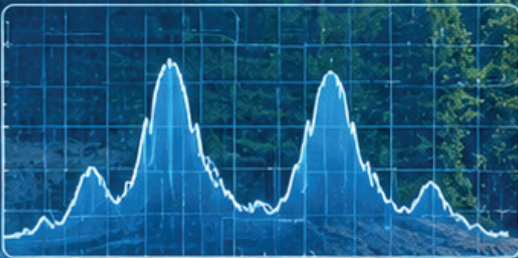


A PRACTICAL APPROACH TO THE APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN HYDRAULIC ENGINEERING

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PREFACE

The accurate estimation of river flow is an important component of hydraulic engineering, particularly in the planning, design, and management of water related infrastructure. Reliable flow estimation contributes to the assessment of hydrological conditions and supports informed decision making in the development and operation of hydraulic structures. However, the complex and nonlinear relationships governing river flow may present significant challenges for conventional estimation approaches, particularly when the available hydrological data exhibit substantial variability.

In recent years, the rapid development of artificial intelligence and machine learning techniques has provided new opportunities for addressing complex engineering problems. Among these approaches, artificial neural networks (ANNs) have attracted considerable attention because of their ability to identify nonlinear relationships between input and output variables without requiring an explicit formulation of the underlying physical relationship. Their flexibility and data driven nature make ANN based approaches particularly relevant to hydrological and hydraulic applications.

This book chapter presents a practical application of artificial neural networks to the estimation of volumetric water flow rate in the Maritsa River. The approach is developed using water flow rate data obtained from multiple rivers and water measurement stations, providing a data driven framework for investigating the applicability of ANN techniques to river flow estimation. Different ANN based approaches are formulated and implemented to examine how alternative modeling configurations can be employed for the estimation of river flow.

A particular emphasis of this chapter is placed on the practical implementation of ANN methodology. The modeling process, data structure, implementation procedures, and evaluation framework are presented in a systematic manner so that the methodology can be followed and reproduced by researchers, engineers, and students working in hydraulic and water resources engineering.

The chapter is intended to contribute to the growing body of literature on artificial intelligence applications in hydraulic engineering by demonstrating how ANN based modeling can be incorporated into practical river flow estimation problems. It is also intended to provide a useful

reference for readers interested in the application of data driven methods to hydrological and hydraulic systems, while highlighting the importance of appropriate model development, systematic evaluation, and careful interpretation of data driven predictions.

1. INTRODUCTION

Fossil fuels cause significant negative impacts on the environment, for this reason, usage of the renewable power sources have gained a major rise, especially recently. During combustion of fossil fuels, considerably high amount of greenhouse gases are released to the environment, that cause ultimate global warming. Although the average temperature increase on a global scale seems to be very small, i.e., in between 0.8 °C and 1 °C; this small increase of temperature causes many negative situations on the humans, animals, plants and nature, causing species to disappear and even causing the ice in glaciers to melt. Accordingly, taking the worldwide situation into account, the number of the energy plants powered depending to carbon based fuels are decreasing, on the other hand, the renewable energy plants powered using renewable sources including hydraulic, wind, solar, geothermal, biomass, and wave energy are increasing. In parallel to these negative situations of the World, policies of many World countries are changed by the experts to be in compatible with the renewable energy usage. Besides, many countries of the World have one type of energy plant that work utilizing renewable energy source, at any rate. Taking renewable energy sources consisting of wind, solar, wave, biomass, geothermal, and many others, hydropower still falls in a place to be most extensively used method in useful power generation. This is mainly due to existence of lots of rivers having high volumetric flow rates as well as having rich water basins in various countries of the World. In Figure 1, cumulative amounts of hydraulic power and the other renewable energies taking Türkiye and the worldwide cases into account are shown:

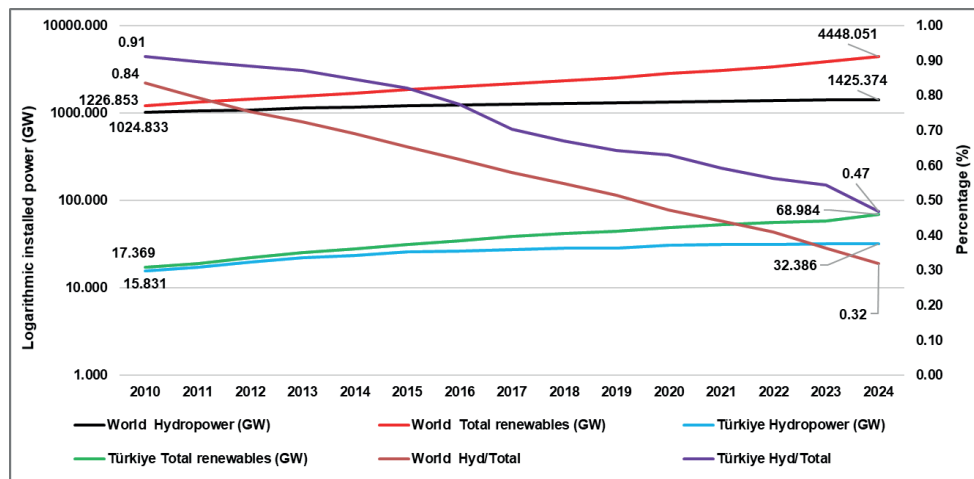


Figure 1. The hydraulic and renewable power status for Türkiye as well as World (IEA, 2025)

In Figure 1, with regards to the big discrepancies between cumulative installed renewable power of Türkiye and the World, y-axis provided on the left is given using the scale of logarithm. But,

to read the rising trends in this figure, the counterpart arithmetic values of those power values considering the year range between 2010 and 2024 are demonstrated in this figure for start and end years of this year range analysis, namely, the installed power values for years 2010 and 2024 are exhibited on the figure. Furthermore, y-axis located on the right of the figure displays the ratios defined by the divisions of the hydraulic installed energy to the total renewable installed energy for Türkiye as well as for the World. These ratios are imparted for the same 15 years in this year range of analysis; however, again, corresponding numerical values are only written for the years including 2010 and 2024. Unlike the installed power values, for the ratios, the declining trends are denoted for Türkiye and the World. As clear from Figure 1, the proportions of hydraulic power for the World as well as Türkiye to their total renewable power installations decline considerably from 2010 to 2024. In spite of these important declines on the values of the ratios, the installations belonging to the hydraulic power given according to the cumulative renewable capacities for the World as well as Türkiye still form a big percentage. It is obvious from the figure that the stature of hydro power among the other renewable power sources is more foremost for Türkiye against the case of World. This insight can be configured easily considering the fact that the function of ratio for Türkiye, obeying to the same year range, all the time stays above the function of ratio for the World, between the stated years between 2010 to 2024. Here, looking on this figure, a simple comparison can be executed on the function of purple colored curve pointing out the case of Türkiye compared with respect to the function of the burgundy colored curve designating the situation of the World. In this respect, taking cognizance of the global case; arriving the year 2024, the installations for the hydraulic power have augmented to 1,425.374 GW from the onset installation of 1,024.833 GW by the year 2010. Besides, when the same year range between 2010 to 2024 is analyzed for the total renewable power installations for the global case; it is observed that they have increased to 4,448.051 GW by 2024, from the installation magnitude of 1,226.853 GW of 2010. Situation of the worldwide has indicated that the ratio of hydraulic power normalized with respect to the cumulative renewable power decreased to 32% considering the year of 2024. However, the same figure for 2010 was 84% initially. In spite of this strong decline of the percentages, at the end of year 2024, it is concluded that hydro-energy is still a significant power generation technology of the World, when compared to the other technologies of renewable power. On the other hand, installations referring to hydraulic power of Türkiye have also enhanced significantly, attaining a magnitude of power installations to 32.386 GW in 2024 from installation magnitude of 15.831 GW in 2010. Beyonds, Türkiye also gives a high importance to other types of renewable power technologies. The country has accomplished the total

renewable power installation value corresponding to 68.984 GW in 2024, which was only 17.369 GW in 2010. The ratio of hydraulic normalized with respect to the cumulative renewable power has also diminished for Türkiye, alike the case of World. In this regards, the ratio which was 91% in 2010 has declined back to the value of 47% in 2024, considering the year span of 14 years. Depending on the rises of other renewable power installation types including especially wind as well as solar power technologies, this situation has caused a substantial proportional decrease of the hydraulic power installations compared against the other types of renewable technologies. This case has occurred in this way for both Türkiye and the World. But despite these circumstances, it is still undeniable that hydroelectric power is of strategic importance, compared on the other renewable power types, including until the end of 2024. Additionally, the value and the installation speed for hydraulic power will be pretty high compared with respect to the other types of renewable power, at least for the three upcoming decades (IEA, 2025).

To obtain energy production from hydropower implementations, the power is produced using the hydro-turbines. The principles of hydropower applications include of collecting as much the water as possible at a high altitude as much as possible to have a big energy content, that is referred as high potential energy, then allowed freely to flow in the penstock of the facility to gradually convert water's potential energy to the kinetic energy. At the last section of the penstock before the contact of the tracked water molecules with the rotating blades of the hydraulic turbines, the water molecules become highly energized in kinetic form to convert this kinetic energy to the mechanical energy in the rotary wings of the turbine. The mechanical energy in the wings manifests itself mechanically in the shaft attached to the turbine, without changing its type. The electric generator engaged to the turbine shaft is responsible of converting the shaft mechanic energy to electrical energy, and the produced electrical power later becomes ready to be given to the grid lines of the city. However, before electricity is transmitted to the city grid, the relevant voltage adjustment is made in the switchyard. The macro energy forms of hydropower plants consisting of potential and kinetic energy types are defined based on the altitude level of the water dam as well as the volumetric flow rate of the water molecules, respectively. Namely, the increase of altitude level and the volumetric flow rate of water result increase of potential and kinetic energies, respectively, and therefore, produced electrical power obtained from the hydro-facility results in enhanced capacity and efficiency of the power plant. In the very distant past, the aim of the engineering of hydropower was not solely to make electricity production, it was taken into account for many different

targets. However, firstly, it was utilized to acquire grinding of grain. Mechanic milling was achieved using the energy that was obtained from the water flow. Nowadays, hydro-energy is still used for such primitive aims; but, recently, the main target of capturing hydropower became to generate huge amounts of electrical power. On the other hand, with regards to the energy generation capacities of hydro facilities, a classification of those power plants can be performed. Among those facilities, in the case of having output power values of the plants to be below 100 kW, micro scale power production is actualized. Besides, if the facility output power is in the range of 100 kW and 30 MW, this is now referred to be small scale of energy production. Finally, the large scale of energy generation consists of power production magnitudes overrunning the values of 30 MW (N-Sci, 2025).

Hydro energy production when compared with respect to the other energy generation methods of renewables or the ones utilizing the fossil fuels, has lots of advantages as well as benefits. The fuel of power production in this method is simply water, it is pretty clean type of source, and it is apart different than fuels of fossil types. The side effects of fossil fuel powered energy generation consists of release of greenhouse gases as well as air is significantly polluted due to those emissions. Those side effects generally do not originate in energy generation using the hydropower technology. On the other hand, in the case of a country having ample amount of water sources with a high quality, this type of power production becomes national and domestic type of energy generation for that country. Türkiye is a good example to this situation, namely, the country is able to produce huge amounts of power utilizing its own and local water sources. The country's rivers generally have high water flow rates, and there is usually a high altitude difference between where the river originates and where it meets the sea or the lake. However, fossil fuels are power sources in which some countries have monopolizations on those and usually these are acquired depending to the chain of the international supply. Accordingly, the increase of the facilities of hydro energy in one country generally causes a significant decrease of that country dependence to these international fossil fuel chain. Furthermore, when compared according to the conventional fuels of fossil types, sources of hydro energy are sources in the form of renewable that become more reliable as well as economic. It is definite that the boost of the facilities of hydropower installations will result in gas productions of the greenhouse to be minimized as well as the accompanied global warming will decline. Additionally, many other positive side benefits can be counted in the case of the hydropower implementations increase. For example, the reservoirs that are created at the dam upstream will collect waters in the case of constructing hydraulic dams, and those can be utilized for some useful aims. In those

reservoirs, some sporting activities such as swimming, fishing, and boating will be performed as recreational opportunity. Else, other prominent advantages may also be provided with the constructions of hydro dam. Exemplarily, continuous power supply to the grid lines of electricity in a direct form is one of the most important advantages of such power plants. Also, in the case of big electric outages, these power facilities can provide energy of back-up feeding the system. In the case of huge floods eventuated due to the river overflows caused by extreme rainfall, big damages may be formed to the centers of cities as well as to the fields separated for agricultural applications. These perilous floods can be swiftly taken under control when hydro dam constructions are implemented, in the way of keeping the extra water at the reservoir formed as artificial constructions. Conversely, some hydro dams are constructed only to supply water to fields separated for agricultural jobs as well as to the centers of cities. However, some are built in order to produce water for both intents including supply of water as well as generation of power (N-Sci, 2025; REN21, 2025).

A schematic representation of a facility of hydraulic energy is shown in Figure 2 and the corresponding terminologies for this sector are indicated on the picture. As seen in this figure that at a higher altitude, water is stored, compared with respect to the end section of the penstock and the level of the turbine wings. Namely, the water potential energy found at high altitudes will be transformed firstly to the energy of kinetic flow during its journey along the penstock. Later the kinetic energy that is possessed by the moving water molecules gradually during the journey of the water along the penstock, will soon be converted to energy of mechanic at the hydro wings, when those molecules get in contact with the mechanical blades of the hydro turbine. There is a simultaneous motion on the side of the shaft connected to the turbine and on the side of the shaft connected to the generator. Namely, all three move simultaneously together. Therefore, the wind mechanical energy then manifests itself as the shaft mechanical energy and finally generator electrical energy. In this regards, the rotation eventuated on the wings of hydro turbine cause simultaneous turn of magnet series embed in the electric generator. Eventually, AC (alternating current) will be generated due to the motion of the electrons, which will be produced with regards to the copper coil turn occurring by the huge magnets. Next, the transformer placed in the power house will utilized the load of AC to transform it to a voltage of higher magnitude load. Finally, the electricity that is continuously produced due to the kinetic water flow will be fed to the grid lines of the city, utilizing the switchyard place mounted close to the hydro dam. On the other hand, huge power lines are generally used in order to convey

the generated electrical power from the switchyard of the water dam facility to the cities, towns, villages, industrial facilities, and so on.

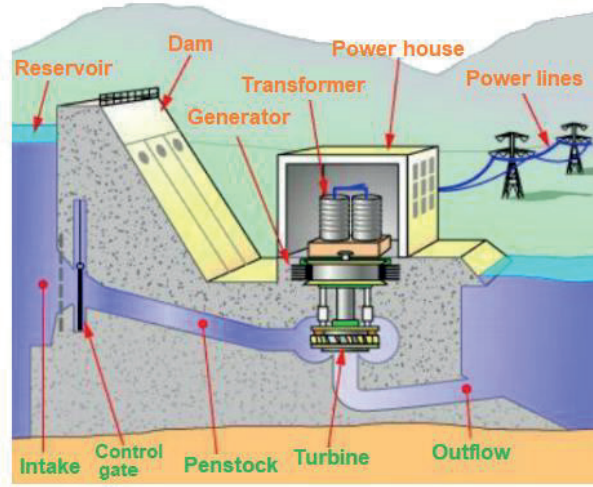


Figure 2. A hydraulic power plant and the flow conversion terminologies

Three different methodologies are generally adopted in the literature to carry on the estimations of implementations for physics and engineering. Those mainly consist of statistical forecasts, physical predictions, as well as utilization of methods of machine learning or artificial intelligence (Jung and Broadwater, 2014; Zhang et al., 2019a). Some physical information is used simply in plain methodology as physical approaches. The utilized information in the forecasts can be pressure of atmosphere, temperature of air, barriers, moisture amount, roughness, and so on (Tascikaraoglu and Uzunoglu, 2014). In the basic or physical guessing methods, the pressure of weather, temperature of the air, the amount of the rain falls, moisture, and the sea wave conditions etc. can be taken into account as the data to be processed. These methods are handled within the subject of numerical forecasts of weather as well as sea phenomena estimations. To exert forecasting of weather by numerical means, a set of mathematical relations as well as some types of physical information is required. For example, in forecasting of power of wind, plain techniques can be utilized to be implemented on the data cloud, that may be found in the shape of medium to long term. However, the computations of computer are pretty complex in the methodology of physical approaches. This issue is considered as the substantial disadvantage of this modelling type. On the other hand, based on the physical methodology, important resources to conduct the computations are needed. Also, many different types of engineering data can be predicted under the utilization of statistical ways. But, these statistical approaches are usually applied to achieve wind speed anticipations. Therefore, those methods are generally limited with the estimations of wind speed. In statistical

approaches, in general, historical wind speed data found in the data cluster as series of time are utilized in order to execute predictions on the future values of the data of wind speed. A wide species of statistical methods is employed for this aim. In this context, models constructed by moving average, autoregressive, autoregressive moving average, autoregressive integrated moving average (ARIMA), as well as seasonal autoregressive integrated moving average are considered. The data found in the historical cluster are processed to acquire a correlation between instantaneous data points. In this way, a correct algorithm will be constituted. In this processing, the initial fragment is referred to be the training, and the final fragment is called as the model testing to capture a good prediction quality of the physical parameter that is needed to be predicted. Herewith, the desired parameter will be forecasted in a good validity as much as possible. Statistical ways are also proper to be implemented to estimations of wind power. Those can be applied to forecasting in the form of ultra-short-term and short-term. In this frame, Liu et al. (2015) performed a recent statistical model consisting of ARIMA as well as empirical mode decomposition (EMD). The configured model was exerted to obtain estimations of wind velocity needed to model powerful system of wind warning for railway. On the other hand, another type of model based on the method of ARIMA was suggested by Kavasseri and Seetharaman (2009). In their study, wind speed predictions belonging to one day or two days' later values are obtained utilizing the data belonging to the region of North Dakota.

Artificial neural networks (ANNs) are recently suggested generally in many scientific studies to be considered as alternative of models that were formerly constructed by plain as well as statistical approaches. Because, anticipations acquired by the models of ANN generally turn out to be better than the conventional models achieved using tools of physical and statistical ways. The ANNs in the literature are usually utilized for obtainment of estimations of wind speed. However, these techniques of ANN are also evaluated recently in different areas of science including power of wind, volumetric flow rate of water, and even some covering aerodynamic coefficient as well as parameter forecasts (Ilhan, 2022; Ilhan et al., 2015). During forecast computation of wind turbine output power in the study of Zhang et al. (2019a), ANN and long short-term memory (LSTM) are used simultaneously. Additionally, in the same study, an analysis was conducted on the characteristics of the error dispersion, considering the mixture model of the Gaussian to obtain anticipations on the output power of wind turbine. On the other hand, estimations in the form of high quality referring to the solar power were acquired by the applied approaches of machine learning. In this regards, an algorithm for machine learning was suggested by Khosravi et al. (2018) in order to perform predictions on the solar irradiance for

each hour. Methods of artificial intelligence is also considered in the literature for obtainment of experimental data forecasts. In this regards, Shi et al. (2018) performed LSTM predictions on the wind power data, in which its source depends to the experimental measurements. The outcomes of the estimations have shown that more precise anticipations were computed by LSTM tool when compared to the conventional neural network methods. Besides, some hybrid mechanisms as artificial learning are taken into account in the literature. For instance, a novel technique in the form of hybrid was proposed by Yu et al. (2018) that had included LSTM, the standard recurrent neural network (RNN), the gated recurrent unit neural network (GRU), as well as the support vector machine (SVM). In the model that was proposed by Yu et al. (2018), it was revealed that outcomes of forecasts of the hybrid model formed of the constitution of four different approaches were superior than the results of the predictions acquired by the solely implemented conventional approaches. Moreover, the identical anticipation methodologies were applied to different scientific disciplines considered in the same study. The outcomes acquired from those distinct disciplines were compared according to the accuracy evaluation of the estimations. E.g., power productions obtained from different renewable technology machines including wind turbines as well as photovoltaic systems were predicted at the same time using the same methodology of Han et al. (2019). They have applied an approach of hybrid learning to those different scientific disciplines simultaneously consisting of the LSTM as well as the copula function. Similarly, a model of hybrid that comprised of learning of LSTM else decomposition virtual node pruning was considered in the study of Zhang et al. (2019b). Their study had indicated that a high anticipation accuracy was acquired in wind velocity estimations.

Apart from those cited scientific works, artificial intelligence is also performed to consist of the audit of some physical parameters, in the way of conducting optimization on the other physical parameters, and the estimations were executed in this way. For example, the shared weight LSTM was proffered by Zhang et al. (2019c), and in this suggested method, the needed training time as well as the amount of the variables that were optimized were diminished to acquire a suitable algorithm in the data cluster. Furthermore, it was reported in this study that the precision of the anticipations was considerably improved with the used proposed shared weight LSTM. On the other hand, LSTM having multi variables that were stacked together was recommended in the study of Liang et al. (2018). In their study, the cloud of data included values of instantaneously measured wind velocity and it was utilized to acquire suitable estimations. They had formed a suitable learning algorithm linking the instantaneously measured wind velocity values to each other and the linkage was specified with respect to some

parameters of meteorology consisting of wind velocity, weather temperature, air pressure, radiation of the sun, moisture, as well as the point of dew. The prediction outcomes have signified that multi variable stacking was sufficient to overpower the indefiniteness, as a result, this type of stacking has demonstrated an estimation performance that was concluded to be competitive. In forecast events, a physical parameter forecast is sometimes needed to include its big data cloud established of its data series in historical form. As commonly crossed in the literature studies, estimations of time-series form the basis of research to forecast the values for future of the considered physical parameter. Here, the input is the same physical parameter, however their time-series data distributions are defined instantaneously and historically. And, these historical instantaneous data distributions provided as input generate the future values of the same physical parameter as output. E.g., in stations used for meteorology evaluations, for executing of the predictions of future magnitudes of weather temperature or air pressure, or in order to conduct forecasts of weather, these data types are stored in such meteorology stations and predictions of weather are performed accordingly. On the other hand, information regarding the weather future conditions directly affect lots of daily performed activities, for example, those may consist of safe voyages of ships as well as aero planes. An algorithm was made to manage forecasts of weather in the study of Zaytar and Amrani (2016). The algorithm took into account a network of deep neural structured depending to the data of historical time-series. Time-series predictions performed by LSTM tool that was implemented on the historical data have denoted that the computation results are better than the results that were acquired using the tools of conventional (Zaytar and Amrani, 2016).

Anticipations of hydraulic works are also eventuated in the literature. In this context, Hewett et al. (2001) developed a machine learning method of artificial intelligence to make forecasts on the flow of water of Okeechobee lake. The referred lake was selected as the study location, and it conveys water to the south provinces of the city of Florida, since this lake is the primary water source of Florida. A table compression of second order was included as an approach of induction which formed the framework of the study in order to develop a machine learning algorithm (Hewett et al., 2001). Also, estimations on the flood hydrograph were realized in the literature. These were mainly conducted referring to the ANNs. In this context, the hybrid model that was used in the study of Tayfur et al. (2018) had taken into account a model of hybrid consisting of genetic algorithm (GA), optimization of ant colony, optimization of particle swarm as well as ANNs. In this study, to perform a proper training on the developed models, data of flow of Tiber river was taken cognizance of. The anticipation outcomes of this

central Italy river have exhibited that the referred four methods were strong tools in predictions of hydrographical events (Tayfur et al., 2018). Flake (2007) had achieved estimations of water flows of river, utilizing the proposed prediction models formed of relevance vector machine (RVM). In this study, the learning machine of the probabilistic kernel-based was used as the developed prediction approach. The computing models of RVM that were used in the study have exposed that high accuracies could be acquired in the predictions of water flow of the river (Flake, 2007). On the other hand, the implementation of the SVM (support vector machine) was suggested as a secure and a technic approach to acquire forecasts of flow in channels of straight compound (Farhadi et al., 2019). In their study, the error parameters were shown to be a lot better than statistical error parameters acquired after the application of the traditional estimation approaches (Farhadi et al., 2019). On the other hand, Sahraei et al. (2021) actualized estimations for stream water flow, utilizing the ANNs. They have used suitable hidden nodes as well as a convenient activation function (Sahraei et al., 2021). As soon as the initial conditions were arranged to their suitable values in their study, it was shown that the performance of forecasting was considerably enhanced during the usage of ANN applied to the water flow of river.

