such as clay, zeolite and natural active carbon are widely preferred, while materials such as biochars and nanomaterials gain importance due to advanced surface properties and high efficiency. In recent years, intensive research on biomass -based adsorbents obtained from agricultural or industrial waste due to environmental sustainability and economic advantages. These biomass derivatives have gained an important place in environmental engineering in terms of both costing and contributing to waste management (Babel and Kurniawan, 2003; Ahmad et al., 2012).

3. Artificial Neural Networks: A Brief Overview

The forms of perception, thinking and learning of people vary significantly from individual to individual. The basis of this difference lies in the fact that the brain structure of each individual has its own perception and learning

mechanisms. People work information about the events they experience through the highly prominent sensory channels in their minds; Some tend to learn through visual images, some with auditory information, and others through emotional experiences, taste or odor (Çelebi, 2008). In today's world, the intensity of knowledge faced by individuals and the complexity of life makes learning processes even more difficult. In this context, although it is open to discussion which information is really necessary, it is important that it is the ability to turn knowledge into permanent learning without anxiety, unhappiness or strain. One of the ways to achieve this goal is to understand the way the brain works and to use it effectively and efficiently in learning processes (Yapıcı, 2008).

The capacity of the human brain to process and storage information has inspired the artificial modeling of learning. The artificial neural networks (ANN) developed with this approach have emerged as an important tool for mathematical and systematic modeling of the learning process.

Artificial neural networks (ANN) are computed modeling systems developed by inspirational of biological nervous systems, especially the interactions of neurons in the human brain with each other. ANNs are not based on the assumption of a predetermined mathematical relationship between input and output variables. In this respect, it is extremely advantageous to be preferred in cases where the mathematical model is not known or quite complex (Miller et al., 2018). ANNs are widely used in many areas such as classification, estimation, pattern recognition and decision -making as a powerful tool for modeling non -linear and complex relationships between variables (Öztemel, 2003).

Basically, ANNs have a multi -layered structure of entrance, hidden and exit layers. The artificial neurons in these layers perform information transmission and processing with the help of the weight of the connections between them. Throughout the training process, these weights are updated by algorithms for error minimization (eg backpropagation). After the training, ANNhas the ability to estimate or classify the data that it has never faced before. Thanks to this learning and generalization skills, it can provide effective results in problems that are difficult to solve with classical algorithms (Reynel-Avila et al., 2022).

One of the most important advantages of ANNs is that it can exhibit competencies similar to cognitive skills such as learning, adaptation and generalization. Because of these features, it is applied successfully in many different disciplines such as engineering, economy, medicine and environmental sciences (Öztemel, 2003; İbrahim et al., 2024).

Especially in the field of Environmental Engineering, ANNs are frequently used to model, predict and optimize the removal of pollutants in wastewater treatment processes. Experimental data used to create these models are usually divided into training, verification and test sets. While the training data provides the formation of the model, the verification data is to set and optimize the model; Test data are used to evaluate the accuracy of the created model. Model Success; Root average square error (RMSE) is evaluated by criteria such as determination coefficient (r^2), square error integral, accuracy and efficiency. The fact that a close harmony between the estimated data and the experimental data shows the reliability of the model (İbrahim et al., 2024).

In adsorption processes, ANNs offer great potential to modeling complex relationships with many parameters. These models allow to predict adsorption behaviors more accurately, as well as contribute to the comprehensive understanding of the process. In recent years, especially in the studies carried out for the removal of organic paints, an increasing interest in the optimization of adsorption conditions and increasing treatment efficiency has been observed (Çimen Mesutoğlu, 2024).

3.1. History of Artificial Neural Networks

Throughout history, human beings have been interested in the idea of gaining motion and intelligence to lifeless objects. Although the efforts to record and storage information dates back to 4000 years ago, the main developments in Artificial Intelligence (ZI) and Artificial Neural Networks (ANN) have taken place in the last fifty years. The foundations of modern artificial intelligence are based on classical philosophers' attempts to explain human thinking with symbolic systems. However, the artificial field of intelligence was officially defined in 1956. At this date, the term "Artificial Intelligence" entered the literature for the first time at a conference held at Dartmouth College in New Hampshire (Lewis, 2014).