In this book, as an innovation, five different ANN methods were utilized in the predictions of volumetric water flow rate of Maritsa river on İpsala water measurement station. With this developed ANN method, the volumetric water flow rate of the Maritsa river at the further downstream was functionally estimated connecting it to the water flow rate of other rivers including Arda, Meriç (Maritsa), Tunca, and Ergene; as well as connecting it to different water flow rate values measured at different water measurement stations found on these rivers consisting of Ivoylovgrad on Arda, Harmanlı, Svilengrad, and Kirişhane on upstream and midstream of Maritsa, Elhova, Suakacağı, and Değirmenyeni on Tunca, İnanlı, Lüleburgaz, and Yenicegörece on Ergene. In the book, a very wide scan of the entire space was performed for 3 different parameters, which are required for the quality operation of the ANN, including the equation number (*EqN*), epoch number (*EN*) and the training percentage (TP), and in this way, a total of 2,000 different models were created for each applied ANN method, and since a total of five different approaches were adopted, an overall cumulative of 10,000 models were tested, and an extraordinary ANN scan was performed. In this way, the best model among the cumulative of 10,000 was determined and reported.

2. MATERIALS AND METHODS

To perform a simulation for cells of nerve system belonging to the biological living organisms, artificial neural networks (ANNs) that are networks belonging to computational issues, are used for this purpose in achieving predictions of the unknown, being stronger than conventional regression systems. The neural network is virtually a newfangled computer architecture as well as a recent algorithmic technique developed as an alternative to conventional computational methodologies. However, it consents very straightforward operations of computations in order to unravel complicated, problems that are ill-defined in terms of their mathematical expressions, problems given in the form of nonlinear structure or problems of the stochastic type (Bilgili, 2010; Bilgili and Ozgoren, 2011).

On the other hand, ANN contributes on the need of especially very little requirements of programming knowledge to permit of finding solutions to complex problems, in particular to the ones that are defined not to be analytic, that are recognized not to be linear, or given in a stochastic and not stationary format. Besides, ANN also enables a manner of self-organization which can be implemented to a wide variety of problems with no need of reprogramming as well as with no need of other attempts in the program (Ay and Kisi, 2014; Cobaner et al., 2014).

In the literature studies concerning physical and engineering sciences, different types of ANNs are found consisting of FFNN, RBNN, and GRNN, respectively known as feed forward neural networks, radial basis neural networks as well as generalized regression neural networks. Besides, ANN generally performs the learning duty by utilizing the methodology of the back-propagation (BP). This methodology is the most widely utilized algorithm in the form of supervised training, considered for neural networks of the feed forward. In networks of BP, the processing of the information is carried out in forward direction. Namely, this is actualizing towards to the output layer from the hidden layer and to the hidden layer from the input layer; in which the sequence involves the latter to be actualized as the first and the former to be materialized as the second. The goal of the network of the back-propagation comprises of devising optimum weights that will produce a vector of output as close as possible to the values of the target belonging to the vector of the output with a chosen accuracy by obtaining a minimization of a prearranged error function (Ay and Kisi, 2014; Bilgili, 2010; Bilgili and Ozgoren, 2011; Cobaner et al., 2014).

On the other hand, the neural network includes an element that is responsible of the basic processing. There is a necessity of performing computations of the layer output, in which the related task is started by the BP. The output layer is the layer where the necessary outputs are found. However, the outputs belonging to the layers of the intermediate are not available, as shown below referring to the Figure 3 (Graupe, 2007):

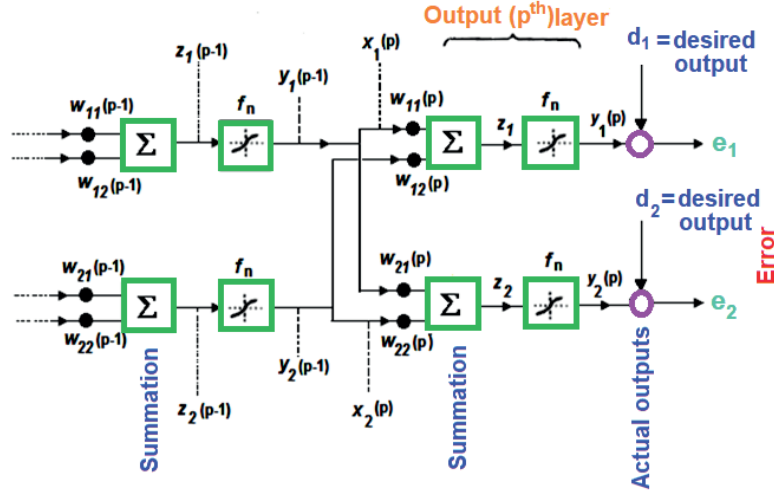


Figure 3. A perceptron of a multi-layer

Referring to the output layer of Figure 3, the energy belonging to the errors is named as the error-energy and it is indicated by the denotation of ε , and accordingly, it is defined by Eq. (1):

$$\varepsilon = \frac{1}{2} \sum_k (d_k - y_k)^2 = \frac{1}{2} \sum_k e_k^2 \quad (1)$$

In Eq. (1), the summations of the successive numbers found in the data set of $N_1 \leq N \leq N_k$ is achieved by the summation formula, and the abbreviation of N here corresponds to the total neuron numbers found in the layer of output. Hereby, the gradient belonging to the ε is taken into account, where:

$$\nabla \varepsilon_k = \frac{\partial \varepsilon}{\partial w_{kj}} \quad (2)$$

Here, with the methodology of taking the steepest gradient into account, Eq. (3) is written:

$$w_{kj}(m+1) = w_{kj}(m) + \Delta w_{kj}(m) \quad (3)$$

With regards to the j^{th} input towards to the neuron's output layer involved in the series with k^{th} order, in which, again considering the steepest descent methodology, Eq. (4) is utilized in order to define Δw_{kj} , as follows:

$$\Delta w_{kj} = -\eta \frac{\partial \varepsilon}{\partial w_{kj}} \quad (4)$$

The denotation of z_k representing the node-output of the perceptron of k is described in terms of the w_{kj} term multiplied by x_j term for the instantaneous consideration that is integrated from 1 to j , i.e., the multiplication is performed inside the sigma formula, as presented in Eq. (5).

$$z_k = \sum_j w_{kj} x_j \quad (5)$$

In Eq. (5), while the 1st entry towards that neuron is x_1 , whereas, x_j corresponds the j^{th} entry towards that neuron. Besides, the output belonging to the perceptron is shown by y_k . This output is specified by a function of nonlinear type:

$$y_k = F_N(z_k) \quad (6)$$

In Eq. (6), the function of the nonlinear type is denoted by the abbreviation of F . Now, following substitution can be performed:

$$\frac{\partial \varepsilon}{\partial w_{kj}} = \frac{\partial \varepsilon}{\partial z_k} \frac{\partial z_k}{\partial w_{kj}} \quad (7)$$

As well as;

$$\frac{\partial z_k}{\partial w_{kj}} = x_j(p) = y_j(p-1) \quad (8)$$

$$\frac{\partial \varepsilon}{\partial w_{kj}} = \frac{\partial \varepsilon}{\partial z_k} x_j(p) = \frac{\partial \varepsilon}{\partial z_k} y_j(p-1) \quad (9)$$

The p indicates the layer of output, and following is defined:

$$\phi_k(p) = -\frac{\partial \varepsilon}{\partial z_k(p)} \quad (10)$$

$$\frac{\partial \varepsilon}{\partial w_{kj}} = -\phi_k(p)x_j(p) = -\phi_k y_j(p-1) \quad (11)$$

$$\Delta w_{kj} = \eta \phi_k(p)x_j(p) = \eta \phi_k(p)y_j(p-1) \quad (12)$$

The input of j to the k^{th} neuron is shown by the symbol of j for the layer of output p . Furthermore,

$$\Phi_k = -\frac{\partial \varepsilon}{\partial z_k} = -\frac{\partial \varepsilon}{\partial y_k} \frac{\partial y_k}{\partial z_k} \quad (13)$$

$$\frac{\partial \varepsilon}{\partial y_k} = -(d_k - y_k) = (y_k - d_k) \quad (14)$$

Considering the nonlinearity for sigmoid function:

$$y_k = F_N(z_k) = \frac{1}{1 + \exp(-z_k)} \quad (15)$$

$$\frac{\partial y_k}{\partial z_k} = y_k(1 - y_k) \quad (16)$$

Eventually, taking Eqs. (13), (14), and (16) into account, Eq. (17) presents ϕ_k , as follows:

$$\phi_k = y_k(1 - y_k)(d_k - y_k) \quad (17)$$

Following statements are composed for the output layer:

$$\Delta w_{kj} = -\eta \frac{\partial \varepsilon}{\partial w_{kj}} = -\eta \frac{\partial \varepsilon}{\partial z_k} \frac{\partial z_k}{\partial w_{kj}} \quad (18)$$

$$\Delta w_{kj}(p) = \eta \phi_k(p) y_j(p-1) \quad (19)$$

For to complete the derivation of the adjustment of weights of output layer, ϕ_k was introduced in Eq. (17).

In the case of propagating back for the r^{th} order of the hidden layer, taking the branch of i into account into the neuron of the order of j , the same case considered as before will eventuate, and ultimately, aligned with Eq. (17), Eqs. (20) and (21) can be formed as follows:

$$\Delta w_{ji} = -\eta \frac{\partial \varepsilon}{\partial w_{ji}} \quad (20)$$

$$\Delta w_{ji} = -\eta \frac{\partial \varepsilon}{\partial z_j} \frac{\partial z_j}{\partial w_{ji}} \quad (21)$$

In the case of noting Eq. (8), and in the case of defining ϕ in Eq. (13), following establishment for Eq. (22) can be formed:

$$\Delta w_{ji} = -\eta \frac{\partial \varepsilon}{\partial z_j} y_i(r-1) = \eta \phi_j(r) y_i(r-1) \quad (22)$$

Keeping right hand side of Eq. (13) in view, Eq. (23) can be acquired as follows:

$$\Delta w_{ji} = -\eta \left[\frac{\partial \varepsilon}{\partial y_j(r)} \frac{\partial y_j}{\partial z_j} \right] y_i(r-1) \quad (23)$$

Here, there is an unachievable term, which is $\partial \varepsilon / \partial y_j$. In the event, $\phi_j(r)$ can be expressed as given with Eq. (24):

$$\phi_j(r) = y_j(r) [1 - y_j(r)] \sum_k \phi_k(r+1) w_{kj}(r+1) \quad (24)$$

In order to reveal the convergence between the output values of ANN algorithm compared according to the target values, the error values including the mean absolute error (MAE), root

mean square error (RMSE), and the correlation coefficient (R) are used. These are respectively presented with Eqs. (25), (26), and (27), as follows:

$$MAE = \frac{1}{N} \sum_{i=1}^N |e(i) - a(i)| \quad (25)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N [e(i) - a(i)]^2} \quad (26)$$

$$R = (\sum_{i=1}^N [e(i) - \bar{e}][a(i) - \bar{a}]) / \left(\sqrt{\sum_{i=1}^N [e(i) - \bar{e}]^2} \sqrt{\sum_{i=1}^N [a(i) - \bar{a}]^2} \right) \quad (27)$$

In Eqs. (25), (26), and (27), the denotation of $e(i)$ is utilized in order to show the estimated data of instantaneous river water flow rate (RWFR) at the instantaneous observation of i . On the other hand, $a(i)$ used in the identical equations demonstrate the actual measured data belonging to the instantaneous river water flow rate (RWFR) at the instantaneous observation of i . The mean magnitudes belonging to the estimated as well as to the actual data needed in computations of the correlation coefficient in Eq. (27), are displayed utilizing the symbols including $\bar{e}$ and $\bar{a}$, respectively. The average values for both data clusters are detected taking all members of actual and estimated data clusters into account. Eventually, the curtailment of N utilized in those equations stand for the total amount of the data samples corresponding to the data clouds consisting of the actual and the estimated. Absolutely, their cumulative values for both data sets are equal with each other. As also presented with the computations of the statistical errors, the specified algorithm for computations as well as the logic formed between the instantaneous data readings are acquired through performing an algorithmic process on all data samples found in the data sets. Usually, the utilized amount of members found in the actual data set increase cause the forecast quality increase implemented on the estimated data set. Because, in this way, the created algorithm will be superior in the training phase. And, the generated algorithm that is better in the training phase will absolutely produce better estimation outcomes at the testing phase.

3. RESULTS AND DISCUSSIONS

3.1. Geography of the Study Area and General Information on the Data

Figure 4 shows the study area including four rivers named as Arda, Meriç (Maritsa), Tunca, and Ergene, as well as the eleven WMSs found on these four rivers. As observed from the figure, on Ergene river, along the upstream to the downstream flow direction of the river, namely, from the north-east towards the south-west geographical directions, İnanlı, Lüleburgaz, and Yenicegörece WMSs are seated on this river, respectively. On the other hand, during the journey of the water flowing in the bed of the Tunca river from north to south, i.e., from the upstream to the downstream, the water passing through a certain cross-sectional area of the river bed flows through the Elhova, Suakacağı, and Değirmenyeni water flow reading points, respectively, on this route. Furthermore, the flow route of the Maritsa river, after oscillating in the upstream, passes respectively through the Harmanlı and Svilengrad water flow rate measurement stations in the middle stream, and accordingly forms a northwest to southeast flow route at the downstream, to reach initially to Kirişhane WMS and pass along the İpsala WMS to finally complete its route, when reaching to the Aegean Sea. Finally, Arda river flowing in the direction from west to east, passes through a single WMS named as Ivoylovgrad, found at the midstream, to continue its flow journey towards the east downstream. In this regards, a cumulative of three, three, four, and one WMSs are found respectively for Ergene, Tunca, Maritsa, and Arda rivers.

Ergene river originates at Yıldız mountains found in the north of Thrace lands of Türkiye, close to the Black Sea. Besides, Tunca and Maritsa rivers originate in Bulgaria, whereas, Arda river also originates in Bulgaria, at an altitude of 1,455 m in Rhodope mountains of the country. During the flow of Ergene river towards downstream, at the first one third route of the river bed, İnanlı and Lüleburgaz WMSs are located, and at the last one third route of the river bed, Yenicegörece WMS is located. On the other hand, just before the İpsala water flow rate measurement station on the north, the river called Maritsa, which flows from north to south and contains the waters of the Arda, Maritsa, and Tunca rivers all together, merges with the Ergene river and, continues its flow under the name of Maritsa, and passes on the İpsala WMS and flows into the sea of Marmara in the southwest. Besides, initial merging of two rivers occurs in between Arda and Maritsa rivers, before the waters of these two rivers reach to the Kirişhane WMS, then Tunca river joins to the initial merged river at the immediate southeast of the initial

merging zone of Arda and Maritsa rivers, again before the water of these three rivers reach to the Kirişhane WMS, in which three rivers form the single river named as Maritsa river. These three rivers that formed the single river named as Maritsa, finally merge with the Ergene river at the southwest, at the upstream side of the İpsala WMS, and finally form again the single river named as Maritsa, and this final river named as Maritsa is poured to the Marmara Sea at the further southwest.

This geography, which includes these rivers and measuring stations, corresponds to a regional area of approximately 73,500 km², including the lands of Türkiye, Bulgaria, and Greece countries. The study focuses on VWFR forecasts on the İpsala WMS, that are associated to the real data readings of VWFR measured at ten different WMSs found on these four different rivers. Therefore, based on a total of five different models, forecast function belonging to the river water flow rate of Maritsa river, that demonstrates the historical data water flow rate distributions of this river flow, was generated to be compared with the real data function including the data cluster of instantaneous water flow rate readings of the water flow. Here, ten water measurement stations including İnanlı, Lüleburgaz, Yenicegörece, Elhova, Suakacağı, Değirmeniyeni, Harmanlı, Svilengrad, Kirişhane, and Ivoylovgrad are exhibited with yellow filled circles on the map of Figure 4, whereas, İpsala water measurement station is signified with red filled circle on the same map of this figure. Since the predictions are directed on the water flow rates of Maritsa river on the İpsala water measurement station, this station is distinguished using red color from the other stations that are shown by yellow color.



Figure 4. Geography of the study area

The values of water volumetric flow rate of four rivers including Ergene, Tunca, Maritsa, and Arda that were stored in the DSI web-site were read both manually and based on programming, considering the water flow rate measurement stations consisting of İnanlı, Lüleburgaz, Yenicegörece, Elhova, Suakacağı, Değirmenyeni, Harmanlı, Svilengrad, Kirişhane, İpsala, and Ivoylovgrad (DSI, 2026). Accordingly, as a novelty, it was concluded and reported that data reading based on programming provided fortissimo speed and more accurate data collecting, compared to the manual data clustering method. In the program based data clustering forming, web scraping method was utilized as the onset preparations of artificial intelligence implementation, i.e., during the data cloud constructing. In this way, a total of 2,469 daily water flow rate values of these cited WMSs were read from the web-site at a significantly high speed. Namely, as a preparatory phase of the AI study, a total of 27,159 instantaneous data readings regarding 11 WMSs had formed the discrete data sets of these 11 stations. The volumetric water flow rate data that was obtained as an eleven data cluster, considering all water measurement stations, using the method of web scraping was carried out together by the preferred Selenium library, in order to extract data from dynamic web pages. Selenium library had provided a superior benefit of automatically controlling the web browser, thus brings a possibility of processing the dynamic contents that are uploaded by the JavaScript.

On the other hand, in order to parse the HTML structure obtained from the web page as well as in order to extract the needed information, the library of BeautifulSoup was used. In this way, the required data found inside the HTML labels were detected to be processed in an organized format. The utilized method is an effective solution especially for the data sources supplying static data, the ones that do not include application programming interface (API) or the data sources having a restricted direct access. Finally, whole data that was obtained with the utilization of the web scraping was predisposed for the data analysis as well as the studies including visualization operations. Since five different approaches were taken into account in the current study, the implemented methods are clearly described in the following sections with the obtained results in more detail.

3.2. 1st Implemented ANN Correlation Method in the Estimation of the Maritsa River Water Flow Rate

In this method, as observed from Figure 5, the data of two water metering stations including Kirişhane and Yenicegörece, that are the ones having the locations closest to the target station,

was used among the data of the total of eleven stations that was obtained by web scraping, in order to forecast the VWFR values of the İpsala WMS.



Figure 5. Visual description of the 1st implemented approach

In this approach, the space was significantly scanned considering large alterations in three parameters, i.e., for the ANN simulations of the 1st approach, equation number (EqN), epoch number (EN) and the training percentages (TP) were changed. The first parameter, namely, the equation number was analyzed in the range of $1 \leq EqN \leq 20$, with an increment of $\Delta EqN = 1$ was implemented to the former equation number to find and study on the next ensuing equation number. These criteria have resulted the analyses of the total trials for equation number corresponding to $\#TT_{EqN} = 20$, in total. Besides, the epoch number, EN , which is the second parameter considered in the analyses of 1st approach of ANN, was studied in the range of $50 \leq EqN \leq 500$, with 50 increment of $\Delta EN = 50$ was taken into account to determine the subsequent epoch number with regards to the previous one. Accordingly, $\#TT_{EN} = [(500 - 50)/50] + 1 = 10$ different equation numbers were put in the ANN analyses. Finally, the training percent, TP , which is the third and the last parameter that was altered in a specific set of values, was studied in the range corresponding to $50 \leq TP \leq 95$, by considering $\Delta TP = 5$ exerted on the prior TP value to find and define the sequential TP value. In this context, $\#TT_{TP} = [(95 - 50)/5] + 1 = 10$ different values of training percentages were taken cognizance of in the 1st approach of ANN. This large scan of the space has ultimately resulted the total of $\#TT = \#TT_{EqN} \times \#TT_{EN} \times \#TT_{TP} = 20 \times 10 \times 10 = 2,000$ trials that were considered

in 1st implemented approach of the ANN study. Since the manual method of running ANN one by one in a big trial set including 2,000 different elements was observed to be so hard, a suitable machine learning loop was created to interpret and continue on the trials in a suitable format. Thus, the human error that may occur while changing the three parameters mentioned above, in a certain order has been significantly eliminated, and the only annoying factor left is the significant time loss due to the application of artificial intelligence by 2,000 times, as described above.

In the 1st approach of the ANN study, the analyses were actualized keeping the training and the testing parts of the ANN; thus whole of the analysis outputs have been given according to the training and testing stages of this algorithm. Besides, the analysis outputs have been revealed for the mean absolute error (MAE), root mean square error (RMSE), and the correlation coefficient (R^2). For each of the error parameters, the followed approach included the exhibition of the three ANN adjustment parameters consisting of the equation number (EqN), the epoch number (EN), as well as the training percentage (TP), demonstrated in the graphics to be given with the combination regulation of $C \binom{3}{2}$. In this regards, considering the MAE analysis outputs, the epoch number (EN) was given as the function of equation number (EqN) initially, the training percent (TP) was functionally linked to the equation number (EqN) secondly, and the training percent (TP) was functionally connected to the epoch number (EN) thirdly and finally. The same approach was also conducted when taking the RMSE and the correlation coefficient (R^2) analysis outputs into account. Thence, a cumulative of $3 \times 3 = 9$ figures were created and reported indicating the ANN analysis outputs for the training part of the algorithm, taking the 1st implemented approach into account. Furthermore, 9 additional figures were generated and reported demonstrating the ANN analysis outcomes for the testing stage of the algorithm, considering the 1st implemented method. When the three combination regulation stated above implemented to the analysis outputs including the three error parameters comprising of MAE, RMSE, and the R^2 , as well as when these mentioned situations were applied to the two stages of the ANN algorithm enclosing the training and the testing stages, the total generated results as well as the number of the results, thus figures correspond to the cumulative value of $9 + 9 = 18$, in the 1st applied methodology. On the other hand, when the ANN outputs were extracted which are showing the results in the cited combination regulation way covering the relations of EN vs. EqN , TP vs. EqN , TP vs. EN ; demonstrating three of the statistical error parameters encapsulating MAE, RMSE, and R^2 ; as well as exhibiting the two

phases of computations such as training and testing, seven different methods to denote the analysis outputs on the figures were developed. Namely, there were 7 different ways of showing each of 18 figures in this 1st implemented approach. Those included the first method of low resolution gridded with the color scale having a wide range of values, the second technique of low resolution non-gridded with the color scale having a wide range of values, the third way of high resolution non-gridded with the color scale having a wide range of values, the fourth process of high resolution gridded having the color scale in a narrow range of values, the fifth procedure of high resolution non-gridded involving the color scale in a narrow range of values, the sixth modality of low resolution gridded consisting of the color scale in a narrow range of values, the seventh modus of low resolution non-gridded inclosing the color scale in a narrow range of values.

In presenting the MAE outcomes of the 1st applied method of testing stage, the 4th option including the process of high resolution gridded having the color scale in a narrow range of values was selected. In this regards, the color scale was regulated to the MAE value range of $11.229 \text{ m}^3/\text{s} \leq MAE \leq 30.665 + \text{m}^3/\text{s}$ in this 4th option, for the *EN* vs. *EqN* representation, instead of the non-implemented adjustment corresponding to the value range of $11.230 \text{ m}^3/\text{s} \leq MAE \leq 127.480 \text{ m}^3/\text{s}$. Here, the value of $11.230 \text{ m}^3/\text{s}$ refers to the lowest value of the MAE in whole of 2,000 simulations considered in the testing stage. On the other hand, the value of $127.480 \text{ m}^3/\text{s}$ stands for the highest value of the MAE in all of 2,000 simulations kept in view in the testing stage. In this frame, the same color patterns were utilized for the MAE values exceeding the value of the $30.665 \text{ m}^3/\text{s}$, shown by $30.665 + \text{m}^3/\text{s}$, in this exerted 4th option. Furthermore, in introducing the MAE results of the 1st implemented method of testing stage, the 4th option including the process of high resolution gridded having the color scale in a narrow range of values was chosen similarly. In this context, the color scale was calibrated to the MAE value range corresponding to $11.229 \text{ m}^3/\text{s} \leq MAE \leq 34.713 + \text{m}^3/\text{s}$ in this 4th option, for the *TP* vs. *EqN* presentation, instead of the non-implemented tuning including the value range of $11.230 \text{ m}^3/\text{s} \leq MAE \leq 152.131 \text{ m}^3/\text{s}$. Here, the value of $11.230 \text{ m}^3/\text{s}$ implies to the smallest value of MAE in entire of 2,000 simulations taken into account in the testing stage. Besides, the value of $127.480 \text{ m}^3/\text{s}$ alludes to the highest value of the MAE in all of 2,000 simulations looked at in the testing stage. Accordingly, the same color patterns were used for the MAE values over the value of the $34.713 \text{ m}^3/\text{s}$, shown by $34.713 + \text{m}^3/\text{s}$, in this exerted 4th option. Lastly, in offering the MAE results of the 1st implemented method of testing stage, the

4th option containing the process of high resolution gridded having the color scale in a narrow range of values was picked once more. Similarly, the color scale was collimated to the MAE value range to fall in between $11.229 \text{ m}^3/\text{s} \leq MAE \leq 23.537 + \text{m}^3/\text{s}$ in this 4th option, for the *TP* vs. *EN* visualization, apart from the non-exerted arrangement embodying the value range of $11.229 \text{ m}^3/\text{s} \leq MAE \leq 25.998 + \text{m}^3/\text{s}$. Here, the value of $11.229 \text{ m}^3/\text{s}$ mentions the minimum value of MAE in the complete of 2,000 computations analyzed in the testing part. Also, the value of $25.998 \text{ m}^3/\text{s}$ insinuates the maximum value of MAE in whole of 2,000 computations studied in the testing stage. Accordingly, the identical color patterns were operated for the MAE values overrunning the value of the $23.537 \text{ m}^3/\text{s}$, shown by $23.537 + \text{m}^3/\text{s}$, in this performed 4th option.

Figures 5a, 5b, and 5c demonstrate *EN* given according to the *EqN*, functional relation of the *TP* with respect to the *EqN*, and *TP* shown against the *EN*, considering the MAE statistical accuracy results of the testing stage of 1st employed approach of ANN. In Figure 6, the color distribution of *EN* is exhibited with respect to the *EqN*. This color pattern of Figure 6a is given at the value of the training percent corresponding to *TP*=0.95. Additionally, Figure 6b depicts the distribution of the color patters that functionally relates the *TP* according to the *EqN*. In this figure, the epoch number was arranged to the value of *EN*=300 that signifies this color pattern. Furthermore, the functional color patterns of *TP* given as per *EN* is exposed in Figure 6c. In Figure 6c, the parameter of equation number was set to the value of *EN*=15 for this color distribution. The artificial intelligence studies have point out that *TP*=0.95 for Figure 6a, *EN*=300 for Figure 6b, as well as *EN*=15 for Figure 6c have yielded the superior outcomes of statistical accuracy result of MAE, considering the total of 2,000 computations; namely the smallest values of MAE are exhibited with these color patterns of Figures 5a, 5b, 5c. In these three figures, MAE outputs of 460 simulation ANN models, considering 1st implemented approach of the testing stage have been revealed. In this context, in Figure 6a, the number of the total studied models shown in this figure corresponds to the multiplication of the utilized epoch number (*EN*) and the equation number (*EqN*) at the constant training percentage (*TP*) of 0.95. I.e., a total of $\#TT_{5a} = \#TT_{EN} \times \#TT_{EqN} = 10 \times 20 = 200$ models are revealed in Figure 6a, in terms of the MAE outputs. Similarly, in Figure 6b, the number of the cumulative computations shown in this figure corresponds to the multiplication of the used training percentage (*TP*) as well as the equation number (*EqN*) at the constant epoch number (*EN*) of 300. But, the 20 models belonging to 20 different equation numbers indicated in Figure 6a at

the $EN=300$ and $TP=0.95$ should be subtracted from the total number of models at these cited values of two parameters considered in Figure 6b, since Figure 6b includes the computations at $EN=300$ and therefore, 20 different models belonging to 20 different equation numbers at $TP=0.95$ must be subtracted from the total number of the trials available in Figure 6b. The subtraction of 20 models were performed from the total amount of simulations considered in Figure 6b, since these 20 model results have already been indicated in Figure 6a. Accordingly, a sum of $\#TT_{5b} = \#TT_{TP} \times \#TT_{EqN} = 10 \times 20 - 20 = 200 - 20 = 180$ new models are depicted in Figure 6b, in terms of the outputs of MAE. All of a piece, a total of $10 \times 10 = 100$ models are considered for ANN simulations in Figure 6c, in terms of color outputs. Figure 6c demonstrates the color patterns of TP vs. EN at the constant $EqN=15$. However, the results of 10 models considering different epoch numbers at $TP=0.95$ and $EqN=15$ have already been demonstrated in Figure 6a, and the MAE outputs of 10 models considering different training percentages at $EN=300$ and $EqN=15$ have already been shown in Figure 6b. Therefore $10+10=20$ models must be subtracted from the total model demonstrations indicated in Figure 6c, namely, $\#TT_{5c} = \#TT_{TP} \times \#TT_{EN} = 10 \times 10 - 10 - 10 = 100 - 20 = 80$ new models are shown in Figure 6c, in terms of the MAE outputs. The total number of the indicated models in Figure 6, therefore corresponds to $\#TT_5 = \#TT_{5a} + \#TT_{5b} + \#TT_{5c} = 200 + 180 + 80 = 460$. On the other hand, among the total of 460 models, the lowest, thus the best MAE output was acquired as soon as the equation number (EqN), the epoch number (EN), and the training percentage (TP) were adjusted respectively to 15, 300, and 0.95, producing this statistical error output of 11.2288. The exact position of the best MAE is exhibited in Figure 6a including EN vs. EqN study, in Figure 6b consisting of TP vs. EqN relation, in Figure 6c comprising of TP vs. EN functional dependence, utilizing the darkest blue color, showing as the lowest values of MAE in the color scales of three figures.

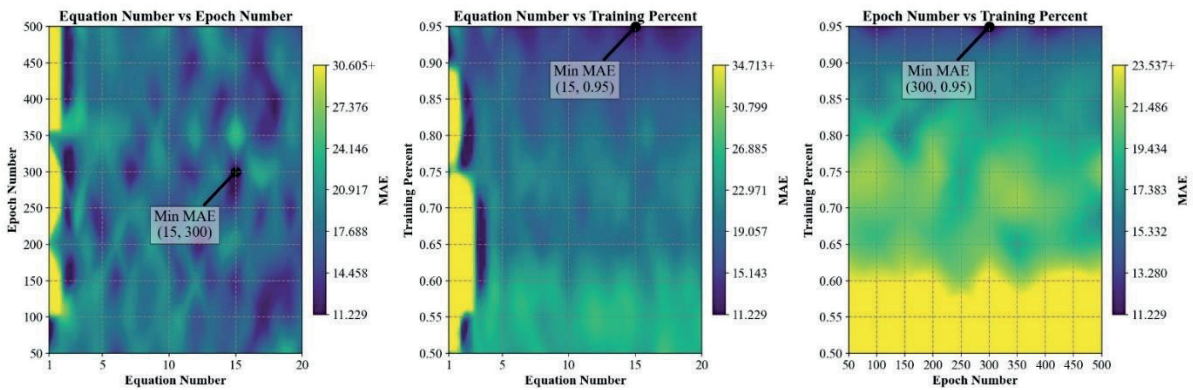


Figure 6. MAE results for **a)** EN vs. EqN , **b)** TP vs. EqN , **c)** TP vs. EN at the testing stage of 1st applied approach of ANN

The MAE statistical output results of 1st applied approach of ANN, considering the training stage of the simulations are presented for EN vs. EqN , TP vs. EqN , TP vs. EN adjustment parameters given respectively in Figures 7a, 7b, and 7c. As in the case of testing part of ANN for the 1st implemented approach, in this training part of ANN study for MAE demonstration, 4th option of result presentation was used. Again the superior results of the MAE in this color shading are exposed with dark blue pattern in three sub-figures of Figure 7. Among three sub-figures of Figure 7, Figure 7a shows the functional color distribution of EN vs. EqN , providing the constant value of the training percentage at $TP=0.95$. Besides, Figure 7b exhibits the TP vs. EqN functional relation, keeping the constant value of epoch number at $EN=450$. Finally, the color distribution showing the correlation between TP and EN that is depicted in Figure 7c has been obtained at the constant value of the equation number, corresponding to the value of $EqN=17$. In this regards, during the regulation of EqN , EN , and the TP to the values of 17, 450, and 0.95 have turned the lowest value of MAE, providing the best accuracy, corresponding to the value of 30.1197. It is not surprising to obtain the simulation outcome of MAE equivalent to the value 30.1197, at the training stage, that is reported to be significantly higher than the former testing MAE value of 11.2288. The ANN algorithm learns the relation between the instantaneous data points at the training stage, to give suitable fits at the testing stage. Accordingly, based on the captured logic at the training stage, better predictions with lower MAE error results are generally obtained at the testing stage. Again the best training 460 MAE outputs are revealed in Figure 7, among the total of 2,000 computations.

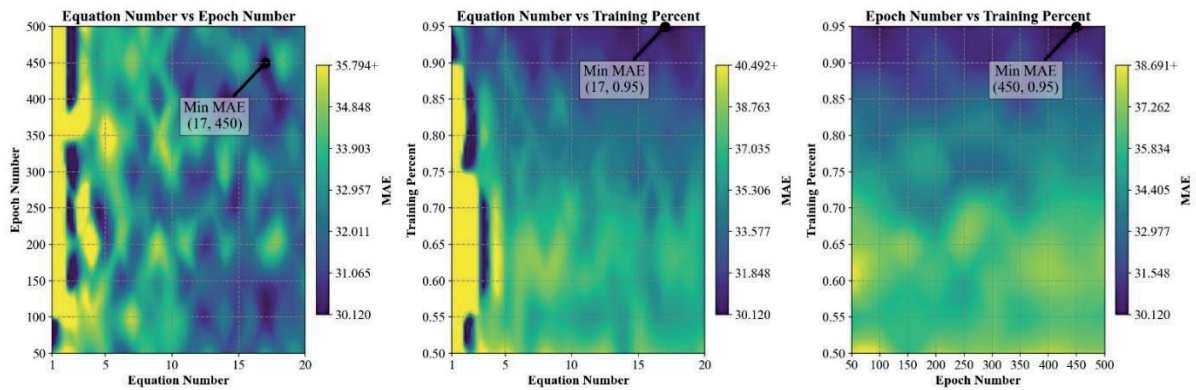


Figure 7. MAE results for a) EN vs. EqN , b) TP vs. EqN , c) TP vs. EN at the training stage of 1st applied approach of ANN

The statistical outputs including root mean square error (RMSE) of 1st applied approach of ANN, consisting of mutual distributions of EN vs. EqN , TP vs. EqN , TP vs. EN artificial intelligence tuning parameters are displayed in Figures 8a, 8b, and 8c, respectively for the

testing stage of ANN tool. The same regulating parameters that were considered in the MAE calculations, were also taken into account in the RMSE calculations. For instance, the results of RMSE statistical error for the testing stage are pointed using the 4th option of the result exhibition. Intercalary, as in the case of former Figures of 6 and 7, a total of 460 models are denoted in Figures 8a, 8b, and 8c. Taking these three figures into account, Figure 8a portrays distribution of EN parameter with respect to the parameter of EqN at the constant value of the training percentage adjusted to $TP=0.95$. Besides, the variation of TP parameter according to the parameter of EqN is portrayed in Figure 8b, reckoning the constant value of epoch number corresponding to $EN=300$. Finally, the functional color distribution of TP parameter defined against the EN adjustment parameter, keeping the constant value of the equation number at the value of $EqN=15$ in view, is shown in Figure 8c. On the other hand, with regards to the combination regulation of $C \binom{3}{2}$, namely, when three setting-up parameters are considered simultaneously, i.e., in the case of adjusting EqN , EN , and TP to the values of 15, 300, and 0.95, respectively, the minimum value of the root mean square error (RMSE) was obtained. These calibration parameters have caused the RMSE value of $3.3509 \text{ m}^3/\text{s}$. The exact location of this value in three sub-figures of Figure 8, is demonstrated by dark blue pattern indicating this value of $3.3509 \text{ m}^3/\text{s}$ RMSE. Besides, box labels are used to indicate the optimum values of the adjustment parameters according to the combination regulation rule, such that the box label of (15, 300) presents the optimum values of EqN and EN , respectively; the box label shown by (15, 0.95) exhibits the optimum values of EqN and TP , respectively; and the box label displayed by (300, 0.95) indicates the optimum values of EN and TP , respectively. In other words, those values of tuning parameters are responsible of returning the lowest value of RMSE at $3.3509 \text{ m}^3/\text{s}$, thus the best one. Other studied 1,999 models have returned relatively poor RMSE results, thus their RMSE values are reported to be higher than the value of $3.3509 \text{ m}^3/\text{s}$ RMSE. Similar to the testing results of RMSE, the training outcomes of RMSE are emceed in Figure 9, for three setting parameters of ANN, considering the combination regulation, and exploiting the 4th choice of outcome exhibition. The statistical error output for RMSE corresponding to $5.4881 \text{ m}^3/\text{s}$ have been obtained during the arrangement of 17 EqN , 450 EN , and 0.95 TP , as seen from Figure 9. In sub-figures of this Figure 9, the dark blue color and the proper labels have been operated as in the case of the former figures, each showing two parameters selected from a total of three regulating parameters.

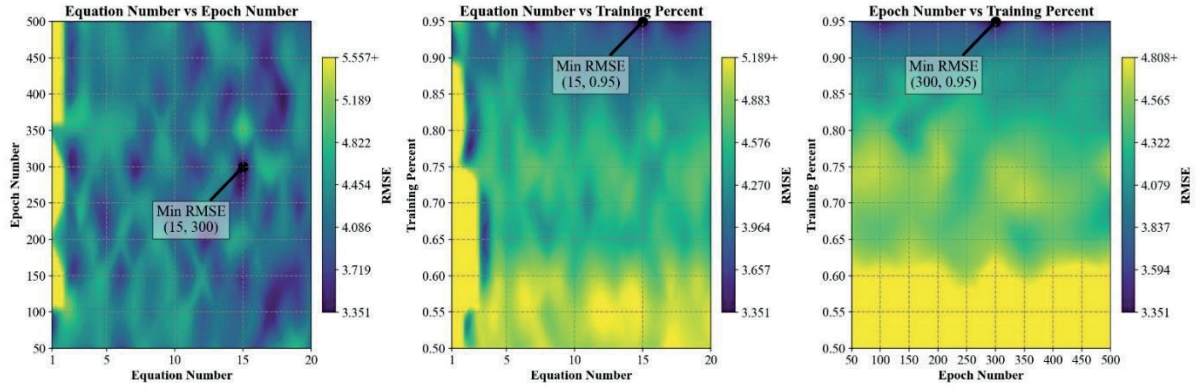


Figure 8. RMSE results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the testing stage of 1st applied approach of ANN

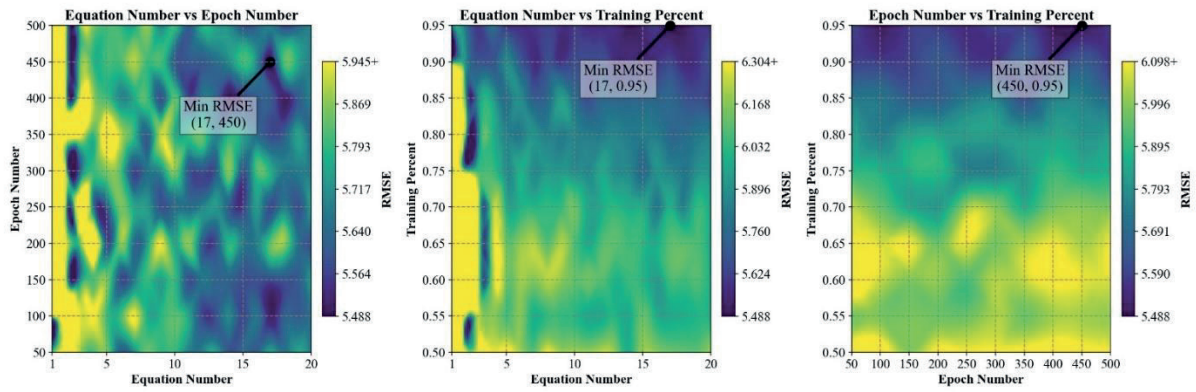


Figure 9. RMSE results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the training stage of 1st applied approach of ANN

In the study, as the third statistical error parameters, the correlation coefficient (R) was used, apart from the statistical error parameters of MAE and RMSE. These three statistical accuracy parameters are described according to the harmony of the predicted data cluster compared with respect to the real measured data set. While the aim is to reduce the magnitudes of MAE and RMSE as much as possible, approaching to zero in the artificial intelligence or machine learning computations; considering the R conformity, the target is to increase the parameter as much as possible to approach the value of unity, namely 1. The magnitudes of the error parameters can be in between none and plus infinity, and may also take the value of the none; when MAE and RMSE error comparison are taken into account on the real observed data. Therefore, their value ranges can be indicated respectively as, $0 \leq MAE < +\infty$ and $0 \leq RMSE < +\infty$. On the other hand, the magnitude of the R can be in between none and the unity, as well as can be equal to the none and the unity. Therefore, its value range can be demonstrated by $0 \leq R \leq 1$. The correlation outputs for the testing and training stages of 1st implemented approach of ANN are exhibited in Figures 10 and 11, respectively. In exhibition of the functional color distributions of the epoch number (EN) against the equation number (EqN), the training percentage (TP) with

respect to the equation number (EqN), as well as the training percentage (TP) defined by the epoch number (EN), the 4th option of the result exhibition is utilized. Besides, similar to the former computations of MAE and RMSE, in Figure 10 and 11, 460 models are displayed both for the testing and training stages for R . In this context, the color functional distribution of EN vs. EqN at the constant training percentage value of $TP=0.55$, the functional color dispersion of TP vs. EqN at the constant epoch number of $EN=100$, the functional color dissolution of TP vs. EN at the constant equation number of $EqN=8$ are respectively evidenced in Figures 10a, 10b, 10c. The best simulation outcomes of R that have been indicated with a total of 460 models among the total of 2,000 simulation models are further eliminated in this way, and the best outcome of the R magnitude has been evidenced in these figures. They are shown in these figures by yellow colors, in which this color indicates the magnitude of the highest, thus the superior value of R , as well as the exact locations in these figures are pointed using black circles. Considering the R computations of 1st exerted approach of ANN, at the setting parameters of EqN , EN , and TP to 8, 100, 0.55, respectively, the value of the maximum R was obtained that corresponded to 0.96469 among the total of 2,000 simulations, and the R values of the remaining 1,999 models were reported to be significantly lower and thus poorer than this cited model. Intercalary, the color functional deployment of EN according to EqN at a fixed training percentage value of $TP=0.50$, the functional color diffusion of TP according to EqN at the fixed epoch number of $EN=150$, the functional color scatter of TP according to EN at the fixed equation number of $EqN=14$ are demonstrated in Figures 11a, 11b, 11c, respectively. The best R computation results that have been represented with a cumulative of 460 models among the total of 2,000 computation models are further riddled in this way, and the superior outcome of the R value has been exhibited in these Figures of 11a, 11b, and 11c. They are similarly depicted in these figures utilizing the yellow colors, in which the yellow presents the values of the highest, thus the best value of R , and the exact locations in these figures are betokened using the circles that are filled with black color. Considering the R imitations of 1st performed ANN approach, at the regulation parameters of EqN , EN , and TP set to 14, 150, 0.5, respectively, the maximum value of the R was acquired that corresponded to 0.97548 among the total of 2,000 computations, and the remaining 1,999 R values of the other models were reported to be pretty lower and therefore poorer than this mentioned model.

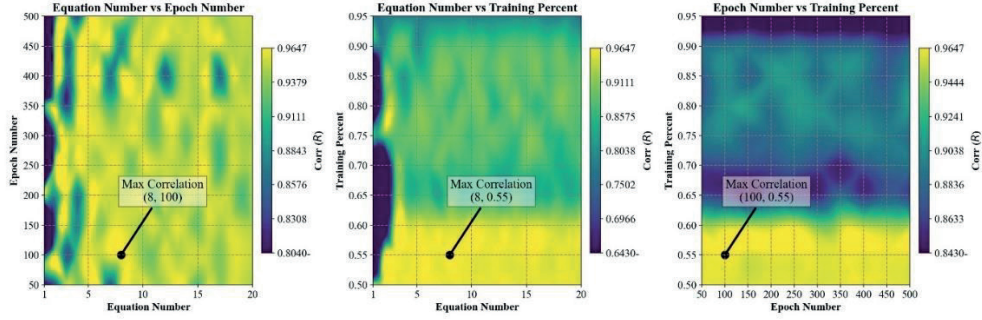


Figure 10. R results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the testing stage of 1st applied approach of ANN

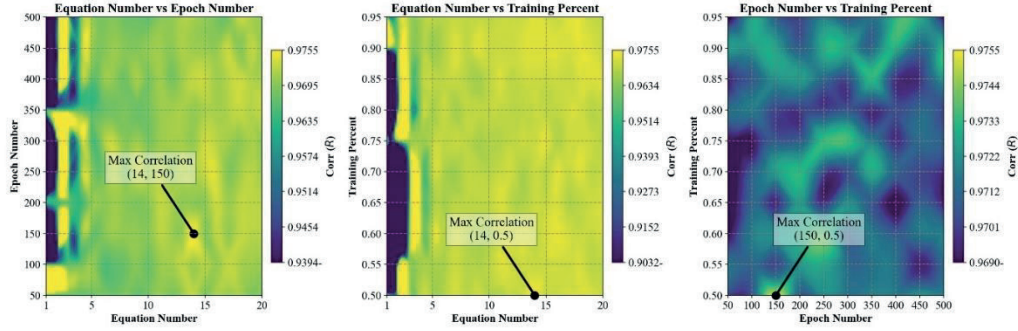


Figure 11. R results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the training stage of 1st applied approach of ANN

On the other hand, Figure 12 considers the alteration of the training percentage (TP) in the range of $0.50 \leq TP \leq 0.95$, with an increment of $\Delta TP = 5$, that have given the smallest thus best results for MAE and RMSE, and the highest thus superior outcomes for the R , considering the testing stage of the 1st implemented approach of ANN. These values for three statistical error parameters report the best outputs among the total 2,000 simulations. In Figure 12, the x -axis stands for the variation of the TP values in this cited range. Besides, three y -axes have been used in the same figure, that correspond to MAE, RMSE, and the R statistical accuracy parameters. Among those, the red color indicates the MAE error parameter, the blue one corresponds to the RMSE accuracy parameter, and the green pattern was used to denote the correlation results of the best models. On the other hand, the values of the MAE , $RMSE$, and the R statistical error parameters for the best simulation outputs have been exhibited in these figures using the same colored pointers. For instance, the red filled circles represent MAE errors, the blue filled squares correspond to the RMSE errors, and green filled triangles stand for the R correlation results. A total of best 16 models were evaluated in this Figure 12. On the other hand, the values of MAE, RMSE, and R outputs of these best 16 models are revealed in Table 1. In this table, the values of the equation number (EqN) and the epoch number (EN) accompanying to the values of the training percentages (TP) generating the best 16 models, that produced the best statistical accuracies are also provided. When Figure 12 and Table 1 are

simultaneously looked, at the value of the training percentage corresponding to $TP=0.50$, the best statistical accuracy parameters including MAE, RMSE, and R have been obtained at this TP value corresponding to $23.543 \text{ m}^3/\text{s}$, $4.852 \text{ m}^3/\text{s}$, and 0.96340 , respectively. This situation is both observed in Figure 12 and Table 1. Namely, 1 model whose EqN and EN adjusted to the values of 6 and 400, respectively at the TP value of 0.5 has turned with those best statistical accuracy values. This forms similarly the same cases during setting the training percentage values corresponding to $TP=0.55$, $TP=0.60$, $TP=0.65$ constituting a total of 4 best models during the analyses of the training percentage in the range of $0.50 \leq TP \leq 0.65$. On the other hand, in the analysis of TP in the range of $0.70 \leq TP \leq 0.95$, an additional model was needed who produced the best R value, apart from the model that has generated the best MAE and RMSE values at each training percentage value analyzed in this range. Therefore, two models for each TP value in the range of $0.70 \leq TP \leq 0.95$ have been taken into account, for revealing the best MAE, RMSE, and the R statistical accuracy values, constituting a total of 12 models in this TP range for the demonstrating of the error results both in Figure 12 as well as Table 1. Under these conditions, regarding the TP range of $0.50 \leq TP \leq 0.95$, a cumulative of 16 models have been analyzed, whose MAE, RMSE, and R statistical error outputs have been indicated in Figure 12 and Table 1. Taking the value of $TP=0.70$ into account to illuminate the range of $0.70 \leq TP \leq 0.95$ into account; in this TP value, 1 model that was adjusted to 11 EqN and 500 EN has given the best statistical accuracy values of mean absolute error and root mean square error corresponding to $17.703 \text{ m}^3/\text{s}$ MAE, $4.208 \text{ m}^3/\text{s}$ RMSE, while 1 another model that was regulated to 7 EqN and 500 EN has procreated the superior correlation coefficient output value of $0.89010 R$. Therefore 2 best models are considered in $TP=0.70$, as well as in the values of training percentages corresponding to $TP=0.75$, $TP=0.80$, $TP=0.85$, $TP=0.90$, $TP=0.95$, that constituted to 12 different models. Shortly, a total of 4 best models are kept in view in the TP value range of $0.50 \leq TP \leq 0.65$, as well as 12 best models are taken into account in the TP value range of $0.70 \leq TP \leq 0.95$, made a total of 16 different models. On the other hand, in Table 1, considering 16 best models that were evaluated and reported to be superior based on the training percentage (TP) analyses taken into account in the range of $0.50 \leq TP \leq 0.95$, a cumulative of 30 statistical accuracy errors including MAE, RMSE, and R were reported. Namely, in this table, among the total number of the indicated errors for MAE, RMSE, and R , corresponding to the total error amount of 30 for a total of best 16 different models evaluated according to the training percentage (TP) values, and reported for their testing stages; the MAE and RMSE outputs corresponding to the values of $11.229 \text{ m}^3/\text{s}$ MAE and $3.351 \text{ m}^3/\text{s}$ RMSE that were obtained as the lowest and best statistical accuracy outputs of one model among the

total of 2,000 models considered in 1st applied approach of ANN, and that were acquired at 0.95 *TP*, 15 *EqN*, and 300 *EN*, were shown formerly at these adjustment parameters in Figures 6 and 8. In this regards, at these adjustment parameters, one model indicated for two errors of MAE and RMSE were presented to be the best among the total of 2,000 models, and accordingly have been exhibited in Figures 6 and 8, as well as in Figure 12 and Table 1. Similarly, in the testing stage for the 1st applied approach of ANN, the best model in terms of the correlation coefficient (*R*) output was acquired at the tuning parameters of 0.55 *TP*, 8 *EqN*, and 100 *EN*, and its value was reported to correspond 0.96469. This model that generated this highest output value of the *R* was reported to be the superior model among the total of 2,000 models in terms of the correlation coefficient and therefore formerly indicated in Figure 10, as well as in the following Figure 12 and Table 1 among the total of 16 best models presenting a total of 30 error values of MAE, RMSE, and *R* given for different training percentage (*TP*) values. Obeying to these remarks, to distinguish the sole model which created the best in terms of MAE and RMSE at a diversity of different *TP*, and to separate the sole model which generated the best in terms of *R* at a diversity of different *TP*; three error outputs covering MAE, RMSE, as well as *R* belonging to two different models are denoted in Table 1, using the bold color.