The implementation of artificial intelligence systems was much more challenging than expected at the beginning. In the period between 1974-1980 and called "AI Winter" (winter of artificial intelligence) in the literature, the researches in this field faced heavy criticisms and state supports decreased significantly. However, in the 1980s, when Britain supported AI research with Japan for competition with Japan, there was a revival in the area (Lewis, 2014).

The development process of artificial intelligence is summarized in chronologically with different periods:

Prehistoric Period: One of the oldest examples of artificial intelligence thought is the effort of Daedalus in Greek mythology to create “artificial people. As of this period, various initiatives related to robotic systems have been encountered. For example, in 1769, the chess developed by Baron von Kempelen was exhibited in the Ottoman palace and brought together the public in Moscow (Wikipedia Contributors, 2018).

Dark Period (1965–1970): In this period, remarkable progress could not be achieved. Computer experts focused on the idea of producing “thinking” machines only with data installation, but these goals have not been achieved. There has been a waiting period in which development paused (Tekin, 2006).

Renaissance Period (1970–1975): This period is a time period in which significant expansions took place in the face of the face. Researchers have started to develop expert systems for fields such as diagnosis of disease and the foundations of today’s artificial intelligence practices have been laid (Tekin, 2006).

Partnership Period (1975–1980): In this process, artificial intelligence researchers directed to cooperation with disciplines such as linguistics and psychology and increased integration between fields. This period, in which AI is considered to be more versatile, prepared the ground for interdisciplinary studies (Lewis, 2014).

Entrepreneurship Period (1980- Our Day): It is the period in which after 1980, artificial intelligence only emerged from laboratory environments and began to apply to real world problems. More complex and need -oriented structures have been developed and widely used in commercial and industrial applications. This period still continues (Tekin, 2006; Lewis, 2014).

3.2. Application Areas of Artificial Neural Networks

With the developing technology, artificial neural networks have started to be used in many areas of daily life and has become rapidly widespread. Automotive, electronics, energy, space research, banking, financial and defense industry, especially in the health sector, are actively involved in many fields (Kaya et al., 2018). Especially with the development of humanoid robot technologies, interest in this field is increasing.

A wide variety of examples are found in the literature for the application areas of ANN. For example, more effective management is provided by using ANN in traffic control systems (Tektaş et al., 2006). In health services, ANNs play an important role in data mining processes and are used as a strong tool in the analysis of patient data (Koyuncugil and Özgülbaş, 2009).

In addition, Karahan (2011) and Emel and Taşkın (2002), in the context of statistical estimation methods, emphasized that artificial neural networks offer an alternative to traditional methods. Meteorological data, especially in the estimation of precipitation amounts, ANN -based models have given successful results (Partal et al., 2011). It is seen that ANNs are used especially in the modeling of complex production processes in the solution of industrial problems (Engin and Döyen, 2004). In electrical power systems, it is considered as an effective solution tool for the realization of load flow analysis (Adepoju et al., 2007).

One of the most remarkable uses of ANN today is the development of humanoid robots. One of the pioneering examples in this field is Humanoid robot called Asimo developed by Honda in 2000. Asimo not only has a humanitarian appearance, but also walks like a human being and runs to reach a speed of 6 kilometers per hour. It takes its name from the initials of the phrase “Advanced Step in Innovative Mobility”. Studies on the development of such robots are still intensively.

In the historical context, it is known that the interest in robot technology is not new. One of the vending vendors exhibited in the Ottoman palace can be considered as a historical example of this interest. Today, together with modern robots such as Asimo, the level of artificial intelligence -based systems is clearly revealed (Wikipedia Contributors, 2018).

3.3. Use of Artificial Neural Networks in Environmental Applications: Sample Events

The place of artificial neural networks (ANN) in environmental engineering applications is increasing and it gives remarkable results, especially in the fields of adsorption and wastewater treatment. Some sample applications in the literature are presented below:

Example 1: Modeling of Boyar substance removal with ANN

In a study on the elimination of methylene blue (MB) paint with active carbon obtained from oak acorn, parameters such as pH of the solution, adsorbant dose, initial concentration and contact time were evaluated with ANN model. The model has produced highly compatible results with experimental data ($R^2 > 0.98$) and it has been shown that ANN may correctly predict adsorption efficiency (Çimen Mesutoğlu, 2024).

Example 2: ANN -based optimization for heavy metal removal

In another study on the removal of PB^{2+} ions with a natural adsorbant, the ANN model was used for optimization for optimization under different

processing parameters. Thanks to this model, optimum conditions, which are difficult to determine by traditional methods, have been detected in a short time (Ibrahim et al., 2024).