Considering the training percentage (*TP*) value in the range of $0.50 \leq TP \leq 0.95$, the best mean absolute error (MAE) and the best root mean square error (RMSE) values were obtained always in the same adjustment parameters. For instance, considering the *TP*=0.75, the lowest and the best error values of 18.479 m³/s MAE and 4.299 m³/s RMSE were achieved at the same regulation parameters of 16 *EqN* and 250 *EN*. On the other hand, when the *TP* was considered in the range of $0.50 \leq TP \leq 0.65$, the MAE, RMSE, and the correlation coefficient (*R*) values were attained in the same adjustment parameters. For example, taking *TP*=0.60 into account, the lowest and the best error values of 21.490 m³/s MAE, 4.636 m³/s RMSE, as well as the highest and the superior error value 0.95950 *R* values were achieved at the same calibration parameters corresponding to 10 *EqN* and 250 *EN*. However, exceeding the *TP* value beyond 0.70, generally lower value of *EqN* and the higher value of *EN* were needed to produce the highest and the superior value of *R* value compared to the *EqN* and the *EN* values that have generated the lowest and the best MAE and RMSE statistical accuracy values at the same value of *TP*. E.g., at the *TP* value of 0.85, while the tuning parameters of 14 *EqN* and 100 *EN* were required to create the lowest and the best MAE and RMSE values corresponding respectively to 16.519 m³/s and 4.064 m³/s, whereas, lower value of *EqN* such as 7 and a higher value of *EN*

such as 250 were needed to produce the highest thus the superior R value corresponding to 0.90651.

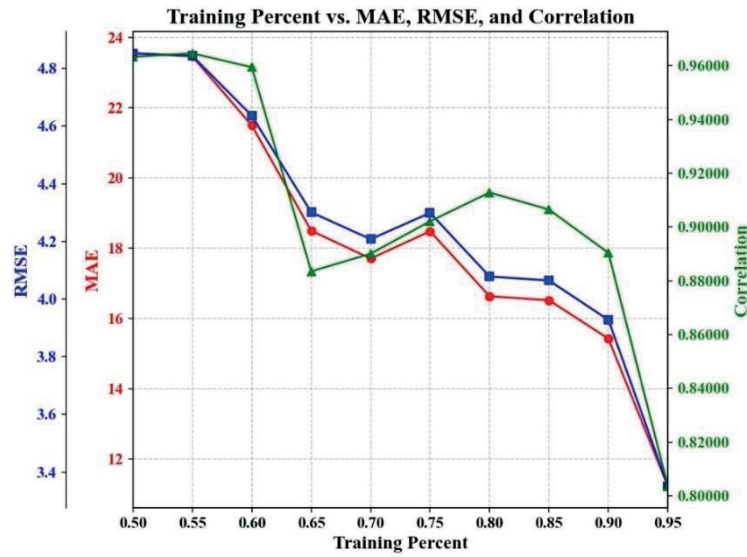


Figure 12. Error outputs of the best 16 models for different TP values at 1st implemented method

Table 1. Error outputs of the best 16 models for different TP values and their EqN and EN values are reported

Training Percent	Equation Number	Epoch Number	Metric	Training Percent	Equation Number	Epoch Number	Metric
0.5	6	400	MAE: 23.543	0.75	16	250	MAE: 18.479
	6	400	RMSE: 4.852		16	250	RMSE: 4.299
	6	400	Corr: 0.96340		15	400	Corr: 0.90215
0.55	8	100	MAE: 23.457	0.8	3	150	MAE: 16.632
	8	100	RMSE: 4.843		3	150	RMSE: 4.078
	8	100	Corr: 0.96469		14	500	Corr: 0.91286
0.6	10	250	MAE: 21.490	0.85	14	100	MAE: 16.519
	10	250	RMSE: 4.636		14	100	RMSE: 4.064
	10	250	Corr: 0.95950		7	250	Corr: 0.90651
0.65	8	350	MAE: 18.496	0.9	7	200	MAE: 15.426
	8	350	RMSE: 4.301		7	200	RMSE: 3.928
	8	350	Corr: 0.88352		18	100	Corr: 0.89038
0.7	11	500	MAE: 17.703	0.95	15	300	MAE: 11.229
	11	500	RMSE: 4.208		15	300	RMSE: 3.351
	7	500	Corr: 0.89010		16	450	Corr: 0.80353

3.3. 2nd Implemented ANN Correlation Method in the Estimation of the Maritsa River Water Flow Rate

In the implementation of the 2nd approach in the outlook of the volumetric water flow rate (VWFR) of Maritsa river, among the total of 11 different water measurement stations (WMSs),

as seen from Figure 13, the data of the nearest locations to the target İpsala station found on each tributary was used, which are feeding the Maritsa river having the target İpsala station, as the last measurement location. In this regards, the utilized WMSs included Ivoylovgrad, Svilengrad, Değirmenyeni, as well as the Yenicegörece which are respectively found in Arda, upstream Maritsa, Tunca, and Ergene rivers. Although these WMSs are referred to be the closest locations to the İpsala WMS found on Maritsa river, these stations are nevertheless found at pretty far downstream regions of this İpsala WMS. Since, the location including the Kirişhane WMS station found on Maritsa river is fed from three different tributaries including Arda, upstream Maritsa, and Tunca rivers; the hypothesis was adopted regarding that the measurements considered in this Kirişhane WMS do not influence the predictions of VWFR of the downstream Maritsa river on the İpsala WMS. Therefore, although Kirişhane WMS is more close, thus found more downstream compared to the WMSs including Ivoylovgrad, Svilengrad, and Değirmenyeni WMSs, the volumetric water flow rate (VWFR) measurements considered in this Kirişhane WMS are excluded in the predictions of VWFR estimations of İpsala WMS.

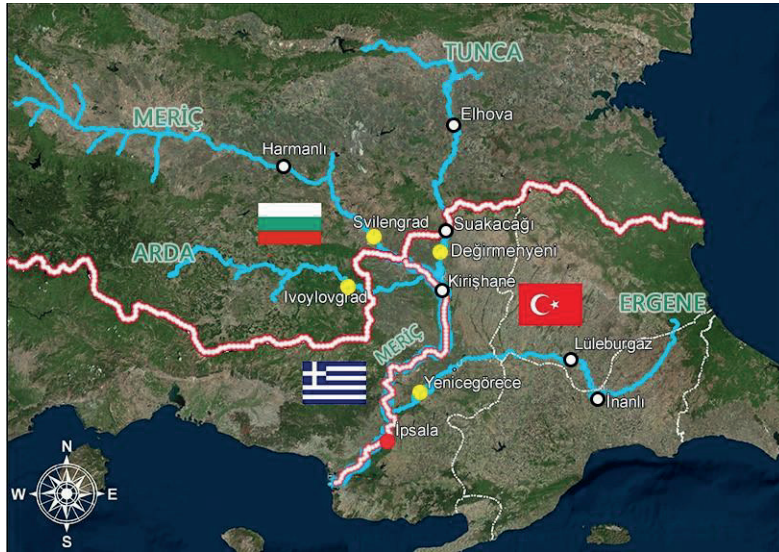


Figure 13. Visual description of the 2nd implemented approach

As formerly explained in the 1st implemented ANN approach, similar following settings were followed in the 2nd exercised ANN method. In this respect, the equation number (EqN) was inspected between the value range of $1 \leq EqN \leq 20$, adopting the increment of $\Delta EqN = 1$ applied to the former EqN value to consider the next EqN for the computational simulations. Thus, also including the equation numbers corresponding to the values of $EqN=1$ and $EqN=20$, which are reported as the limit values of this EqN value range, the total number of the equation numbers that were taken into account in computational simulations of the 2nd approach included

20 different analyses. Furthermore, the adjustment value range for the parameter epoch number (EN) was considered to fall in the range of $50 \leq EN \leq 500$, interiorizing the step increase of the value of $\Delta EN = 50$ performed to the prior value of this parameter to expose the ulterior value of the same parameter. In this context, a total of 10 different analyses were regarded including the limit values of the EN value range, corresponding to the values of $EN=50$ as well as $EN=500$. Finally, the value range for the regulation parameter of the training percentage (TP) was analyzed to include $50 \leq TP \leq 95$. A step increment of $\Delta TP = 5$ was actualized on the former training percentage value to take the next training percentage value into account for the ANN computations. In this wise, withal considering the limit values of the TP value range including $TP=50$ and $TP=95$, a cumulative of 10 different analyses were realized. In the light of these explanations, Table 2 gives the implemented methodology in terms of the calibration parameters and their value ranges including EN , EqN , and the TP , taking the 2nd applied ANN method:

Table 2. Calibration parameters for the 2nd applied ANN method

Equation Number (EqN) :	1, 2, 3, 4, 5, ... , 16, 17, 18, 19, 20
Epoch Number (EN) :	50, 100, 150, 200, 250, 300, 350, 400, 450, 500
Training Percent (TP) :	50, 55, 60, 65, 70, 75, 80, 85, 90, 95

With regards to the adjustment parameters given in Table 2, for the 2nd implemented ANN method, the 4th choice including the process of high resolution gridded having the color scale in a narrow range of values was picked for the demonstration of the best error parameters consisting of MAE, RMSE, and R among the total of 2,000 studied computation models. In this context, Figure 14 exhibits the best MAE value for testing stage among 460 different models shown by color distribution. Figure 14a, 14b, and 14c disclose the epoch number (EN) functional color scatter according to the equation number (EqN) at the constant training percentage (TP) value of 0.95, the training percentage (TP) depending on the equation number (EqN) at the constant epoch number (EN) of 450, the training percentage (TP) related on the epoch number (EN) at the constant equation number (EqN) of 17, respectively. In these three sub-figures of Figure 14, the darkest blue color was employed in showing the smallest thus the best MAE value corresponding to the value of $11.8580 \text{ m}^3/\text{s}$, i.e., was obtained at the regulation parameters of 17 EqN , 450 EN , 0.95 TP . Following the similar procedure in training stage of 2nd implemented ANN method, at the EqN , EN , and TP values respectively standing for 20, 500, 0.95; the best model having the smallest MAE value that corresponded to $36.3140 \text{ m}^3/\text{s}$

was procured. Here, in Figure 14, again 460 models have been pointed and 4th choice of result exhibition was considered. The cited best model in Figure 14 is indicated by the black filled circle in this three sub-figures. Figure 14a presents EN against the EqN at the constant value of 0.95 TP , Figure 14b shows TP with respect to the EqN at the fixed value of 450 EN , Figure 14c indicates TP depending on EN considering static 17 EqN . Furthermore, the exact coordinates that were explained to be shown by black circles belonging to the value of 11.8580 m^3/s MAE; were produced at 17 EqN and 450 EN at the EN vs. EqN graph of Figure 14a, generated at 17 EqN and 0.95 TP at the TP vs. EqN graph of Figure 14b, procured at 450 EN and 0.95 TP at the TP vs. EN graph of Figure 14c. On the other hand, Figure 15 stands for MAE training results of 2nd employed ANN method, in which the outcomes are revealed regarding 4th choice including the process of high resolution gridded having the color scale in a narrow range of values. In this figure, 460 different models in total have been handled and their analysis outputs are demonstrated in terms of MAE, shown in Figures 15a, 15b, and 15c. Within the scope of the results obtained by following the same techniques, in the 2nd applied method of ANN, else in the training phase of the algorithm and at 20 EqN , 500 EN and 0.95 TP ANN regulation values; the smallest and best error result corresponding to the value of 36.3140 m^3/s MAE was obtained and the results are reported in Figure 15 according to the 2-fold combinations of 3 different setting parameters enclosing of EN vs. EqN , TP vs. EqN , and TP vs. EN .

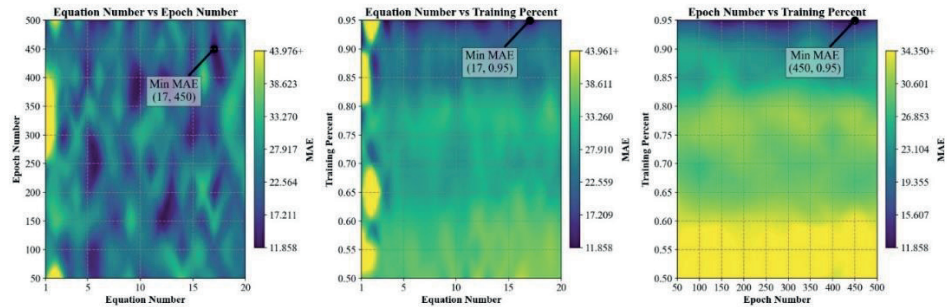


Figure 14. MAE results for a) EN vs. EqN , b) TP vs. EqN , c) TP vs. EN at the testing stage of 2nd applied approach of ANN

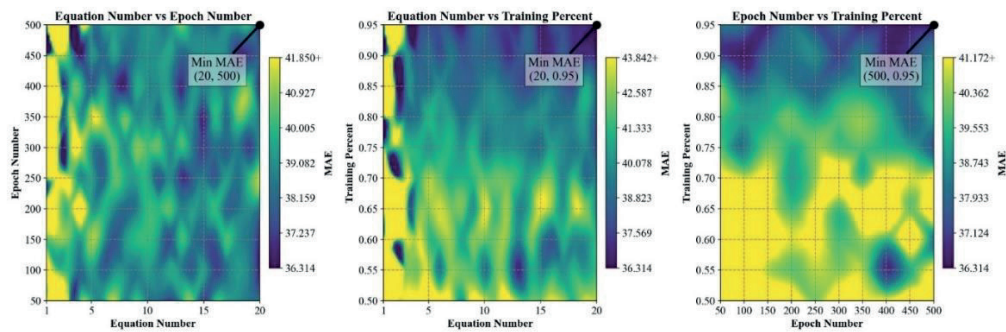


Figure 15. MAE results for a) EN vs. EqN , b) TP vs. EqN , c) TP vs. EN at the training stage of 2nd applied approach of ANN

The same ANN regulating parameters considering the 2nd exercised approach have actualized the lowest and therefore the best value of RMSE, as in the case of MAE output. This situation has eventuated both in testing and training fragments of ANN. Namely, considering ANN testing stage, the same tuning parameters have simultaneously returned the smallest and thus best MAE and RMSE results; whereas, taking ANN training portion into account, the same regulation parameters have simultaneously brought about the smallest and accordingly the best MAE as well as RMSE outcomes. Videlicet, when the testing section of ANN was taken into cognizance of, at the values of adjustment parameters corresponding to 17 *EqN*, 450 *EN*, and 0.95 *TP*, as in the case of MAE, the best statistical accuracy value of RMSE was determined and reported to be the smallest among 2,000 different models, at the value of 3.4435 m³/s. Similarly, with regards to ANN training part, when the ANN parameters were set to 20 *EqN*, 500 *EN*, and 0.95 *TP*, as in the case of MAE, the superior statistical error value of RMSE was detected and reported to be the minimum among 2,000 separate models, at the value of 6.0261 m³/s. The RMSE output of testing and training stages for this 2nd applied approach of ANN are depicted in Figures 16 and 17, respectively. In both Figures of 16 and 17, 460 different simulation models among the total of 2,000 are indicated for each. Again, 4th choice having the process of high resolution gridded with the color scale presented in a narrow range of values was adopted for both figures. In Figures 16a and 17a, the RMSE color distribution of *EN* according to *EqN* is demonstrated for testing and training stages, respectively. Besides, in Figures 16b and 17b, the RMSE color scatter of *TP* with respect to the *EqN* is shown for testing and training portions, respectively. Finally, in Figures 16c and 17c, the RMSE color dispersion of *TP* against *EN* is displayed for testing and training fragments, respectively. Namely, considering the selection of 2 parameters from the total of 3 ones including *EqN*, *EN*, and *TP* for Figure 16; Figure 16a shows *EN* vs. *EqN* at the fixed value of 0.95 *TP*, Figure 16b demonstrates *TP* vs. *EqN* at the stable value of 450 *EN*, and Figure 16c indicates *TP* vs. *EN* at the constant *EqN* value corresponding to 17. With regards to the choice of 2 parameters from the cumulative of 3 consisting of *EqN*, *EN*, and *TP* for Figure 17; Figure 17a presents *EN* vs. *EqN* at the same value of 0.95 *TP*, Figure 17b exhibits *TP* vs. *EqN* at the identical value of 500 *EN*, and Figure 17c points *TP* vs. *EN* at the equal *EqN* value set to 20. The exact locations of the top RMSE statistical value of 3.4435 m³/s at testing stage, computed at 17 *EqN* and 450 *EN* and shown in *EN* vs. *EqN* graph of Figure 16a, procured at 17 *EqN* and 0.95 *TP* and exposed in *TP* vs. *EqN* graph of Figure 16b, propagated at 450 *EN* and 0.95 *TP* and evidenced in *TP* vs. *EN* graph of Figure 16c, are remarked utilizing black color filled circles. Similarly, the exact locations of the topnotch RMSE statistical value of 6.0261 m³/s at training phase, simulated at

20 EqN and 500 EN and signified in EN vs. EqN graph of Figure 17a, generated at 20 EqN and 0.95 TP and proved in TP vs. EqN graph of Figure 17b, procreated at 500 EN and 0.95 TP and denoted in TP vs. EN graph of Figure 17c, are stated using circles filled with black color. On the other hand, in all sub-figures of both Figures 16 and 17, namely, the lowest and the best magnitudes of RMSE for testing and training stages are represented by the dark blue color.

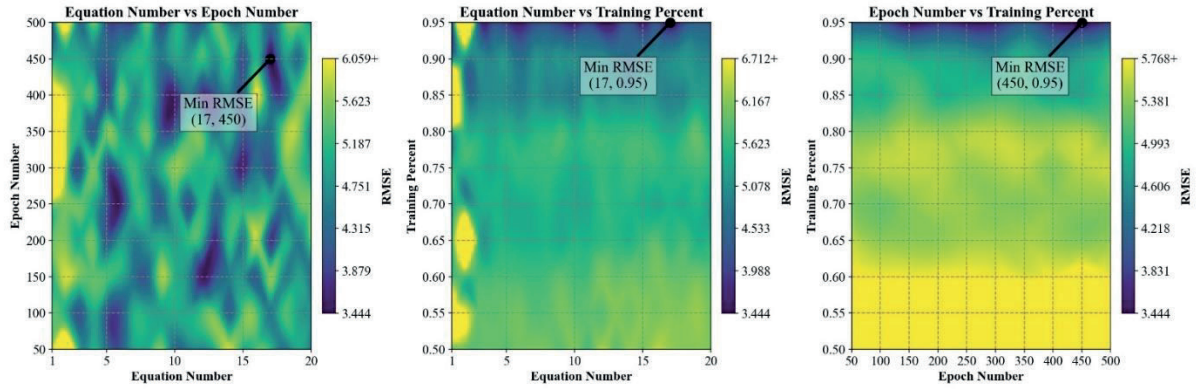


Figure 16. RMSE results for a) EN vs. EqN , b) TP vs. EqN , c) TP vs. EN at the testing stage of 2nd applied approach of ANN

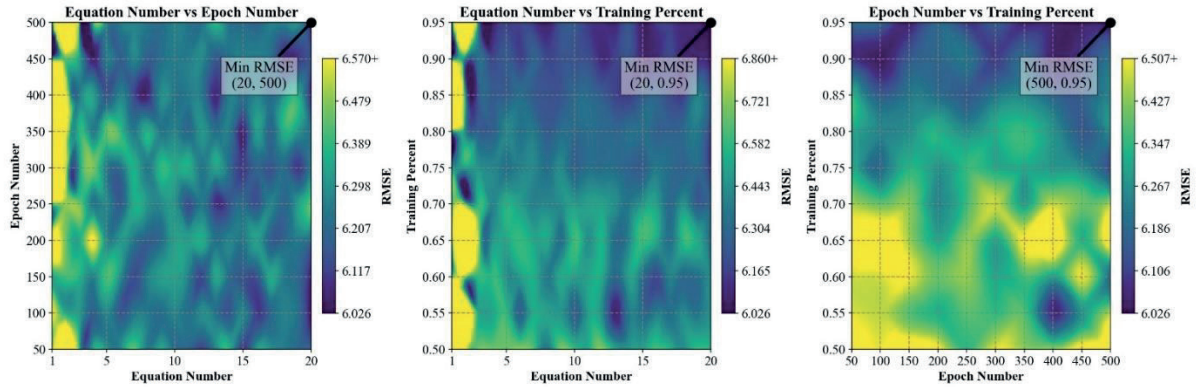


Figure 17. RMSE results for a) EN vs. EqN , b) TP vs. EqN , c) TP vs. EN at the training stage of 2nd applied approach of ANN

In the 2nd applied approach of ANN, while the correlation scatter of testing data set is indicated in Figure 18, considering the training data cluster, it is presented in Figure 19. As similar to former analyses, a total of 460 models have been taken into consideration and shown both in Figures 18 and 19 in terms of the correlation outputs, among the total of 2,000 implemented models. On the other hand, these figures were created with the 4th option, which was used before in demonstration of the results. The subfigures of both Figures 18 and 19 were created by considering 2 combinations among the ANN's 3 tuning parameters. The EN dispersion shown according to EqN is demonstrated in Figure 18a, at the fixed value of the training percentage (TP) corresponding to 0.55. Besides, the TP distribution indicated with respect to the EqN is

exhibited in Figure 18b, at the constant value of 400 epoch number (EN). Furthermore, the TP variation given based on EN is displayed in Figure 18c, at the stationary value of 6 equation number (EqN). In the EN graph against EqN shown in Figure 18a, by setting the equation number (EqN) to 6 and keeping the number of epochs (EN) constant at 400, in the TP graph with respect to EqN signified in Figure 18b, by adjusting the equation number (EqN) to 6 and keeping the training percentage (TP) constant at 0.55, in the TP graph based on EN shown in Figure 18c by regulating the number of epochs (EN) to 400 and keeping the training percentage (TP) constant at 0.55, the highest and thus the best correlation (R) testing output was computed and this value corresponded to 0.94609 R . Furthermore, in the EN parameter expressed against EqN evidenced in Figure 19a, by the regulation of the equation number (EqN) to 13 and keeping the epoch number (EN) static at 400, in the TP parameter stated depending on EqN signaled in Figure 19b, by arranging the equation number (EqN) to 13 and keeping the training percentage (TP) steady at 0.55, in the TP parameter remarked on EN exposed in Figure 19c, by calibrating the number of epochs (EN) to 400 and keeping the training percentage (TP) unaltered at 0.55, the highest and thus the superior correlation (R) training output was specified and this value of R was found to be equal to 0.97318 R . In both Figures 18 and 19, the exact locations of the best correlation outputs obtained as 0.94609 R and 0.97318 R in the test and training stages, respectively, are shown using black filled circles in these figures. On the other hand, the yellow pattern was utilized as the best ANN output results of those locations, obtained from ANN computations.