Example 3: The removal of multiple pollutants in industrial wastewater

In the application performed on wastewater from a textile enterprise, numerous pollutant parameters (for example, paint, chemical oxygen requirement (COD), color and dissolved substances) were analyzed at the same time. Thanks to the multi-input model developed with ANN, the removal rates of these parameters were effectively estimated and system performance has been optimized (Reynel-Avila et al., 2022).

Example 4: Estimation of isotherm and kinetic parameters with ANN

In a study on the estimated study of Langmuir and Freundlich Isotherm parameters, as well as Kinetic model coefficients through ANN, the estimation performance of the model was found to be higher than the classical graphical methods. This method has made a significant contribution to accelerating and optimizing the experimental process (Miller et al., 2018).

4. Advantages, Difficulties and Future Perspectives for Artificial Neural Networks

4.1. Advantages of Artificial Neural Networks

Artificial neural networks (ANN) are powerful artificial intelligence systems developed in inspired by the way the human brain processes learning and knowledge. The most important advantages are:

- **Learning with data:** ANNs have the ability to learn through wide data sets in pattern recognition, classification and regression problems (Haykin, 2009). These features allow them to provide solutions with high accuracy rates in cases where traditional statistical methods fail.
- **Modeling non -linear relationships:** ANNs have complex and non -linear relationships modeling. Therefore, it provides advantage in multiple variable systems (Basheer and Hajmeer, 2000).
- **Generalization ability:** It may also estimate by making generalizing a certain extent against new data other than training data.
- **Adaptive Structure:** ANN architectures can be restructured for different problems. The number of inputs can be changed to different types of problems by changing the number of hidden layers and neurons.

4.2. Limitations and Difficulties

Although ANNs are strong tools, there are various limitations:

- **Lack of explanation:** The “Black Box” nature causes the internal functioning of the model to be fully understood by the user (Castelvecchi, 2016). This may pose a risk, especially in areas such as health or finance where critical decisions are taken.
- **Overfitting:** Models that adapt to training data may perform low performance in new data. This problem becomes apparent when appropriate verification techniques are not used (GoodFellow et al., 2016).
- **High data requirement:** YSAs usually require large amounts of and labeled data to provide successful results. This may be limiting in applications where data collection is difficult.
- **Calculation power requirement:** Especially deep structures contain a large number of parameters requires high processor power and long training period.

4.3. Developing Trends: Deep Learning and Hybrid Models

In recent years, the greatest contribution to the development of artificial neural networks has made the Deep Learning approach. Deep learning allows more effectively to learn complex data patterns thanks to multi-layered artificial neural networks. In areas such as image recognition, natural language processing and sound recognition, results approaching human performance have been obtained (LeCun et al., 2015).

In addition, hybrid models stand out. These models aim to improve performance by combining artificial neural networks with other artificial intelligence techniques (eg genetic algorithms, blurred logic, decision trees, etc.) (Zhang, 2003). For example, blurred logic for the structural parts of a problem can be used for genetic algorithm for parameter optimization, ANN for the prediction model.

4.4. Future Research Areas

In the future, the following research areas are expected to stand out for artificial neural networks:

- **Explainable AI:** Making ANN models more transparent and interpreted and interpreted is critical for areas such as medicine and law.
- **Few-shot Learning with small data:** Research is increasing on effective learning of ANNs in applications where the amount of data is limited.

- **Hardware -based neural networks:** Neuromorphic Computing is developed and more efficient architectures that consume less energy for ANN to work on embedded systems or mobile devices.
- **Biological Inspired Models:** It is expected that new network structures to be created by more detailed modeling of real nervous systems are expected to offer more efficient results (Krichmar and Edelman, 2002).
- **Ethical and Social Dimensions:** The effects of ANN -based systems on decision processes, gender prejudices, privacy and data safety will be at the center of artificial intelligence research in the coming years.

5. Conclusion

Industrial activities and increasing population pressure lead to pollution of water resources and this necessitates the development of effective treatment technologies. In this context, adsorption methods; It is one of the most prominent alternatives with its low cost, environmentally friendly and high -efficiency features. However, the fact that adsorption processes are dependent on a large number of variables and the difficulties in modeling them by classical methods require that these techniques be supported by more advanced tools.

In this section, how artificial neural networks (ANN) can be used effectively in adsorption -based treatment systems. ANN is a powerful calculation tool that reduces the cost and time of experimental processes, thanks to its ability to learn complex system behaviors, model non -linear relationships, and generalize limited data. The application examples in the literature show that ANN models offer an effective solution not only for the purpose of estimating, but also for system optimization and process analysis.

In the future, ANN -based modeling approaches are expected to be adopted in a wider scale in environmental applications. The integration of developing areas such as deep learning, hybrid structures and explainable artificial intelligence will further expand the reliability and application areas of these technologies. In addition, in line with sustainable environmental management goals, the integration of biomass -based low -cost adsorbents with ANN models has the potential to offer innovative solutions both economically and ecologically.

As a result, this interdisciplinary interaction between artificial intelligence and environmental engineering will play an important role in the development of more effective, flexible and sustainable methods in wastewater treatment.

References

- Adepoju, G. A., Ogunjuyigbe, S. O. A. and Alawode, K. O. (2007). Application of neural network to load forecasting in Nigerian electrical power system. *The Pacific Journal of Science and Technology*, 8(1), 68-72.
- Ahmad, M., Lee, S. S., Dou, X., Mohan, D., Sung, J. K., Yang, J. E. and Ok, Y. S. (2012). Effects of pyrolysis temperature on soybean stover-and peanut shell-derived biochar properties and TCE adsorption in water. *Bioresource Technology*, 118, 536-544.
- Babel, S. and Kurniawan, T. A. (2003). Low-cost adsorbents for heavy metals uptake from contaminated water: a review. *Journal of Hazardous Materials*, 97(1-3), 219-243.
- Bailey, K., Basu, A. and Sharma, S. (2022). The Environmental Impacts of Fast Fashion on Water Quality: A Systematic Review. *Water* 14, 1073.
- Balcı, B. (2007). *Atıksulardan tekstil boyar maddelerinin sürekli ve kesikli sistemlerde ağaç kabuğu* (Eucalyptus camaldulensis) kullanılarak adsorpsiyon ile giderilmesi (Yüksek lisans tezi). Çukurova Üniversitesi, Fen Bilimleri Enstitüsü, Adana.
- Basheer, I. A. and Hajmeer, M. (2000). Artificial neural networks: fundamentals, computing, design, and application. *Journal of Microbiological Methods*, 43(1), 3-31.
- Behnamfard, A. and Salarirad, M. M. (2009). Equilibrium and kinetic studies on free cyanide adsorption from aqueous solution by activated carbon. *Journal of hazardous materials*, 170(1), 127-133.
- Berkem, A.R. and Baykut, S. (1980). *Fizikokimya*. İstanbul Üniversitesi Yayınları, 42: 1111.
- Castelvecchi, D. (2016). Can we open the black box of AI? *Nature*, 538(7623), 20-23.
- Chattoraj, D. and Freundlich, H. M. (1906). Over the Adsorption in Solution. *Journal of Physical Chemistry A*, 57, 385-470.
- Çelebi, K. (2008). *Beyin temelli Öğrenme Yaklaşımının Öğrenci Başarısı ve Tutumuna Etkisi* (Yüksek lisans tezi). Selçuk Üniversitesi, Fen Bilimleri Enstitüsü, Konya.
- Çimen Mesutoğlu, Ö. (2024). The use of artificial neural network for modelling adsorption of Congo red onto activated hazelnut shell. *Environmental Monitoring and Assessment*, 196(7), 630.
- Dubinin, M. M. (1947). The equation of the characteristic curve of activated charcoal. In *Dokl. Akad. Nauk. SSSR*, 55, 327-329.
- Emel, G. G. and Taşkın, Ç. (2002). Genetik Algoritmalar ve Uygulama Alanları. *Uludağ Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 21(1), 129-152.