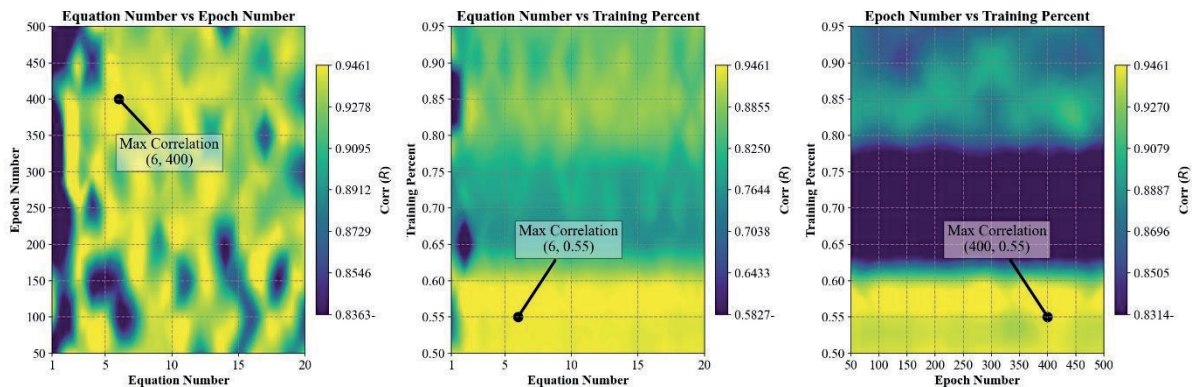


Figure 18. R results for a) EN vs. EqN , b) TP vs. EqN , c) TP vs. EN at the testing stage of 2nd applied approach of ANN

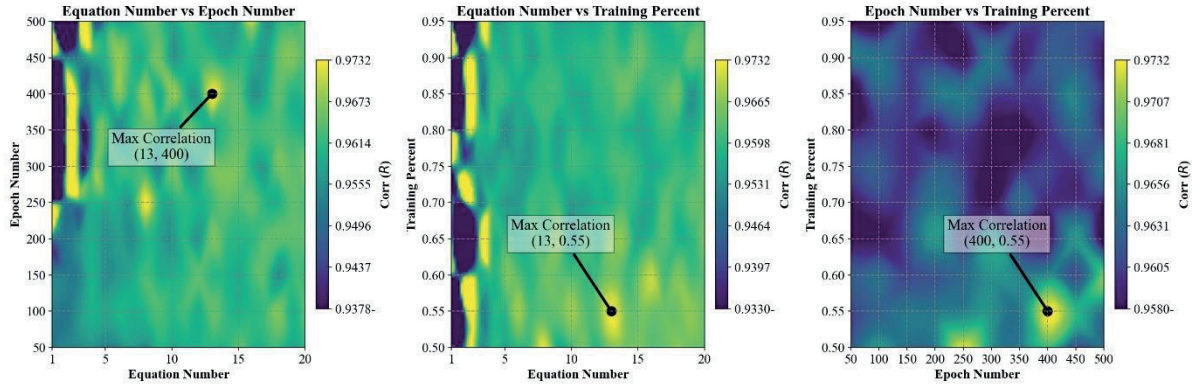


Figure 19. R results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the training stage of 2nd applied approach of ANN

On the other hand, Figure 20 takes into account the change of the TP parameter keeping the range of $0.50 \leq TP \leq 0.95$ in view, implementing an increment of this parameter at $\Delta TP = 5$, that have produced the smallest as well as best outcomes for statistical accuracy parameters including MAE and RMSE, and the highest therefore the superior findings for the correlation coefficient (R), based on the testing fragment of the 2nd exerted approach of the ANN. Accordingly, it is reported that these values considering three statistical error parameters refer to the best upshots among the total 2,000 reckons. In Figure 20, the change of the training percentage (TP) values is exhibited on the x -axis, taking this cited range into account. Moreover, three y -axes have been utilized in this Figure 20. Those axes indicate the statistical accuracy parameters consisting of RMSE, MAE, and the correlation coefficient of R shown in the figure, from left to right, respectively. Among these three axes, the MAE error parameter is indicated by the red color, the RMSE accuracy parameter is demonstrated by the blue one, and the correlation outcomes of the best models are characterized with the utilization of the green pattern. Additionally, the magnitudes of the MAE, RMSE, and the R statistical accuracy parameters for the best computation outputs have been stated in these figures with the usage of the identical colored pointers. For example, the circles that are filled with red color exemplify the MAE errors, the squares that are filled with blue color illustrate the RMSE errors, and the triangles that are filled with green color limn the results of the R correlation. A cumulative of best 17 models were commentated in this Figure 20. On the other hand, the magnitudes of MAE, RMSE, and R corollaries of these best 17 models are brought to light in Table 3. On the side, the tuning values of the equation number (EqN) and the epoch number (EN) according to the alteration of the values of the training percentages (TP) that have created the best 17 models, namely that have disclosed the best statistical error outputs are provided as well in Table 3. In this regards, when Figure 20 and Table 3 are simultaneously handled, during the adjustment of

the training percentage value set to $TP=0.50$, the superior statistical accuracy error values covering MAE and RMSE have been acquired at this value of TP come up to the magnitudes of $33.051 \text{ m}^3/\text{s}$ and $5.749 \text{ m}^3/\text{s}$, respectively. This identical situation is both seen in Figure 20 as well as in Table 3. Namely, a model whose EqN and EN parameters are set to the magnitudes corresponding respectively to 11 and 400 at the TP value of 0.50 has eventuated with these topnotch statistical accuracy magnitudes. However, here the statistical accuracy value for the correlation coefficient considering this model is not expressed, i.e., the R value regarding $TP=0.50$, $EqN=11$, and $EN=400$ adjustments is not included in Figure 20 and Table 3. Because, another model is found at the value of TP corresponding to the magnitude of 0.50 that has turned with the best value of the correlation coefficient at this TP value. Namely, the model that has given the best R at 0.50 TP was reported as the model having the adjustment parameters set to 17 EqN and 200 EN , generating the correlation coefficient of 0.94531 R , that is reported to be better than the R value obtained at $TP=0.50$, $EqN=11$, and $EN=400$. Besides, this situation generates alike the similar cases during adjusting the training percentage (TP) values corresponding to $TP=0.55$, $TP=0.60$, $TP=0.65$, $TP=0.70$, $TP=0.75$, $TP=0.80$, $TP=0.85$, $TP=0.90$, and $TP=0.95$ producing an additional model for every of these training percentage values, considering the range of $0.55 \leq TP \leq 0.95$. Namely, when the TP is considered in the range of $0.50 \leq TP \leq 0.95$, one more model was required that generated the ideal R value, outside of the model that has eventuated the superior MAE as well as RMSE values at every training percentage value analyzed in this range. Consequently, two models for every TP value in the range of $0.50 \leq TP \leq 0.95$ have been considered, for displaying the best MAE, RMSE, as well as the R statistical accuracy values, making a cumulative of 20 models in this TP range for exhibiting of the error outcomes both in Figure 20 plus Table 3. Under these conditions, referring to the TP range of $0.50 \leq TP \leq 0.95$, a total of 20 models have been analyzed, whose MAE, RMSE, and R statistical accuracy outputs have been presented in Figure 20 and Table 3. Furthermore, the value of $TP=0.70$ can be also considered as an another example to clarify the formation of the need of 2 models at this training percentage value. With regards to this $TP=0.70$ value, as also revealed in Figure 20 and Table 3, 1 model that was regulated to 20 EqN and 100 EN has generated the superior statistical accuracy values of MAE and RMSE at the values of $27.650 \text{ m}^3/\text{s}$ MAE, $5.258 \text{ m}^3/\text{s}$ RMSE, respectively, whereas, 1 another model that was set to 10 EqN and 350 EN has brought about the output result of best correlation coefficient, that is reported to correspond to the value of 0.81036 R . Accordingly, 2 tiptop models are evaluated and reported to be the best, at $TP=0.70$, as well as this situation has also taken place in this way in the other TP values found in the range of $0.50 \leq TP \leq 0.95$, apart from $TP=0.70$. In the

ANN computations implemented to a large space of analysis, in general the model that has produced the lowest and thus best MAE magnitudes have also generated the smallest and thus the superior RMSE magnitudes. On the other hand, although the lowest and best values of statistical accuracy parameters including MAE and RMSE were generally provided by the same model; keeping some exceptions in view, the highest and therefore the best value of the correlation relation (R) was not always provided by the model giving the lowest and best MAE and RMSE. In this frame, regarding the 2nd implemented approach of ANN, the exceptions were not eventuated. As a result, always another model was found for a certain value of TP to give the highest and best value of the correlation coefficient (R), apart from the model that has generated the lowest and best values of the MAE and RMSE at the same value of training percentage (TP). Consequently, considering the analysis that was conducted for training percentage (TP) in the range of $0.50 \leq TP \leq 0.95$, a total of 10 TP values were analyzed, as well as this resulted the analysis of 2 models for each TP , causing a cumulative of 20 models taken into account in Figure 20 and Table 3. Since the smallest and best MAE and RMSE statistical accuracy values are always belong to the same model in Figure 20 and Table 3, although a cumulative of 30 statistical accuracy errors covering MAE, RMSE, and R are exposed in this figure and table, the total number of the models considered for ANN analyses in this figure and table correspond to 20. For instance, as seen in Figure 20, at $TP=0.65$, while one model produces the best values of MAE and RMSE corresponding respectively to 28.838 m³/s and 5.370 m³/s at this value of TP , shown respectively by red color filled circle and blue color filled square, whereas, another model generates the best value of R corresponding to 0.79409 at this value of TP , portrayed by green color filled triangle.

In Table 3, among the cumulative amount of the expressed errors for MAE, RMSE, as well as R , corresponding to the cumulative error amount of 30 for a total of superior 20 different models evaluated depending on the training percentage (TP) values for the 2nd implemented approach of ANN, and reported for their testing fragments; the MAE and RMSE results at the values of 11.858 m³/s MAE and 3.444 m³/s RMSE that were achieved to be the minimum and topnotch statistical error outputs of one model among the cumulative of 2,000 models taken into account in 2nd exerted approach of ANN, and that were computed at 0.95 TP , 17 EqN , and 450 EN , and were shown before at these regulation parameters in Figures 14 and 16. In this regards, at these setting parameters, one model displayed for two errors of MAE and RMSE were demonstrated to be the best among the cumulative of 2,000 models, and thus have been picturized in Figures 14 and 16, else in Figure 20 and Table 3. Alike, in the testing fragment of 2nd performed

approach of ANN, the superior model regarding the correlation relation (R) result was accomplished at the tuning parameters of 0.55 TP , 6 EqN , and 400 EN , and its magnitude was reported to be 0.94609. This model that has come into the open as the biggest output value of the correlation coefficient and was reported to be the best model among the cumulative of 2,000 models due to the correlation coefficient and thus that was formerly exhibited in Figure 18, as well as this model is now shown as the best in the following Figure 20 and Table 3, among the total of 20 best models representing a total of 30 error values consisting of MAE, RMSE, and R given for discrete training percentage (TP) values. With regards to these explanations, in order to distinguish the unique model which caused the best in terms of MAE and RMSE at a variety of different TP , as well as in order to separate the unique model which induced the best in terms of R at a variety of different TP ; three error outputs enclosing MAE, RMSE, and R belonging to two different models are exposed in Table 3, utilizing the bold pattern.

Taking into account the training percentage (TP) magnitude in the range of $0.50 \leq TP \leq 0.95$, the best mean absolute error (MAE) and the best root mean square error (RMSE) values were acquired all the time in the same regulation parameters, as formerly expressed. However, in general, in the value range of TP of $0.50 \leq TP \leq 0.75$, at a certain value of TP , in order to obtain the highest and best correlation coefficient (R) value; one regulation parameter among EqN and EN has to be increased and the remaining has to be decreased, compared with respect to the EqN and EN values that generated the smallest and best values of MAE and RMSE, at the same value of TP . For example, considering $TP=0.70$, the smallest and best values of MAE and RMSE were obtained at 20 EqN and 100 EN . At these values of TP , EqN , and EN , the correlation coefficient value was reported not to be the highest. But, the diminish of the 20 EqN to 10 and the augmentation of the 100 EN to 350 EN at this value of 0.70 TP has caused to obtain the highest value of the correlation coefficient (R). Considering the values of $TP=0.80$ and $TP=0.85$, at a certain value of TP , to acquire the greatest and superior correlation coefficient (R) value; two regulation parameters of EqN and EN have to be augmented, compared according to the EqN and EN values that produced the minimum and best values of MAE and RMSE, at the same value of TP . For instance, with regards to the $TP=0.85$, the minimum and thus best values of MAE and RMSE were computed as soon as the adjustment ANN parameters were set to 10 EqN and 400 EN . However, at these magnitudes of TP , EqN , as well as EN , the R value was reported not to be the maximum. Therefore, the augmentation of the 10 EqN to 12 and the rise of the 400 EN to 450 EN at this value of 0.85 TP has resulted to generate the biggest value of the correlation coefficient (R). Finally, at the TP values of 0.90 and 0.95, to compute the

correlation coefficient (R) of the highest; the EqN values are kept the identical with the EqN values of the models producing the smallest and best values of MAE and RMSE at the given TP , whereas, the EN values are decreased according to the EN values of the models generating the minimum and superior values of MAE and RMSE at the given TP . When the case of 0.90 TP is focused, the 14 EqN and 400 EN have resulted the smallest and best MAE and RMSE, at this value of the training percentage. However, at those ANN adjustment parameters, the correlation coefficient (R) was not detected to be the highest. Accordingly, the EqN was kept the same as 14 as in the case of the former value and the former EN value of 400 is decreased to 300 at this 0.90 TP value, which resulted the maximum and thus the superior value of the correlation coefficient (R).

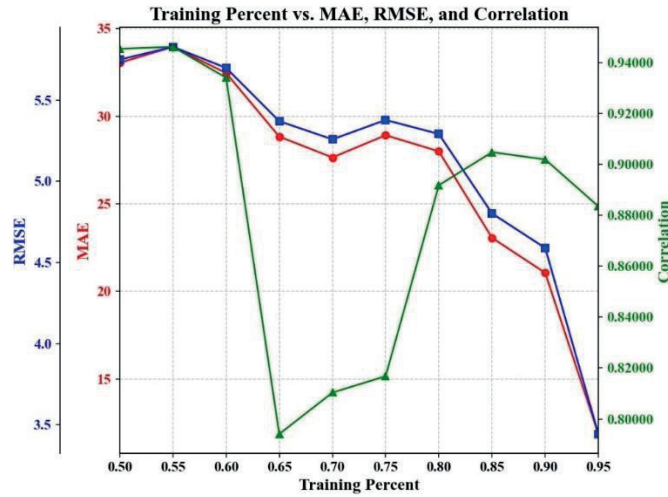


Figure 20. Error outputs of the best 20 models for different TP values at 2nd implemented method

Table 3. Error outputs of the best 20 models for different TP values and their EqN and EN values are reported

Training Percent	Equation Number	Epoch Number	Metric	Training Percent	Equation Number	Epoch Number	Metric
0.5	11	400	MAE: 33.051	0.75	4	400	MAE: 28.918
	11	400	RMSE: 5.749		4	400	RMSE: 5.378
	17	200	Corr: 0.94531		9	400	Corr: 0.81681
0.55	7	200	MAE: 33.966	0.8	4	50	MAE: 28.001
	7	200	RMSE: 5.828		4	50	RMSE: 5.292
	6	400	Corr: 0.94609		10	450	Corr: 0.89176
0.6	7	350	MAE: 32.472	0.85	10	400	MAE: 23.059
	7	350	RMSE: 5.698		10	400	RMSE: 4.802
	17	300	Corr: 0.93399		12	450	Corr: 0.90473
0.65	9	450	MAE: 28.838	0.9	14	400	MAE: 21.061
	9	450	RMSE: 5.370		14	400	RMSE: 4.589
	9	50	Corr: 0.79409		14	300	Corr: 0.90188
0.7	20	100	MAE: 27.650	0.95	17	450	MAE: 11.858
	20	100	RMSE: 5.258		17	450	RMSE: 3.444
	10	350	Corr: 0.81036		17	400	Corr: 0.88345

3.4. 3rd Implemented ANN Correlation Method in the Estimation of the Maritsa River Water Flow Rate

In predictions of the VWFR of the target WMS of İpsala, the data of 9 different WMS was taken into account excluding Kirişhane and including İnanlı, Lüleburgaz, Yenicegörece, Elhova, Suakacağı, Değirmenyeni, Harmanlı, Svilengrad, and Ivoylovgrad. Accordingly, the data of 10 different WMS including İpsala, in ANN VWFR estimations have been kept in view. Although four different tributaries of Maritsa including Arda, upstream Maritsa, Tunca, and Ergene are mixed at the downstream to form a single river of Maritsa, before the rivers meet, they exist as different arms carrying water to the main stream Maritsa. For this reason, in 3rd implemented approach of ANN; before the different tributaries are joined together at upstream, water measurement stations found at these different arms are considered in VWFR predictions of Maritsa river on İpsala WMS. On the other hand, as formerly expressed, the data of Kirişhane WMS was excluded from the forecasts in this 3rd approach. The reason for the exclusion was that the geographical location of the Kirişhane station, the section of the Maritsa river that it coincides with in its flow route, that is, the point where this station is located in the Maritsa river, is fed by the Arda, upstream Maritsa and Tunca branches; therefore, a hypothesis was constructed on the conclusion that the measurements belonging to the Kirişhane station would not have an effect on the estimation. Therefore, the data belonging to the water measurements at the Kirişhane point were not taken into account in this 3rd exerted method. In addition, in order to describe the average flow rates of the Arda, upstream Maritsa, Tunca, and Ergene branches forming the downstream Maritsa; the average values of the water flow rates measured at the water measurement stations of the relevant river located on each of these river branches, before the merging of these rivers, were taken into consideration. Accordingly, the value of the average water flow rate of Arda tributary was determined considering the water flow rate of the Arda river measured at Ivoylovgrad WMS, since only one WMS is found on this river. In other words, the mean water flow rate of Arda tributary was assumed to be equal to the water flow rate of the river on Ivoylovgrad WMS. On the other hand, to speak about the mean VWFR of upstream Maritsa tributary, the average value of VWFR of upstream Maritsa was determined according to the water flow rates of upstream Maritsa measured at measurement stations including Harmanlı and Svilengrad. Similarly, to refer to the mean VWFR of Tunca tributary, the average value of VWFR of Tunca was detected based on the water flow rates of Tunca measured at measurement stations consisting of Elhova, Suakacağı, and Değirmenyeni. Finally, in order to resort to the mean VWFR of Ergene tributary, the mean value of VWFR of Ergene

was established with regards to the water flow rates of Ergene measured at measurement stations comprising of İnanlı, Lüleburgaz, and Yenicegörece. Namely, in this 3rd implemented approach, with the described above method, the average water flow rate values of the tributaries including Arda, upstream Maritsa, Tunca, and Ergene including a total of four different data clusters formed of instantaneous VWFR data readings were determined to become the input data clusters of ANN algorithm, in order to predict the VWFR of downstream Maritsa river at İpsala WMS. In this frame, this 3rd touch of ANN is defined in Figure 21. The WMS found on Arda river is demonstrated by yellow color, the ones located on the upstream Maritsa river are exhibited by blue color, the stations existing on Tunca river are displayed by orange color on the map, and the WMSs found on Ergene river are indicated by pink color. Accordingly, the same map color pattern found on each of those tributaries mention that the average flow rate of the relevant river should be calculated according to the average values of the instantaneous measurements obtained from all of those WMSs located on the relevant river.



Figure 21. Visual description of the 3rd implemented approach

As in the case of former two approaches of ANN, the same path and method were followed in generating the results and considering the adjustment parameters and their interpretation. Besides, the calibration parameters for this applied ANN method considering the 3rd approach are set to the same values of EqN , EN , and TP , namely, the same value ranges of those parameters were utilized in the ANN algorithm for VWFR predictions. In this context, Figure 22 portrays MAE visual outputs of 460 models among the total of 2,000 models, for their testing stages of the implemented 3rd approach of ANN. Figure 22a exhibits the functional color dispersion of EN parameter with an incremental change of $\Delta EN = 50$ having the range of $50 \leq EN \leq 500$ defined with respect to the EqN parameter with an incremental change of $\Delta EqN =$

1 having the range of $1 \leq EqN \leq 20$. In Figure 22a demonstrating the graphical representation of EN according to EqN , the best model that was acquired during the adjustments of equation number (EqN) to 15 as well as epoch number (EN) to 350. Besides, Figure 22b indicates the functional color distribution of TP parameter with a step change of $\Delta TP = 0.05$ having the range of $0.50 \leq TP \leq 0.95$ specified depending on the EqN parameter with a step change of $\Delta EqN = 1$ having the range of $1 \leq EqN \leq 20$. In Figure 22b showing the graphical view of TP on EqN , the superior model that was achieved during the tuning of equation number (EqN) to 15 as well as training percentage (TP) to 0.95. Finally, Figure 22c displays the functional color variation of TP parameter with a pace alteration of $\Delta TP = 0.05$ having the range of $0.50 \leq TP \leq 0.95$ stated as regards to EN parameter with a pace alteration corresponding to $\Delta EN = 50$ having the range of $50 \leq EN \leq 500$. In Figure 22c denoting the graphical image of TP on EN , the topnotch model that was attained during setting the epoch number (EN) to 350 else training percentage (TP) to 0.95. Actually, three figures respectively shown in Figures 22a, 22b, and 22c corresponding to variations of EN vs. EqN , TP vs. EqN , and TP vs. EN demonstrate the same model in terms of the best model among 2,000 tried distinct models, and 460 shown models in these three figures. I.e., the best model pointing the lowest value of $9.8476 \text{ m}^3/\text{s}$ MAE are evidenced to be the best model among 2,000 trials, however their exact coordinates on these figures are indicated with different approaches. In Figure 22a, its place is signified by the coordinates of (15, 350) in EN vs. EqN curve, where first coordinate of 15 standing for EqN and second coordinate of 350 corresponding to EN . In Figure 22b, its place is disclosed by the coordinates of (15, 0.95) in TP vs. EqN curve, where first coordinate of 15 standing for EqN and second coordinate of 0.95 corresponding to TP . In Figure 22c, its place is exhibited by the coordinates of (350, 0.95) in TP vs. EN curve, where first coordinate of 350 standing for EN and second coordinate of 0.95 corresponding to TP .

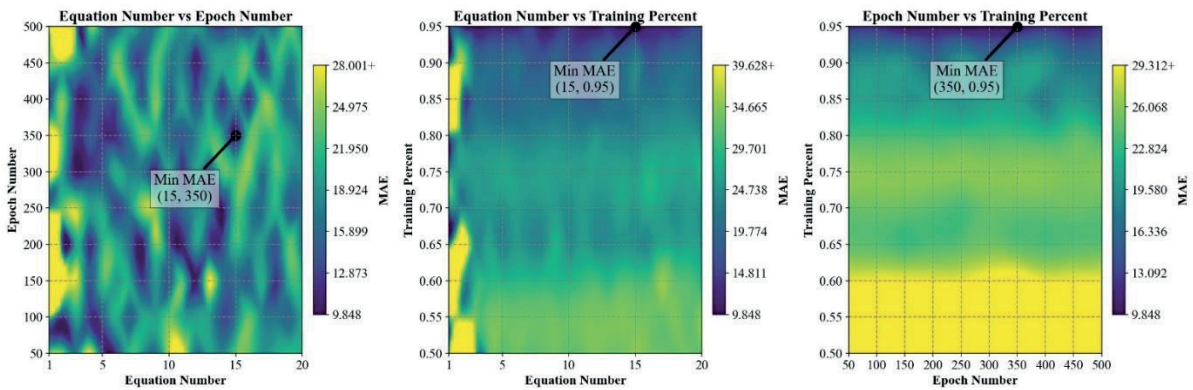


Figure 22. MAE results for **a)** EN vs. EqN , **b)** TP vs. EqN , **c)** TP vs. EN at the testing stage of 3rd applied approach of ANN

Similar to the visual output of MAE results at their testing stages, stated by 3 adjustment parameters considered as combination of 2; the visual MAE outputs again expressed by 3 adjustment parameters taken as combination of 2 are presented in sub-figures of Figure 23, and shown in this figure now for their training stages. As seen from Figure 23, the smallest and best value of 38.9589 m^3/s MAE at the training stage, indicated by dark blue color, was obtained at 11 EqN , 250 EN , and 0.95 TP values.