- Eren, Z. and Acar, F. N. (2004). Uçucu kül adsorpsiyonu ile reaktif boya giderimi. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, 10(2), 253-258.
- Engin, O. and Döyen, A. (2004). Artificial immune systems and applications in industrial problems. *Gazi University Journal of Science*, 17(1), 71-84.
- Foo, K. Y. and Hameed, B. H. (2010). Insights into the modeling of adsorption isotherm systems. *Chemical Engineering Journal*, 156(1), 2-10.
- Gemici, B. T. and Özden, A. (2022). Kestane kabuğu kullanılarak sulu çözelti-lerden boyar madde gideriminin izoterm, kinetik ve termodinamik analizi. *Gümüşhane Üniversitesi Fen Bilimleri Dergisi*, 12(4), 1158-1167.
- Ghaedi, A. M. and Vafaei, A. (2017). Applications of artificial neural networks for adsorption removal of dyes from aqueous solution: A review. *Advances in Colloid and Interface Science*, 245, 20-39.
- Gok, O. and Mesutoglu, O. C. (2017). Olive pomace as a low-cost adsorbent for the removal heavy metals. *Journal of the Faculty of Engineering and Architecture of Gazi University*, 32(2), 507-516, 2017.
- Goodfellow, I., Bengio, Y., Courville, A. and Bengio, Y. (2016). *Deep learning* (Vol. 1, No. 2). Cambridge: MIT press.
- Haykin, S. (2009). *Neural Networks and Learning Machines* (3rd ed.). Pearson Education.
- Ho, Y. S. and McKay, G. (1999). Pseudo-second order model for sorption processes. *Process Biochemistry*, 34(5), 451-465.
- Ibrahim, M., Haider, A., Lim, J. W., Mainali, B., Aslam, M., Kumar, M. and Shahid, M.K. (2024). Artificial neural network modeling for the prediction, estimation, and treatment of diverse wastewaters: A comprehensive review and future perspective. *Chemosphere*, 142860.
- Kang, M., Ma, B., Bardelli, F., Chen, F., Liu, C., Zheng, Z., wu S. and Charlet, L. (2013). Interaction of aqueous Se (IV)/Se (VI) with FeSe/FeSe₂: implication to Se redox process. *Journal of Hazardous Materials*, 248, 20-28.
- Kanwal, A., Rehman, R., Imran, M., Samin, G., Jahangir, M. M. and Ali, S. (2023). Phytoremediative adsorption methodologies to decontaminate water from dyes and organic pollutants. *RSC Adv.* 13, 26455–26474.
- Karahan, M. (2011). *İstatistiksel tahmin yöntemleri: Yapay sinir ağları ile ürün talep tahmini uygulaması* (Doktora tezi). Selçuk Üniversitesi, Sosyal Bilimler Enstitüsü, Konya
- Karlaftis, M. G. and Vlahogianni, E. I. (2011). Statistical methods versus neural networks in transportation research: Differences, similarities and some insights. *Transportation Research Part C: Emerging Technologies*, 19(3), 387-399.

- Katheresan, V., Kansedo, J. and Lau, S. Y. (2018). Efficiency of various recent wastewater dye removal methods: A review. *Journal of Environmental Chemical Engineering*, 6(4), 4676-4697.
- Kaya, Ü., Oğuz, Y. and Şenol, Ü. (2018). An Assessment of Energy Production Capacity of Amasra Town Using Artificial Neural Networks. *Turkish Journal of Electromechanics and Energy*, 3(1), 22- 26.
- Kayacan, S. (2007). *Kömür ve koklarla sulu çözeltilerden boyar maddelerin uzaklaştırılması* (Yüksek lisans tezi). Ankara Üniversitesi, Fen Bilimleri Enstitüsü, Ankara.
- Kenda, G. T., Fotsop, C. G., Tchuifon, D. R. T., Kouteu, P. A. N., Fanle, T. F. and Anagho, S. G. (2024). Building TiO₂-doped magnetic biochars from Citrus sinensis peels as low-cost materials for improved dye degradation using a mathematical approach. *Appl. Surf. Sci. Adv.* 19, 100554.
- Khaled, A., El Nemr, A., El-Sikaily, A. and Abdelwahab, O. (2009). Treatment of artificial textile dye effluent containing Direct Yellow 12 by orange peel carbon. *Desalination*, 238(1-3), 210-232.
- Koyuncugil, A. and Özgülbaş, N. (2009). Veri madenciliği: Tıp ve sağlık hizmetlerinde kullanımı ve uygulamaları. *Bilişim Teknolojileri Dergisi*, 2(2).
- Krichmar, J. L. and Edelman, G. M. (2002). Machine psychology: autonomous behavior, perceptual categorization and conditioning in a brain-based device. *Cerebral Cortex*, 12(8), 818-830.
- Langmuir, I. (1916). The constitution and fundamental properties of solids and liquids. Part I. Solids. *Journal of the American Chemical Society*, 38(11), 2221-2295.
- LeCun, Y., Bengio, Y. and Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436-444.
- Lewis, T. (2014). *A Brief History of Artificial Intelligence*. LiveScience Retrieved.
- Lin, J. and Wang, L. (2009). Comparison between linear and non-linear forms of pseudo-first-order and pseudo-second-order adsorption kinetic models for the removal of methylene blue by activated carbon. *Frontiers of Environmental Science & Engineering in China*, 3, 320-324.
- Miller, J. N., Miller, J. C. and Miller R. D. (2018). *Statistics and chemometrics for analytical chemistry*. Pearson education.
- Özdemir, Ç. S. (2019). Equilibrium, kinetic, diffusion and thermodynamic applications for dye adsorption with pinecone. *Separation Science and Technology*, 0(0), 1-9.
- Öztemel, E. (2003). *Yapay Sinir Ağları*. Papatya Yayıncılık.
- Pang, X., Sellaoui, L., Franco, D., Dotto, G. L., Georgin, J., Bajahzar, A. and Li, Z. (2019). Adsorption of crystal violet on biomasses from pecan nutshell, para chestnut husk, araucaria bark and palm cactus: experimental study