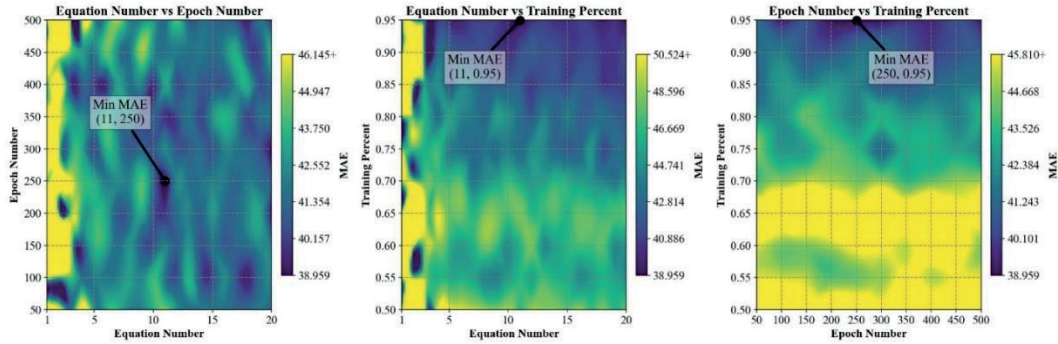


Figure 23. MAE results for a) EN vs. EqN , b) TP vs. EqN , c) TP vs. EN at the training stage of 3rd applied approach of ANN

The RMSE outputs of 460 models among 2,000, for testing and training stages are picturized in Figures 24 and 25, respectively. In Figure 24, at 15 EqN , 350 EN , and 0.95 TP adjustments, the smallest value of RMSE corresponding to the best was simulated. At these regulation parameters, the RMSE for the testing stage was detected to be 3.1381 m^3/s . Besides, in Figure 25, at 11 EqN , 250 EN , and 0.95 TP adjustments, the smallest value of RMSE corresponding to the superior was computed. At these tuning parameters, the RMSE for the training step was established to be 6.2417 m^3/s . In both Figures of 24 and 25, the dark blue pattern was wielded to point the pattern of the lowest and best values of this statistical error parameter, and the locations of this pattern are demonstrated in sub-figures of both figures, by utilizing circles filled with black color.

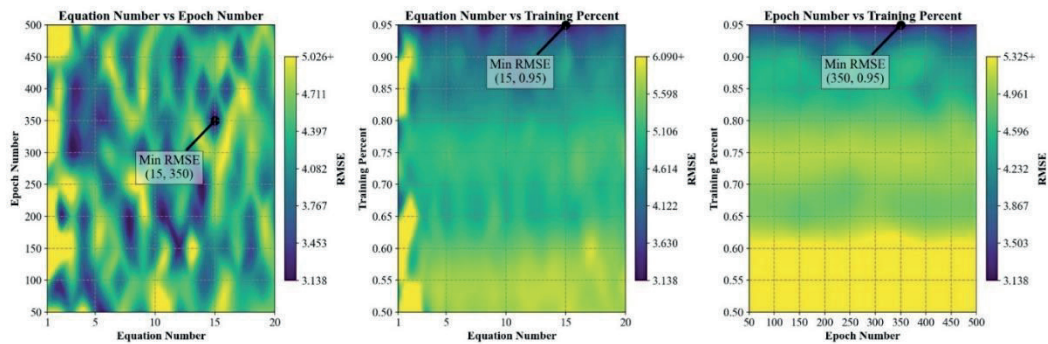


Figure 24. RMSE results for a) EN vs. EqN , b) TP vs. EqN , c) TP vs. EN at the testing stage of 3rd applied approach of ANN

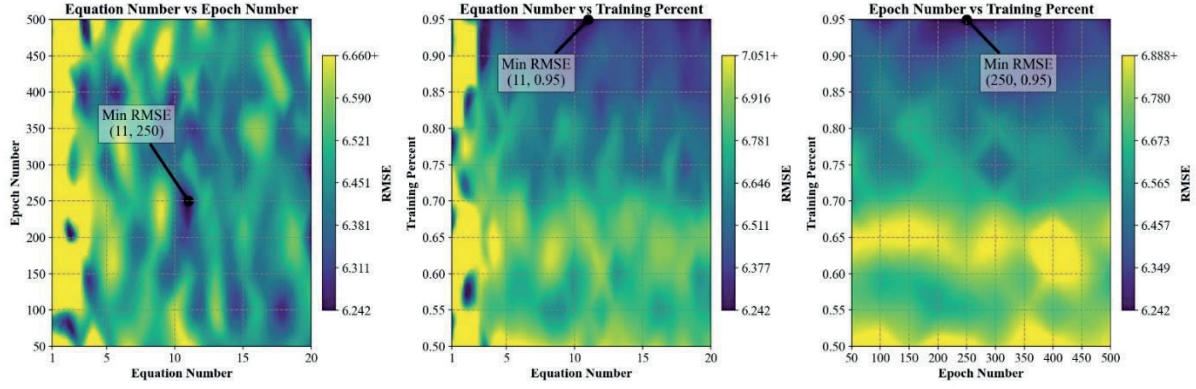


Figure 25. RMSE results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the training stage of 3rd applied approach of ANN

The results of the correlation coefficients (R) of 460 models selected from the total of 2,000, for testing and training phases are respectively exposed in Figures 26 and 27. When 3 adjustment parameters including EqN , EN , and TP were picked to correspond to the values of 17, 450, and 0.5, respectively, as pointed in Figure 26, the highest and best R value was reckoned. When 3 regulation parameters were bound to these values, the correlation coefficient concerning the testing fragment was identified to be equal to 0.92038 R . Moreover, as soon as the same ANN regulation parameters were set to the values of 9, 200, and 0.55 for EqN , EN , and TP , respectively, as betokened in Figure 27, the top and superior value of R was determined. At these cited parameters of tuning, the testing fragment R value was appointed to be 0.95786 R . In both Figures of 26 and 27, the yellow pattern was wielded to indicate the pattern of the highest and superior values of this statistical correlation parameter, and the locations of this pattern are portrayed in sub-figures belonging to both figures, by the usage of the circles filled with black color.

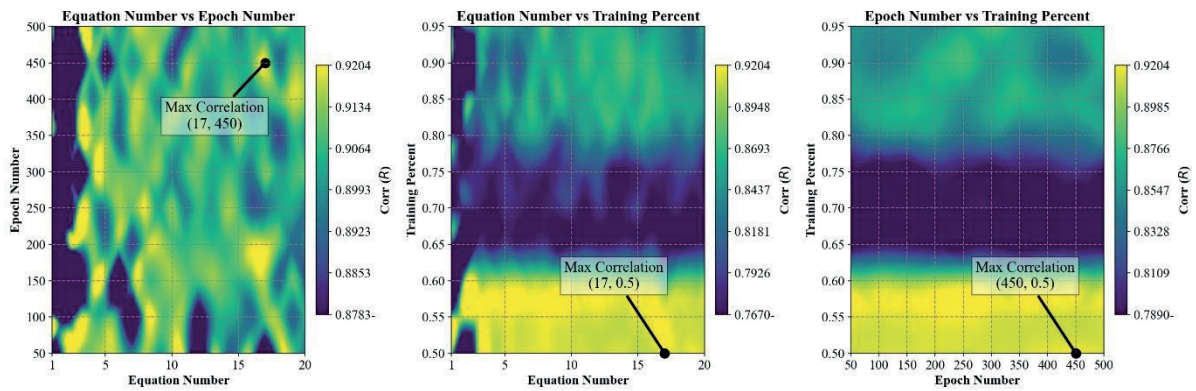


Figure 26. R results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the testing stage of 3rd applied approach of ANN

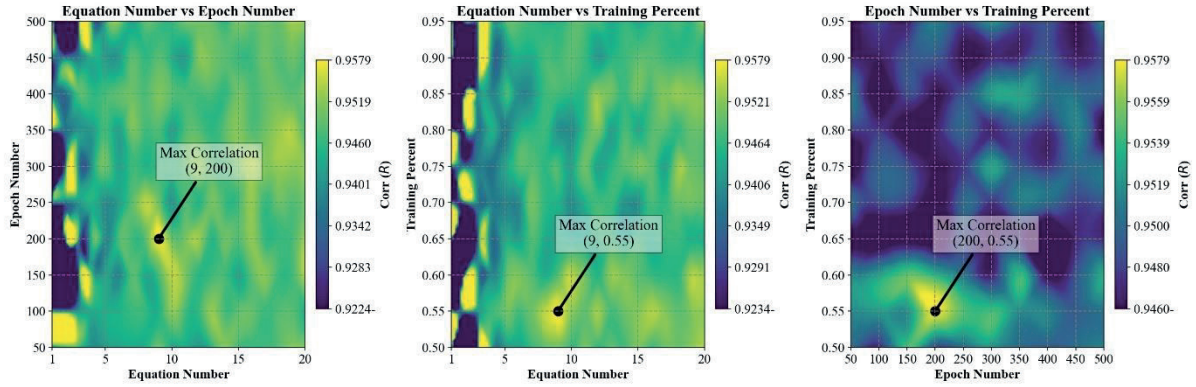


Figure 27. R results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the training stage of 3rd applied approach of ANN

On the other hand, the statistical accuracy error values consisting of MAE, RMSE, and R , considering 3rd implemented approach of ANN are signed in Figure 28. A total of 20 models are analyzed in this figure, similar to 2nd applied approach of ANN. In this figure, these error values are shown according to the alteration of the training percentage (TP), considered in the range of x-axis of the figure given with the range of $0.50 \leq TP \leq 0.95$. Besides, those are also reported in a similar manner provided in Table 4. In Table 4, the best accuracy results of ANN computations are exhibited using the bold pattern, and which were previously indicated to be the superior models in this 3rd ANN approach, given in Figures 22, 24, and 26. In this regards, the MAE and RMSE statistical accuracy results, as shown in Figure 28 and Table 4 were obtained to be the smallest in the case of setting 15 EqN , 350 EN , and 0.95 TP . The best MAE and RMSE values obtained at these parameters, among the total of 2,000 models of 3rd approach, have given the MAE at 9.848 m^3/s , whereas RMSE at 3.138 m^3/s . Besides, the correlation coefficient (R) result that is produced at the regulation parameters of 15 EqN , 350 EN , and 0.95 TP emerged not to be the highest thus best R , considering whole 2,000 computations or taking this value of training percentage (TP) of 0.95 into account. Namely, the computed 0.83662 R value was reported not to be the highest among the others. Therefore, the R value of 0.83662 is not included in Table 4 at 0.95 TP , while at this value of 0.95 TP , the highest R was detected and reported to be 0.88484, however still not the highest and best value of 2,000 models of 3rd approach of ANN. This value of correlation coefficient was reported at 8 EqN and 300 EN , considering the TP value of 0.95. However, one other model is found among the others which have turned with the highest R magnitude corresponding to the value of 0.92038 at the EqN , EN , and TP parameter magnitudes corresponding respectively to 17, 450, and 0.50. At these scheme parameters, the MAE and RMSE came forward not to be the smallest and thus best values, i.e., the magnitudes of 33.1071 m^3/s and 5.7539 m^3/s were conducted not

to be the lowest and best values among 2,000 models of 3rd approach of ANN or among taking this value of training percentage (TP) of 0.50 of 3rd approach into account. For this reason, these values of MAE and RMSE at 17 EqN , 450 EN , and 0.50 TP are not included in Table 4. But, at the TP value of 0.50, modifying EqN and EN to 1 and 350, respectively generated the lowest and best values of MAE and RMSE at this 0.50 TP magnitude, corresponding to 31.708 m³/s and 5.631 m³/s, respectively. These values of MAE and RMSE corresponded to the lowest and best values of this TP of 0.50, however not the lowest and best value of 2,000 models of 3rd approach of ANN. The training percentage (TP) causes generally the decrease of the MAE and RMSE statistical accuracy parameters with respect to the increase of TP , as demonstrated in Figure 28. Nevertheless, the augmentation of TP in the range of $0.50 \leq TP \leq 0.95$ pans out a fluctuation of the correlation scatter (R) in this range. Namely, as demonstrated in Figure 28, a decrease of the general trend of R is eventuating considering the rise of the TP in the range of $0.50 \leq TP \leq 0.60$, whereas, a sudden drop of the R value is occurring when the training percentage is in the range of $0.60 \leq TP \leq 0.70$. On the other hand, exceeding the value of TP corresponding to $TP=0.70$ originates a sudden boost of the R parameter until the value of the training percentage is attained to the value of $TP=0.95$.

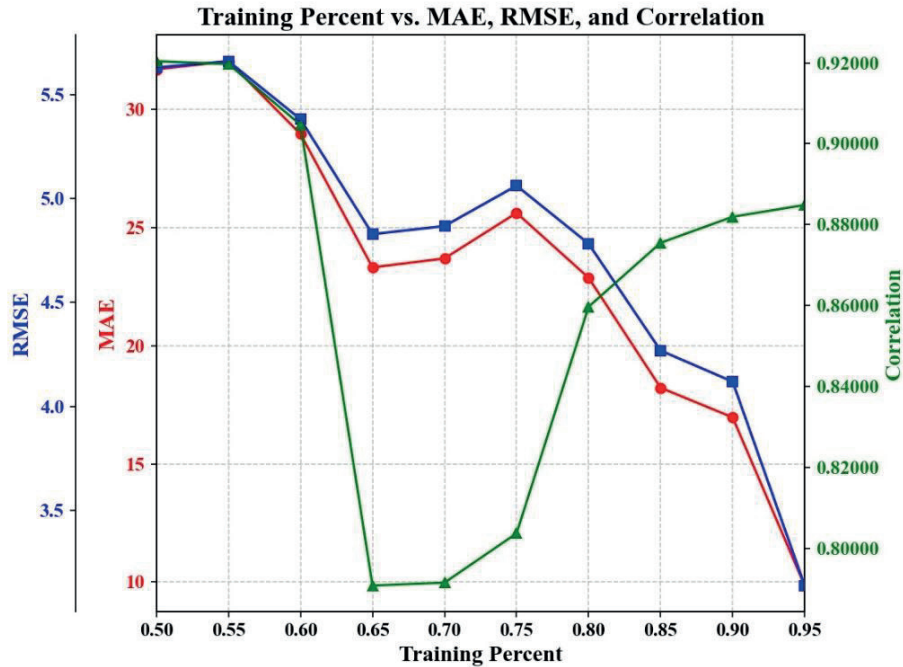


Figure 28. Error outputs of the best 20 models for different TP values at 3rd implemented method

Table 4. Error outputs of the best 20 models for different *TP* values and their *EqN* and *EN* values are reported

Training Percent	Equation Number	Epoch Number	Metric	Training Percent	Equation Number	Epoch Number	Metric
0.5	1	350	MAE: 31.708	0.75	3	450	MAE: 25.627
	1	350	RMSE: 5.631		3	450	RMSE: 5.062
	17	450	Corr: 0.92038		12	450	Corr: 0.80364
0.55	19	450	MAE: 32.050	0.8	7	400	MAE: 22.879
	19	450	RMSE: 5.661		7	400	RMSE: 4.783
	8	250	Corr: 0.91969		13	500	Corr: 0.85968
0.6	9	250	MAE: 28.968	0.85	12	400	MAE: 18.222
	9	250	RMSE: 5.382		12	400	RMSE: 4.269
	6	250	Corr: 0.90467		16	350	Corr: 0.87549
0.65	5	150	MAE: 23.319	0.9	11	200	MAE: 16.968
	5	150	RMSE: 4.829		11	200	RMSE: 4.119
	16	100	Corr: 0.79075		14	250	Corr: 0.88192
0.7	2	250	MAE: 23.700	0.95	15	350	MAE: 9.848
	2	250	RMSE: 4.868		15	350	RMSE: 3.138
	15	300	Corr: 0.79146		8	300	Corr: 0.88484

3.5. 4th Implemented ANN Correlation Method in the Estimation of the Maritsa River Water Flow Rate

With regards to the stored data considering the VWFR values of the rivers measured at 11 different WMSs, 4th approach was considered in a similar manner of the former 3rd approach of ANN. The only difference in the 4th approach of ANN has been to include the data of Kirişhane WMS, unlike the 3rd approach of ANN, since it was now adopted in this approach that this WMS might influence the predictions of the water flow rate of the downstream Maritsa measured at İpsala WMS. Due to the fact that the downstream Maritsa is fed by four different tributaries including Arda, upstream Maritsa, Tunca, and Ergene; the constructed WMSs on these tributaries were considered, in order to find the average values of each tributary, by adopting a progress that was performed by taking the average of the flow rate measurements at all water measurement stations on the relevant river. Here, the calculated value of the average volumetric flow rate obtained for each tributary was adopted to be the average water flow rate of the relevant river. In this frame, the average water flow rate of the first tributary of Arda was determined by directly considering the instantaneous measurements executed at Ivoylovgrad WMS, because only this station is constructed on Arda river. However, the average value of the VWFR for upstream Maritsa tributary was described by averaging the instantaneous measurements of the water flow rate of the Maritsa river measured at Harmanlı and Svilengrad WMSs. Similarly, the average water flow rate of Tunca tributary was defined by averaging the

instantaneous measurements of the water flow rate of Tunca river measured at Elhova, Suakacağı, and Değirmeniyeni WMSs. Finally, Ergene tributary's average VWFR was represented by taking the average VWFR instantaneous values of this river on WMSs including İnanlı, Lüleburgaz, and Yenicegörece. As formerly described, this same methodology was adopted in 3rd approach of ANN, however, in the 3rd approach, VWFR instantaneous values of midstream Maritsa tributary measured at Kirişhane WMS was not included in the estimations of the VWFR of downstream Maritsa at İpsala WMS. But, in this 4th approach, the historical data cluster including the VWFR of midstream Maritsa at Kirişhane WMS was included in the VWFR estimations of downstream Maritsa at İpsala WMS. In Figure 29 standing for the methodology of 4th approach, as well which demonstrates the study zone, the same coloring patterns were adopted for the WMSs, as in the case of former 3rd approach. In other words, the water measurement stations located on the same river branches are shown in this map of Figure 29, using the same color pattern, in order to indicate that their averages of water flow rate of those stations were taken to demonstrating the average VWFR of the relevant river. But additionally in this map, in order to also indicate the inclusion of Kirişhane WMS found in midstream of Maritsa on the guesses of VWFR of downstream Maritsa at İpsala WMS, Kirişhane WMS is indicated on this map, utilizing the black color.

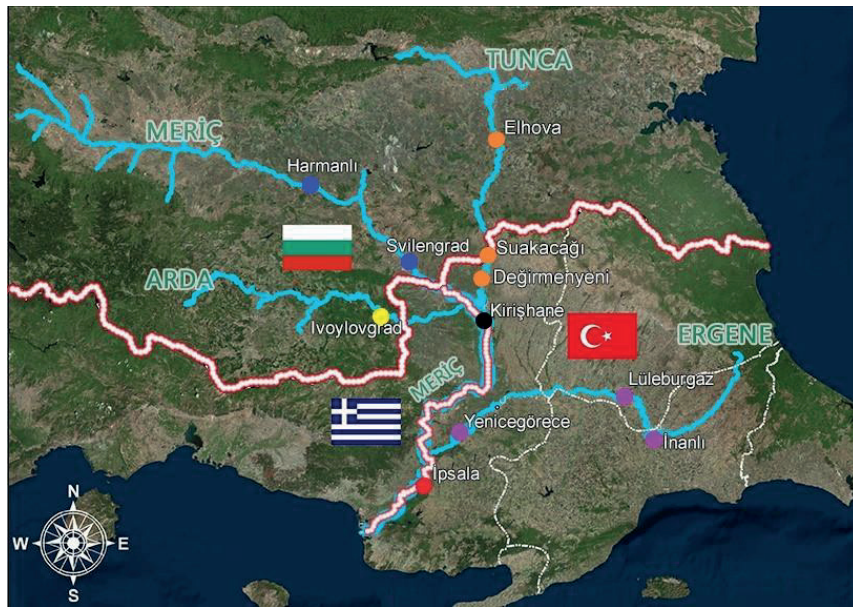


Figure 29. Visual description of the 4th implemented approach

Identical calibration parameters regarding 4th implemented ANN approach was considered, as in the case of the calibration parameters belonging to the 1st, 2nd, and 3rd approaches of ANN. Namely, the setting parameters and their value ranges exhibited in Table 2 are also adopted

similarly in this 4th approach of the ANN. On the other hand, Figures 30 and 31 depict the ANN mean absolute error (MAE) statistical accuracy computations depending on the testing and training stages, respectively. In the testing phase, the MAE statistical accuracy parameter was determined as 10.1934 m³/s, while in the training phase, the same parameter was reported as 31.5871 m³/s. With reference to the sub-figures of Figure 30, namely in Figure 30a limning the functional color distribution of *EN* defined according to *EqN* calibration parameters at the fixed magnitude of the training percentage (*TP*) of 0.95, minimum and the best value of the 10.1934 m³/s MAE parameter that was exhibited by the dark blue color was captured at these calibration parameters to correspond to the magnitudes of 17 *EqN* and 50 *EN*. With reference to the sub-figure of Figure 30b depicting the functional color scatter of *TP* specified according to *EqN* adjustment parameters at the stationary magnitude of the epoch number (*EN*) of 50, minimum and the superior value of the 10.1934 m³/s MAE parameter that was shown by the dark blue color was acquired at these setting parameters to correspond to the values of 17 *EqN* and 0.95 *TP*. With reference to the sub-figure of Figure 30c displaying the functional color dispersion of *TP* assigned according to *EN* regulation parameters at the constant magnitude of the equation number (*EqN*) of 17, minimum and the topnotch value of the 10.1934 m³/s MAE parameter that was evidenced by the dark blue color was generated at these tuning parameters to correspond to the set of 50 *EN* and 0.95 *TP*. With reference to the sub-figures of Figure 31, namely in Figure 31a that demonstrated the functional color variation of *EN* stated based on *EqN* calibration parameters at the identical magnitude of the training percentage (*TP*) of 0.95, the lowest and therefore the best value of the 31.5871 m³/s MAE parameter which was displayed using the dark blue color was produced at these calibration parameters to correspond to the magnitudes of 19 *EqN* and 300 *EN*. With reference to the sub-figure of Figure 31b pointing the functional *TP* color scatter described according to *EqN* gauge parameters at the equivalent value of the epoch number (*EN*) of 300, least and for this reason the topnotch value of the 31.5871 m³/s MAE parameter that was picturized by the dark blue color was achieved at these gauge parameters to stand for the values of 19 *EqN* and 0.95 *TP*. With reference to the sub-figure of Figure 31c presenting the functional color alteration of *TP* appointed with respect to the *EN* collimated parameters at the still magnitude of the equation number (*EqN*) of 19, the smallest and the tiptop of the 31.5871 m³/s MAE parameter that was signified utilizing the dark blue color was propagated at these adjustment parameters to correspond to the dual values of 300 *EN* and 0.95 *TP*. Ultimately, when the sub-figures of Figure 30 are evaluated together, it is seen and reported that the best MAE result is obtained corresponding to the value of 10.1934 m³/s at the setting parameters of 17 *EqN*, 50 *EN*, and 0.95 *TP*. Similarly, when the sub-figures of Figure

31 are appraised together, it is observed and reported that the superior MAE outcome is acquired corresponding to the value of $31.5871 \text{ m}^3/\text{s}$ at the tuning parameters of 19 EqN , 300 EN , and 0.95 TP .

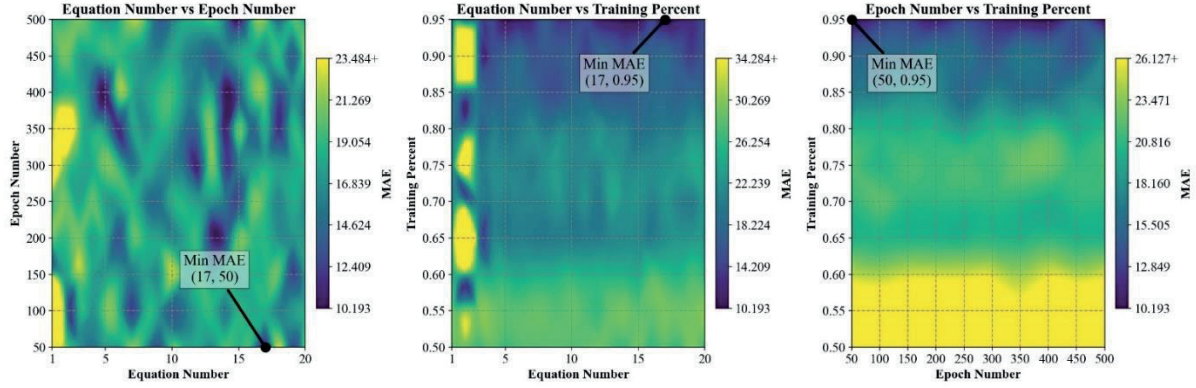


Figure 30. MAE results for **a)** EN vs. EqN, **b)** TP vs. EqN, **c)** TP vs. EN at the testing stage of 4th applied approach of ANN

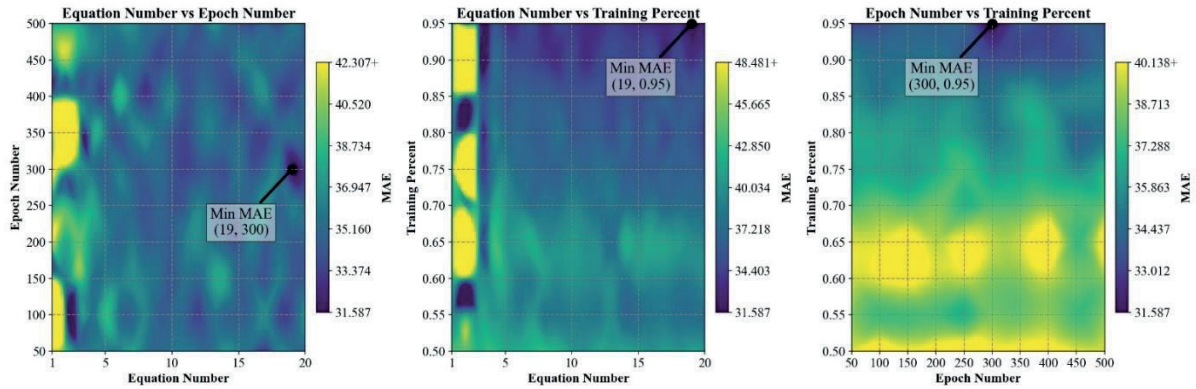


Figure 31. MAE results for **a)** EN vs. EqN, **b)** TP vs. EqN, **c)** TP vs. EN at the training stage of 4th applied approach of ANN

On the other hand, the output scene of RMSE and R parameters are revealed in Figures 32, 33, 34, and 35, for the 4th applied approach of ANN. Figures 32 and 33 report the RMSE testing and training fragments of 4th implemented approach of ANN, respectively, while Figures 34 and 35 report the R testing and training components of 4th method of ANN, respectively. The smallest RMSE magnitude at the testing stage was conducted to correspond to the value of $3.1927 \text{ m}^3/\text{s}$, whereas the lowest magnitude of RMSE for training portion was executed to correspond to the $5.6201 \text{ m}^3/\text{s}$. Taking the 4th implemented ANN approach into account, these two minimum values of RMSE for testing and training stages were disclosed to be the best magnitudes of this error parameter, which are demonstrated in Figures 32 and 33, respectively. Furthermore, the maximum magnitude of the correlation coefficient (R) at the testing phase was managed to correspond to the value of 0.94521, whereas the highest magnitude of R for training

portion was governed to correspond to the 0.96877. Taking the 4th implemented ANN approach into account, these two biggest values of the correlation coefficient (R) for testing and training fragments were divulged to be the best magnitudes of this statistical correlation parameter, that are shown in Figures 34 and 35, respectively.

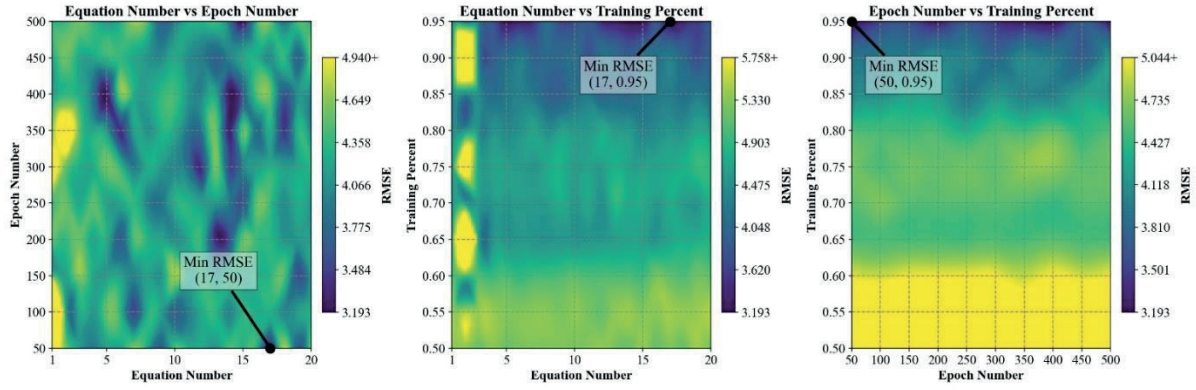


Figure 32. RMSE results for **a)** EN vs. EqN, **b)** TP vs. EqN, **c)** TP vs. EN at the testing stage of 4th applied approach of ANN

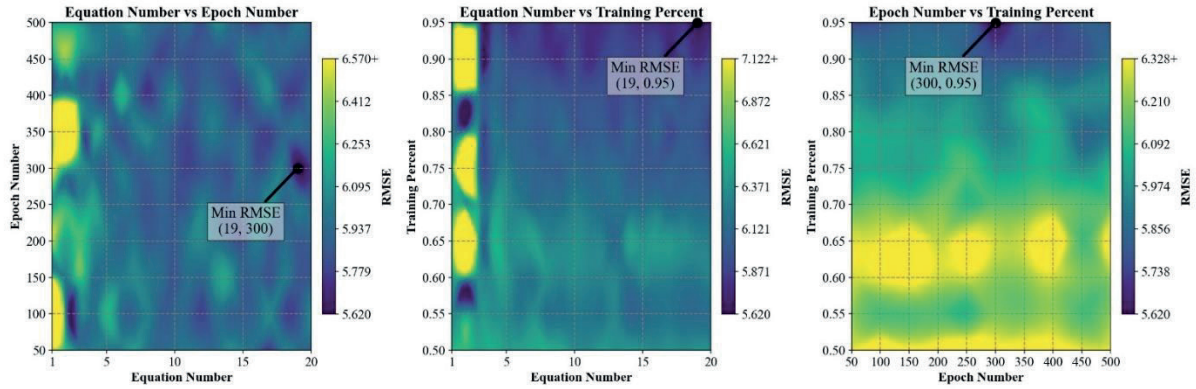


Figure 33. RMSE results for **a)** EN vs. EqN, **b)** TP vs. EqN, **c)** TP vs. EN at the training stage of 4th applied approach of ANN

The exact locations of best result of $3.1927 \text{ m}^3/\text{s}$ RMSE regarding Figures 32a, 32b, and 32c are exposed in these figures for EN vs. EqN , TP vs. EqN , and TP vs. EN color distributions, respectively. Namely, at the EN vs. EqN functional color scatter diagram, when the binary expression including (EqN , EN) are set respectively to (17, 50) at the fixed parameter of 0.95 TP ; at the TP vs. EqN functional color distribution diagram, as soon as the binary statement consisting of (EqN , TP) are arranged respectively to (17, 0.95) at the stationary value of the parameter of 50 EN ; at the TP vs. EN functional color variation diagram, during the adjustment of the binary term covering (EN , TP) corresponding to (50, 0.95) at the stable value of the EqN corresponding to 17; this best value of $3.1927 \text{ m}^3/\text{s}$ RMSE was computed. Eventually, combining the adjustment parameters considered initially as combinations of 2 of 3 yield the

best RMSE output of $3.1927 \text{ m}^3/\text{s}$ to be acquired at 17 EqN , 50 EN , and 0.95 TP . The exact locations of superior outcome of $5.6201 \text{ m}^3/\text{s}$ RMSE considering Figures 33a, 33b, as well as 33c are disclosed in cited figures for EN vs. EqN , TP vs. EqN , else TP vs. EN color alterations, respectively. I.e., at the functional color scatter diagram of EN vs. EqN , when the binary abbreviation containing (EqN , EN) are modified respectively to (19, 300) at the unaltered parameter of 0.95 TP ; at the TP vs. EqN functional color sprinkled diagram, in the case of the binary denotation enclosing (EqN , TP) are substituted respectively to (19, 0.95) at the static value of the parameter of 300 EN ; at the TP vs. EN functional color dispersion diagram, in the course of the tuning of the binary term comprising of (EN , TP) corresponding to (300, 0.95) at the unchanged value of the EqN corresponding to 19; this top value of $5.6201 \text{ m}^3/\text{s}$ RMSE was simulated. On the upshot, joining the regulation parameters taken into account initially as combinations of 2 of 3 turn the superior RMSE output of $5.6201 \text{ m}^3/\text{s}$ to be produced at 19 EqN , 300 EN , and 0.95 TP .

On the other hand, the definite locations of most quality outcome of 0.94521 R respecting Figures 34a, 34b, and 34c are revealed in stated figures for EN vs. EqN , TP vs. EqN , and TP vs. EN color alteration, respectively. Scilicet, referring to the diagram dealing with functional color scatter of EN vs. EqN , when the binary expression encapsulating (9, 200) are entered for (EqN , EN), respectively, at the uniform parameter of 0.55 TP ; mentioning the diagram handling functional color distribution of TP vs. EqN , as soon as the binary expression embodying (9, 0.55) are substituted for (EqN , TP), respectively, at the unvarying magnitude of the parameter of 200 EN ; pointing to the diagram tackling with functional color relation of TP vs. EN , in the event of the binary term compassing (200, 0.55) are inserted for (EN , TP), respectively, at the unaltered value of the EqN balanced to 9; this superior value of 0.94521 R was reported. At last, combining these three regulation parameters considered initially as combinations of 2 of 3 generate the best R result of 0.94521 to be attained at 9 EqN , 200 EN , and 0.55 TP . The precise locations of highest quality result of 0.96877 R attributing Figures 35a, 35b, plus 35c are uncovered in remarked figures using EN vs. EqN , TP vs. EqN , and TP vs. EN color shading, respectively. I.e., looking at the diagram striving functional color dispensation of EN vs. EqN , as the binary abbreviation comprising of (14, 250) are replaced for (EqN , EN), respectively, at the settled parameter of 0.55 TP ; stressing the diagram taking over functional color sprinkle of TP vs. EqN , in the form of the binary curtailment consisting of (14, 0.55) are switched for (EqN , TP), respectively, at the equal value of the parameter of 250 EN ; indicating the diagram dealing with functional color correlation of TP vs. EN , throughout of the binary term comprehending

(250, 0.55) are attached to (EN, TP) , respectively, at the fixed value of the EqN set to 14; this utmost value of 0.96877 R was recorded. In brief, merging the tuning parameters kept in view initially as combinations of 2 of 3 give the superior R finding of 0.96877 to be cultivated at 14 EqN , 250 EN , and 0.55 TP .

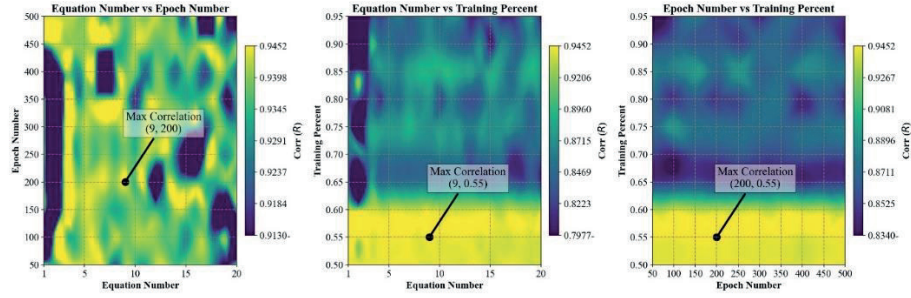


Figure 34. R results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the testing stage of 4th applied approach of ANN

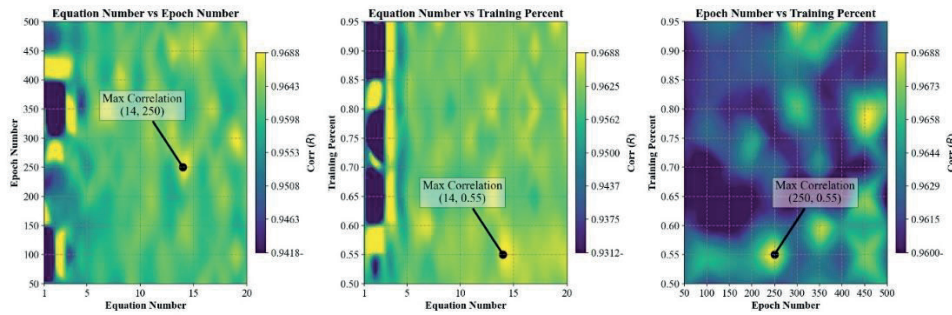


Figure 35. R results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the training stage of 4th applied approach of ANN

Besides, the error values of the statistical accuracy parameters including MAE, RMSE, as well as R , with regards to the 4th exerted methodology of the ANN are exhibited in Figure 36. A total of 19 models are analyzed in this figure, different from the former applied approaches of ANN. In Figure 36, the values of the cited error parameters are displayed on y-axis regarding to the variation of the training percentage (TP), taking the cognizance of x-axis of Figure 36 specified depending on the range of $0.50 \leq TP \leq 0.95$. On the other hand, those values of the error parameters are also reported alike given in Table 5. In Table 5, the tiptop accuracy outcomes of ANN simulations are presented utilizing the pattern of bold, as well as which were formerly displayed to be the best models in this 4th ANN methodology, portrayed in Figures 30, 32, and 34. In this frame, the statistical accuracy outcomes of MAE and RMSE, as shown in Figure 36 and Table 5 were achieved to be their minimum values in the case of arranging EqN , EN , and TP to the magnitudes of 17, 50, and 0.95. The topnotch MAE and RMSE values acquired at these parameters, among the cumulative of 2,000 models of 4th methodology, have resulted the

MAE at 10.193 m³/s, whereby RMSE at 3.193 m³/s. Besides, the correlation coefficient (R) outcome that is generated at the tuning parameters corresponding to 17 EqN , 50 EN , and 0.95 TP appeared not to be the highest as well as the best R , when referring all 2,000 trials or when stressing this cited value of training percentage (TP) corresponding to 0.95. I.e., the detected 0.81119 R magnitude was managed not to be the maximum among the others. On account of this, the R value of 0.81119 is not tabulated in Table 5 at 0.95 TP , while at this magnitude of 0.95 TP , the biggest R was determined and reported to correspond to the value of 0.88062, but still not the maximum and superior value of 2,000 models of this 4th methodology of ANN. This magnitude of the correlation coefficient was given at 19 EqN and 150 EN , taking the TP value of 0.95 into account. Yet, one other model is found among the others which have resulted in the highest R value corresponding to 0.94521 at the EqN , EN , as well as TP parameter magnitudes corresponding to 9, 200, and 0.55, respectively. At these tuning parameters, the MAE and RMSE came into the open not to be the lowest and thus superior values, i.e., the magnitudes of 28.8684 m³/s and 5.3729 m³/s were governed not to be the minimum and superior values among 2,000 different trials of 4th methodology of ANN or among considering the value of training percentage (TP) of 0.55 of 4th methodology. That's why, these values of MAE and RMSE at 9 EqN , 200 EN , and 0.55 TP are not placed in Table 5. However, at the TP magnitude of 0.55, shifting EqN and EN to 12 and 350, respectively created the lowest and best magnitudes of MAE and RMSE at this 0.55 TP value, coinciding to the values of 26.642 m³/s and 5.162 m³/s, respectively. These magnitudes of MAE else RMSE came across to the minimum and best values belonging to this training percentage value (TP) of 0.55; yet do not correspond to the minimum and superior value of 2,000 models regarding the 4th ANN methodology. In general, the change of the training percentage (TP) effectuates the drop of the MAE as well as RMSE statistical error parameters according as increment of TP , as offered in Figure 36. Even so, the TP jump to higher values in the range of $0.50 \leq TP \leq 0.95$ accomplishes a significant fluctuation of the correlation coefficient (R) in this value range. In this context, as clarified in Figure 36, a decline of the general trend of R is actualizing depending on the advance of the TP considering the range of $0.50 \leq TP \leq 0.60$. On the other hand, an abrupt decline of the correlation coefficient (R) value is taking place as soon as the training percentage corresponds to the range of $0.60 \leq TP \leq 0.65$. But, passing beyond the TP value corresponding to $TP=0.65$ brings forth a fluctuating rise of the R parameter until the magnitude of the training percentage is reached to the value at $TP=0.95$. This means: Although the trend of the correlation coefficient (R) is increase considering the range of $0.65 \leq TP \leq 0.95$, to arrive the value of 0.88062 R at 0.95 TP , from the value of 0.85687 R at 0.65 TP ; there are two important drops of the correlation

harmony parameter occurring at $TP=0.80$ and $TP=0.90$, when these two readings are compared to the immediate former instantaneous readings of training percentage values consisting of $TP=0.75$ and $TP=0.85$.

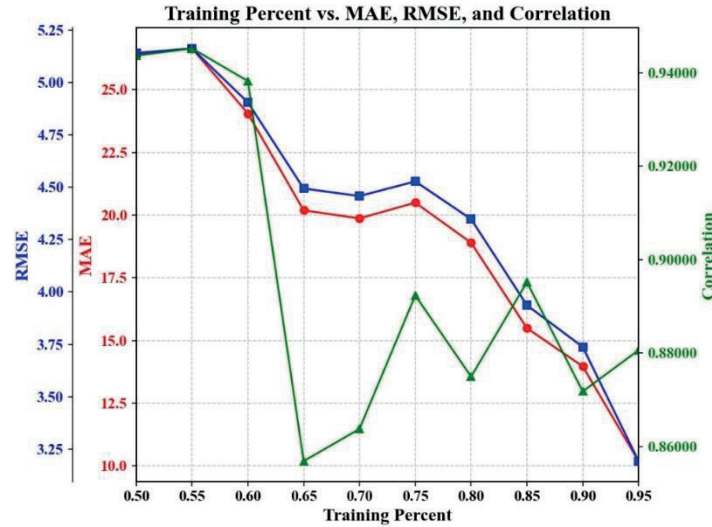


Figure 36. Error outputs of the best 19 models for different TP values at 4th implemented method

Table 5. Error outputs of the best 19 models for different TP values and their EqN and EN values are reported

Training Percent	Equation Number	Epoch Number	Metric	Training Percent	Equation Number	Epoch Number	Metric
0.5	16	450	MAE: 26.419	0.75	7	100	MAE: 20.495
	16	450	RMSE: 5.140		7	100	RMSE: 4.527
	17	450	Corr: 0.94366		7	100	Corr: 0.89234
0.55	12	350	MAE: 26.642	0.8	15	250	MAE: 18.897
	12	350	RMSE: 5.162		15	250	RMSE: 4.347
	9	200	Corr: 0.94521		9	350	Corr: 0.87495
0.6	6	350	MAE: 24.051	0.85	9	250	MAE: 15.495
	6	350	RMSE: 4.904		9	250	RMSE: 3.936
	9	100	Corr: 0.93823		11	150	Corr: 0.89518
0.65	8	250	MAE: 20.189	0.9	19	450	MAE: 13.968
	8	250	RMSE: 4.493		19	450	RMSE: 3.737
	11	150	Corr: 0.85687		9	450	Corr: 0.87178
0.7	12	400	MAE: 19.868	0.95	17	50	MAE: 10.193
	12	400	RMSE: 4.457		17	50	RMSE: 3.193
	10	250	Corr: 0.86376		19	150	Corr: 0.88062

3.6. 5th Implemented ANN Correlation Method in the Estimation of the Maritsa River Water Flow Rate

In this approach of ANN, the volumetric water flow rate (VWFR) of the downstream Maritsa river, measured at the İpsala water measuring station (WMS) found on this Maritsa river, was

estimated using the data dump folders created with historical time-series volumetric water flow rate (VWFR) data of 11 different water measuring stations (WMSs). As a result, the VWFR data of all 11 stations located on 4 different river branches, were included in the estimates in a way that a separate column matrix was created for each station. As a result, in the estimation of the VWFR of the downstream Maritsa river passing through the İpsala station where the data estimation is needed, the data of the volumetric water flow rate (VWFR) of the downstream Maritsa river passing through this station was accepted as the function output, and the VWFR data of the other 10 stations located on the four river branches including Arda, upstream Maritsa, midstream Maritsa, Tunca, and Ergene tributaries were accepted as the function input and a mathematical relationship was established in between the input and the output. In this regards, the VWFR value for Arda tributary measured at Ivoylovgrad WMS, the VWFR values for upstream Maritsa tributary measured at Harmanlı and Svilengrad WMSs, the VWFR magnitude for midstream Maritsa tributary measured at Kirişhane WMS, the VWFR magnitudes for Tunca tributary measured at Elhova, Suakacağı, and Değirmenyeni WMSs, the VWFR values for Ergene tributary measured at İnanlı and Lüleburgaz WMSs are all directly included in the VWFR data estimations of downstream Maritsa measured at İpsala WMS, without performing any averaging or other mathematical operations. In this respect, Figure 37 introduces the considered study area demonstrating the adopted methodology regarding 5th implemented approach of ANN.



Figure 37. Visual description of the 5th implemented approach

In this 5th exerted ANN approach, the ANN tuning parameters are considered to have same values and value ranges, as formerly shown in Table 2 that exhibited the regulation parameter values and their ranges for the 2nd approach. Accordingly, the identical methodology that is

adopted up to 4th implemented approach in terms of the ANN calibration parameters is also adopted for the 5th applied approach of ANN. On the other hand, as in the case of former implemented approaches, MAE, RMSE, and R functional color distributions are indicated with respect to mutual adjustment parameters selected as 2 from the total of 3. This methodology of result exhibition is similarly exerted both for testing and training stages in this 5th implemented approach. In Figures 38 and 39, the statistical accuracy error of MAE results considering testing and training fragments are demonstrated, respectively. In the testing stage, the parameter of the MAE statistical accuracy is reported to correspond to 11.5819 m³/s, as depicted in Figure 38, while the same parameter for the training stage, as betokened in Figure 39, is reported at the value of 27.6297 m³/s. Attributing to Figure 38, the minimum thus the best 11.5819 m³/s MAE magnitude was identified at the ANN adjustment parameters of 16, 400, as well as 0.95, respectively coinciding to equation number (EqN), epoch number (EN), and the training percentage (TP). Alike, in the case of attributing to Figure 39, regulation parameters of 18, 100, and 0.95 set respectively for EqN , EN , and TP have effectuated 27.6297 m³/s MAE, which was identified to be the minimum and therefore the superior one.

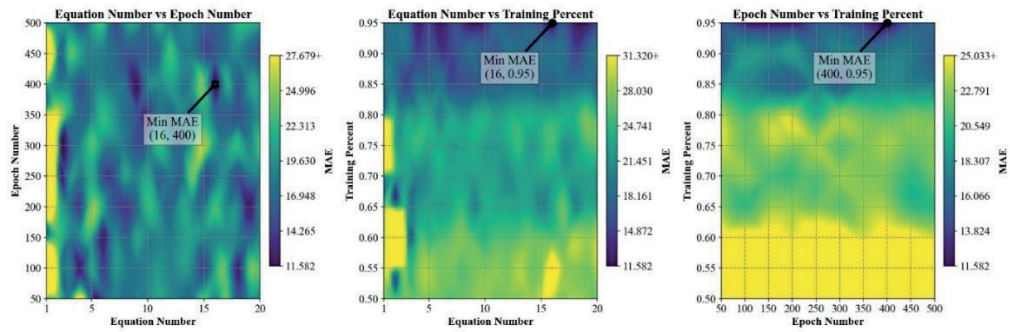


Figure 38. MAE results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the testing stage of 5th applied approach of ANN

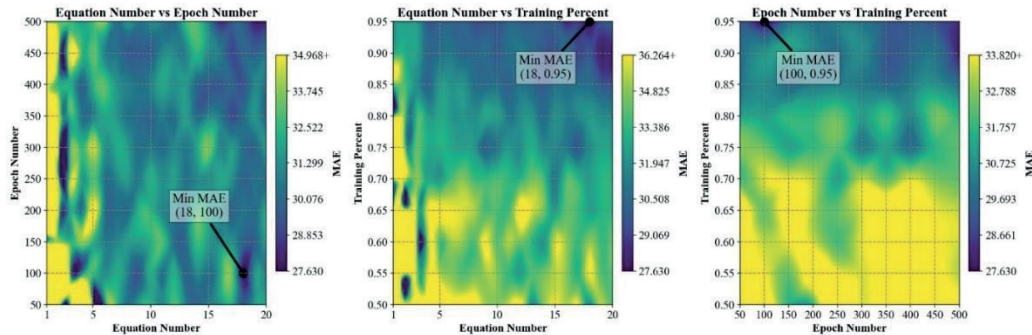


Figure 39. MAE results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the training stage of 5th applied approach of ANN

The output color scenes of RMSE statistical error parameter are shown in Figures 40 and 41, paying attention to testing and training ranks, respectively. In this frame, as revealed in Figure 40, the RMSE statistical accuracy value was determined and reported at the value of 3.4032 m^3/s , with regards to the testing stage of ANN based on this 5th approach. The same figure turned out to be 5.2564 m^3/s , depending on the training fragment of ANN referring to this 5th approach, as exposed in Figure 41. The smallest and best testing RMSE output vista of 3.4032 m^3/s , that is reported in Figure 40, was procured as soon as the ANN setting parameters were arranged to the values of 16 *EqN*, 400 *EN*, and 0.95 *TP*. Whereas, the lowest and best training RMSE output vista of 5.2564 m^3/s , with regards to Figure 41, was acquired during setting ANN regulation parameters to 18 *EqN*, 100 *EN*, plus 0.95 *TP*.