- and theoretical modeling via monolayer and double layer statistical physics models. *Chemical Engineering Journal*, 378, 122101.
- Partal, T., Kahya, E. and Cıgızoğlu, K. (2011). Yağış verilerinin yapay sinir ağları ve dalgacık dönüşümü yöntemleri ile tahmini. *İTÜ Dergisi/d*, 7(3).
- Reynel-Ávila, H. E., Aguayo-Villarreal, I. A., Diaz-Muñoz, L. L., Moreno-Pérez, J., Sánchez-Ruiz, F. J., Rojas-Mayorga, C. K. and Bonilla-Petriciolet, A. (2022). A review of the modeling of adsorption of organic and inorganic pollutants from water using artificial neural networks. *Adsorption Science & Technology*, 2022, 9384871.
- Priya, A. K., Yogeshwaran, V., Rajendran, S., Hoang, T. K., Soto-Moscoso, M., Ghfar, A. A. and Bathula, C. (2022). Investigation of mechanism of heavy metals (Cr^{6+} , Pb^{2+} & Zn^{2+}) adsorption from aqueous medium using rice husk ash: Kinetic and thermodynamic approach. *Chemosphere*, 286, 131796.
- Sarıkaya, Y. (2007). *Fizikokimya*, Gazi Kitabevi, Ankara, 633-653
- Tekin, H. (2006). Yapay Zekâ. *Journal of Yasar University*, 1(1), 81- 93.
- Tektaş, M., Akbaş, A. and Topuz, V. (2006). *Yapay Zekâ Tekniklerinin Trafik Kontrolünde Kullanılması Üzerine Bir İnceleme*. İstanbul: Marmara Üniversitesi.
- Temkin, M. I. and Pyzhev, V. (1940). Recent modifications to Langmuir isotherms. *Acta Physicochimica URSS*, 12, 217-222.
- Waranusantigul, P., Pokethitiyook, P., Kruatrachue, M. and Upatham, E. S. (2003). Kinetics of basic dye (methylene blue) biosorption by giant duckweed (*Spirodela polyrrhiza*). *Environmental pollution*, 125(3), 385-392.
- Weber Jr, W. J. and Morris, J. C. (1963). Kinetics of adsorption on carbon from solution. *Journal of the sanitary engineering division*, 89(2), 31-59.
- Wikipedia Contributors. (2018). *Wolfgang von Kempelen*. Wikipedia. https://en.wikipedia.org/wiki/Wolfgang_von_Kempelen
- Yapıcı, M. (2008). *Beyin Temelli Öğrenme Açısından Öğretmen ve Ders*. Üniversite ve Toplum. Cilt 8, Sayı 2.
- Yıldız, N. (2001). Toprak Kirleticisi Bazı Ağır Metallerin (Zn, Cu, Cd, Pb, Co ve Ni) Belirlenmesinde Kullanılan Yöntemler. *Atatürk Üniversitesi Ziraat Fakültesi Dergisi*, 32(2), 207-213.
- Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, 50, 159-175.