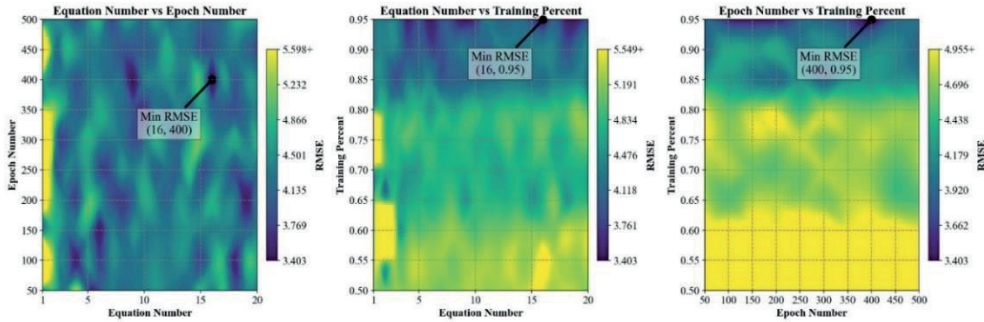


Figure 40. RMSE results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the testing stage of 5th applied approach of ANN

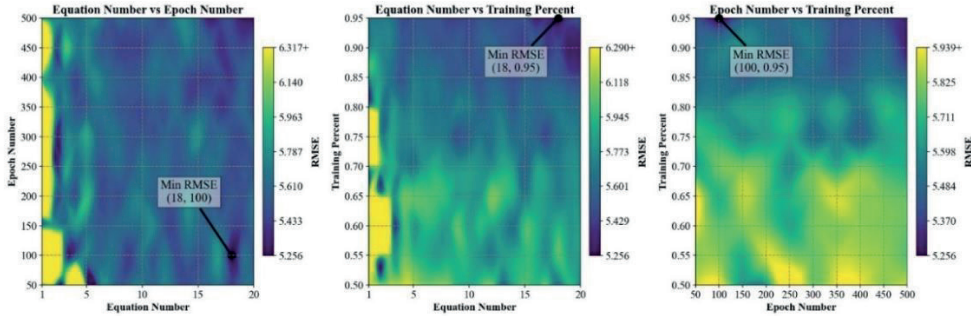


Figure 41. RMSE results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the training stage of 5th applied approach of ANN

The functional correlation (R) color scatter that indicates the harmony between the real and its counterpart predictions for volumetric water flow rate (VWFR) of downstream Maritsa river, measured at İpsala water measurement station (WMS), on the other hand, is displayed both for testing and training phases. The result output vistas are designated in Figures 42 as well as 43, respectively. In this context, as depicted in Figure 42, the highest magnitude of the statistical correlation (R) scatter was conducted to be 0.96293, as per the testing fragment of the 5th

approach of ANN. Besides, as per the training rank of ANN at this 5th approach, as portrayed in Figure 43, the statistical correlation of R , considering among its all correlation coefficient functional color scatter, was calculated at the highest value of 0.98186. The vista belonging to the supreme and accordingly the best R testing output corresponding to the value of 0.96293, that is visualized in Figure 42, was achieved in the course of adjusting parameters of ANN arranged to the values of 8 EqN , 250 EN , and 0.55 TP . Yet, the vista standing for the supreme and thus the superior R training output corresponding to the value of 0.98186, that is visualized in Figure 43, was made in the case of setting ANN calibration parameters to the values corresponding to 19 EqN , 500 EN , intercalary to 0.90 TP .

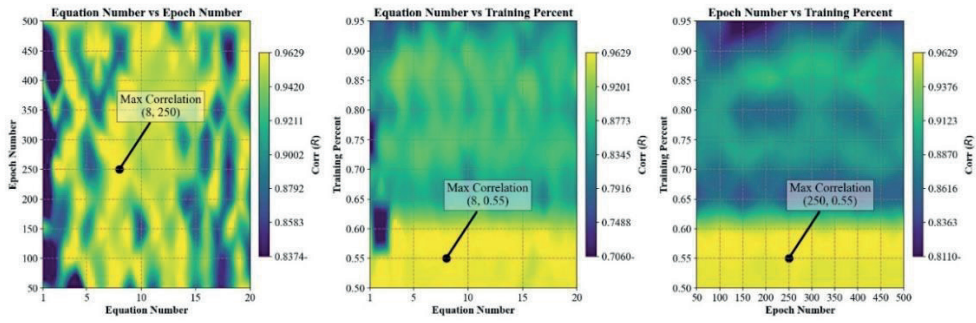


Figure 42. R results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the testing stage of 5th applied approach of ANN

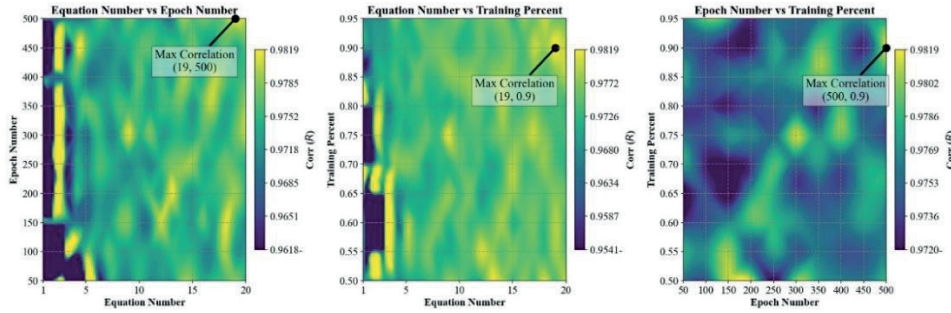


Figure 43. R results for a) EN vs. EqN, b) TP vs. EqN, c) TP vs. EN at the training stage of 5th applied approach of ANN

Furthermore, the error values about the parameters of the statistical accuracy comprising of MAE, RMSE, plus R , according as 5th performed technique of ANN are evidenced in Figure 44. A whole of 19 models are investigated in Figure 44, as similar to the 4th ANN methodology. In Figure 44, the functional variation of the magnitudes of the three statistical accuracy parameters are pointed on y-axis concerning the alteration of the values belonging to the training percentage (TP). The training percentage (TP) demonstrated on x-axis takes the cognizance of Figure 44 established with respect to the range of $0.50 \leq TP \leq 0.95$. Additionally, the reported values of the error parameters of Figure 44 are also tabulated in Table

6. In this regards, Table 6 presents the tabulation of the best accuracy results of the computations of the ANN under the usage of the bold indicator. Besides, these are previously denoted to be the best models regarding this 5th ANN methodology, and these were formerly paid attention in Figures 38, 40, and 42. Accordingly, the statistical precision results of MAE as well as RMSE, as revealed in Figure 44 and Table 6 were attained to possess their minimum values during the arrangement of EqN , EN , else TP to the values at 16, 400, and 0.95. The topflight MAE and RMSE values that are acquired at these tuning parameters, with regards to the total 2,000 models of 5th approach, have induced 11.582 m³/s MAE, whereas 3.403 m³/s RMSE. Nevertheless, the outcome belonging to the correlation coefficient (R) that is formed at the calibration parameters of 16 EqN , 400 EN , and 0.95 TP eventuated not to be the maximum and the superior value of R , based on the whole 2,000 tests or in the case of underlining this mentioned magnitude of the training percentage (TP) corresponding to 0.95. Well, the determined value of 0.78833 R was figured out not to be the highest R value among the others. Therefore, the R value of 0.78833 is not given in Table 6 for training percentage of 0.95 TP , however at this value of 0.95 TP , the utmost correlation coefficient was computed and conducted to have the value of 0.88368 R . But, this value of R is still concluded not to be the greatest and best value of correlation coefficient of 2,000 models found in this 5th ANN methodology. This value of the correlation coefficient was obtained setting EqN to 9 and EN to 400, in the case of adjusting the TP value to 0.95. However, another model is captured among the other trials that have produced the maximum value of R at the value of 0.96293. This value of the correlation coefficient (R) was found with the setting parameters of 8 EqN , 250 EN , as well as 0.55 TP , as given in Table 6, and presented in Figure 44. At these parameter magnitudes arranged to the specified values, similarly, the MAE and RMSE statistical accuracy values emerged to be the smallest and thus best of the considered TP of 0.55. Namely, although the magnitudes of 26.165 m³/s MAE and 5.115 m³/s RMSE were concluded not to be the lowest and best values inside 2,000 discrete trials considering 5th ANN methodology, they are taken into account as the smallest and best MAE and RMSE values among the all models found at $TP=0.55$ of 5th method. That's the reason of inclusion of these MAE and RMSE values accompanying to the highest and best 0.96293 R value together in Table 6 at 8 EqN , 250 EN , and 0.55 TP . When evaluated from another point of view, the highest and best correlation coefficient (R) value obtained in the setting parameters of Figure 42, as well as during the adjustment of $TP=0.55$, also produced the lowest MAE and lowest RMSE and therefore the best MAE and best RMSE values for the mentioned TP at the same values of EqN and EN . And, these results are included in Table 6, as such. Since only, at the setting of $TP=0.55$, a sole model

gives the best MAE, RMSE, and R values simultaneously, but at the other TP values, one model produces the smallest and best MAE and RMSE, and another model generates the highest and best R value. Thus, in the range of $0.50 \leq TP \leq 0.95$, only one model for $TP=0.55$ was considered in Table 6 and since there were two models for $TP=0.50$, $TP=0.60$, $TP=0.65$, $TP=0.70$, $TP=0.75$, $TP=0.80$, $TP=0.85$, $TP=0.90$, and $TP=0.95$, a total of $9 \times 2 + 1 = 19$ models were created to be tabulated in this table and the results are also shown in Figure 44.

Without observing the small increases, generally, the variation of the training percentage (TP) causes a drop of the MAE else the RMSE statistical precision parameters according as the rise of TP , as offered in Figure 44. On the other hand, again a fluctuating trend is emerging for the correlation coefficient (R) in the case of the training percentage (TP) found in the range of $0.50 \leq TP \leq 0.95$ augments to greater values. In this respect, as brightened in Figure 44, there is a small decline of the general R inclination materialized according to the enhancement of the TP taking the range of $0.50 \leq TP \leq 0.60$ into account. Whereas, a sudden fall regarding the correlation coefficient (R) values are originating in the event of the training percentage to be within the disparity of $0.60 \leq TP \leq 0.65$. If surpassing over the TP magnitude set to $TP=0.65$ results in a temporary peak point of correlation coefficient at $TP=0.85$, with a former small drop occurring at $TP=0.80$. On the other hand, exceeding $TP=0.85$ till reaching $TP=0.95$ sets in the reduction of the correlation coefficient to 0.88368 R , which was before at the peak of 0.91606 R . As a result, the correlation coefficient (R) results obtained as a result of the ANN investigation of the models established as a result of scanning the space showed that these correlation coefficient values, which reached peak values in the vicinity of 0.96 R in cases where TP values were as small as 0.55, decreased to the magnitudes of 0.88 R as a result of the increase in TP to its maximum values, like $TP=0.95$.

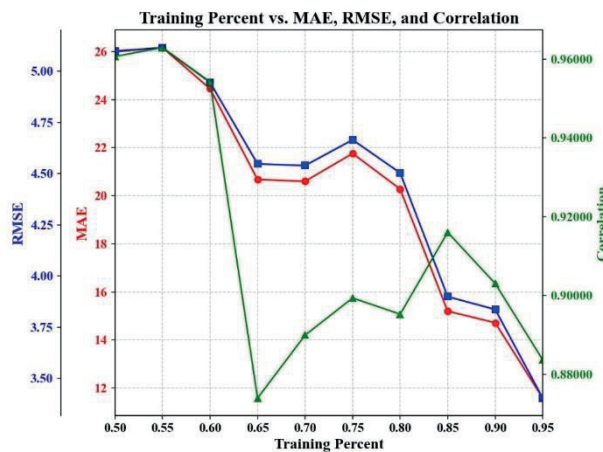


Figure 44. Error outputs of the best 19 models for different TP values at 5th implemented method

Table 6. Error outputs of the best 19 models for different TP values and their EqN and EN values are reported

Training Percent	Equation Number	Epoch Number	Metric	Training Percent	Equation Number	Epoch Number	Metric
0.5	7	300	MAE: 25.992	0.75	17	300	MAE: 21.762
	7	300	RMSE: 5.098		17	300	RMSE: 4.665
	2	250	Corr: 0.96069		8	500	Corr: 0.89939
0.55	8	250	MAE: 26.165	0.8	6	250	MAE: 20.281
	8	250	RMSE: 5.115		6	250	RMSE: 4.503
	8	250	Corr: 0.96293		14	100	Corr: 0.89527
0.6	4	350	MAE: 24.455	0.85	3	300	MAE: 15.201
	4	350	RMSE: 4.945		3	300	RMSE: 3.899
	13	100	Corr: 0.95425		4	200	Corr: 0.91606
0.65	9	500	MAE: 20.678	0.9	6	50	MAE: 14.719
	9	500	RMSE: 4.547		6	50	RMSE: 3.837
	11	200	Corr: 0.87397		10	300	Corr: 0.90305
0.7	4	450	MAE: 20.605	0.95	16	400	MAE: 11.582
	4	450	RMSE: 4.539		16	400	RMSE: 3.403
	6	450	Corr: 0.88995		9	400	Corr: 0.88368

3.7. Comparison of the Results

Table 7 tabulates the best testing results of five used methods that have generated the lowest MAE, RMSE, and highest R among the total of 10,000 models. In this table, the number of run provided in odd numbers including Run-1, Run-3, Run-5, Run-7, and Run-9 demonstrate the best MAE and RMSE statistical accuracy values, respectively given for 1st, 2nd, 3rd, 4th, and 5th approaches. On the other hand, the number of run indicated in even numbers including Run-2, Run-4, Run-6, Run-8, and Run-10 exhibit the superior R statistical accuracy magnitudes, respectively presented again for these 1st, 2nd, 3rd, 4th, and 5th methodologies. Namely, a total of 10 models reported as the best are selected from the total of these referred 10,000 models, and granted in Table 7. On the other hand, the comparison of these 10 models in terms of their functional data distributions that are shown with respect to their counterpart real observed data cluster is displayed in Figure 45, referring to the testing stage. Since the total amount of the data utilized in artificial intelligence of ANN corresponds to 2,469, in which the results put forward include different training percentage (TP) values, the curves are represented in testing stage depending on the model having the maximum value of the training percentage of $TP=0.95$, or minimum value of the testing percentage, among the total of selected 10 best models. Therefore, this model has resulted the testing number of observed data samples to correspond to the value of $\#_{testing} = 2,469 \times 0.05 = 123$, for the comparison data amount of 10 models. And, the ANN simulated data functions are accordingly given with respect to the real data set, with the

utilization of 123 data in cumulative, as remarked in Figure 45. The best of the best statistical accuracy value in terms of MAE and RMSE parameters of Table 7 is Run-5 of Case-3, given in the table utilizing the red color. This model has generated the lowest MAE as well as RMSE at 15 *EqN*, 350 *EN* and 0.95 *TP*. In a similar manner, the best of the best statistical error value of *R* parameter of Table 7 is reported to be Run-2 of Case-1, denoted in the table using the blue color. This model has created the highest *R* at 8 *EqN*, 100 *EN*, 0.55 *TP*. In this regards, the models that are exemplified by Run-5 and Run-2 of Table 7 have induced 9.8476 m³/s MAE and 3.1381 m³/s RMSE as well as 0.96469 *R*, respectively. Besides, when Run-2 and Run-5 are compared among themselves, it is concluded and reported that best model should be the Run-5, since this has generated two statistical accuracy results to be superior than the other tested 9,999 models including MAE and RMSE, whereas, Run-2 has produced only one statistical accuracy outcome to be better than the other tested 9,999 models consisting *R*. On the other hand, as similar to Table-7, Figure 45 has also comprised of red and blue colors for Run-5 and Run-2 referring to the models producing the best MAE and RMSE as well as *R*, respectively, besides, these and the other eight models are compared against the real testing data cloud curve shown by black continuous color.

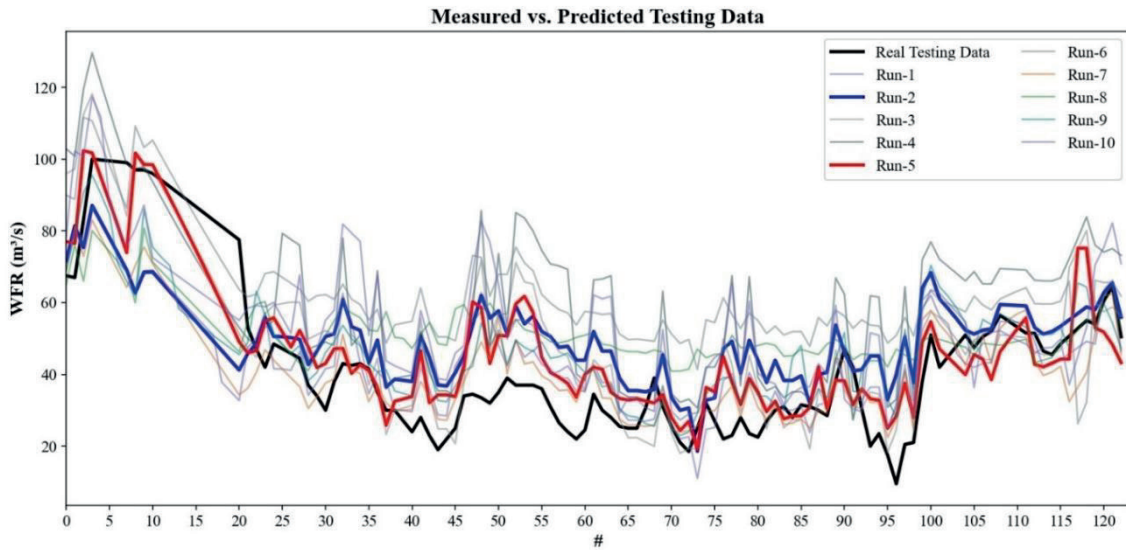


Figure 45. Real testing data presented according to best ten models of five utilized methodologies

Table 7. Statistical error testing outputs of ten best models of five used methodologies

ID	Approach	Method	Equation Number	Epoch Number	Training Percent	MAE	RMSE	Corr
Run-1	Case-1	Testing	15	300	0.95	11.2288	3.3509	0.76782
Run-2	Case-1	Testing	8	100	0.55	23.4568	4.8432	0.96469
Run-3	Case-2	Testing	17	450	0.95	11.8580	3.4435	0.76660
Run-4	Case-2	Testing	6	400	0.55	37.5986	6.1318	0.94609
Run-5	Case-3	Testing	15	350	0.95	9.8476	3.1381	0.83662
Run-6	Case-3	Testing	17	450	0.50	33.1071	5.7539	0.92038
Run-7	Case-4	Testing	17	50	0.95	10.1934	3.1927	0.81119
Run-8	Case-4	Testing	9	200	0.55	28.8684	5.3729	0.94521
Run-9	Case-5	Testing	16	400	0.95	11.5819	3.4032	0.78833
Run-10	Case-5	Testing	8	250	0.55	26.1650	5.1152	0.96293

Table 8 tabulates the best training outcomes of five utilized methods that have actualized the lowest MAE, RMSE, and highest R among the total of 10,000 models. In this table, again a total of 10 different models are compared, however now for the training stage. On the other hand, the comparison of these 10 models due to their functional data dispersions that are demonstrated by their corresponding actual observed data set is exhibited in Figure 46, attributing to the training stage. Since the cumulative amount of the data used in ANN corresponds to 2,469, in which the results put forward consist of discrete training percentage (TP) values, the curves are represented in training fragment attached to the model having the minimum value of the training percentage of $TP=0.50$ among the cumulative of chosen 10 superior models. Accordingly, this model has exposed the training number of observed data samples to correspond to the amount of $\#_{training} = 2,469 \times 0.5 = 1,235$, for the comparison data quantity of 10 models. And, the ANN computed data functions are thus given with respect to the real data cluster, with the usage of 1,235 data in total, as asserted in Figure 46. The superior of the best statistical accuracy magnitude in terms of MAE and RMSE of Table 8 is Run-19 belonging to Case-5, given in the table using the blue color. This model has produced the lowest MAE and RMSE at 18 EqN , 100 EN , 0.95 TP . Alike, the superior of the best statistical error value of R of Table 8 is determined to be Run-20 of Case-5, depicted in the Table 8 utilizing the red color. This model has generated the maximum R value at 19 EqN , 500 EN , 0.90 TP . In this context, the models that are symbolized by Run-19 and Run-20 of Table 8 have created 27.6297 m^3/s MAE and 5.2564 m^3/s RMSE as well as 0.98186 R , respectively. Yet, when Run-19 and Run-20 are compared among themselves, it is brought to an issue and reported that superior model should be the Run-19, since the model has turned two statistical

error outcomes to be better than the other tested 9,999 models consisting of MAE and RMSE, on the other hand, Run-20 has procured only one statistical error result to be superior than the other tested 9,999 models including R . Furthermore, as in the case of Table-8, Figure 46 has also included of dashed structure of blue and red colors for Run-19 and Run-20 attributing to the models generating the superior MAE and RMSE as well as R , respectively; else, these two and the other eight models are compared with respect to the actual testing data cluster curve displayed by continuous type of black color.

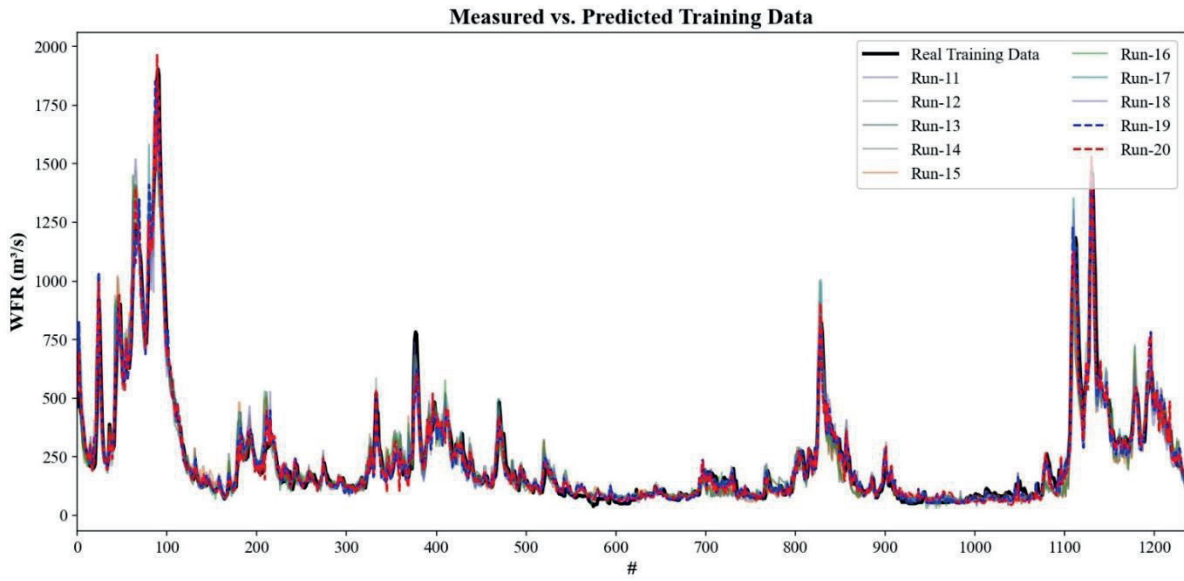


Figure 46. Real training data presented according to best ten models of five utilized methodologies

Table 8. Statistical error training outputs of ten best models of five used methodologies

ID	Approach	Method	Equation Number	Epoch Number	Training Percent	MAE	RMSE	Corr
Run-11	Case-1	Training	17	450	0.95	30.1197	5.4881	0.97304
Run-12	Case-1	Training	14	150	0.50	35.8994	5.9916	0.97548
Run-13	Case-2	Training	20	500	0.95	36.3140	6.0261	0.96196
Run-14	Case-2	Training	13	400	0.55	36.8709	6.0721	0.97318
Run-15	Case-3	Training	11	250	0.95	38.9589	6.2417	0.94818
Run-16	Case-3	Training	9	200	0.55	44.0073	6.6338	0.95786
Run-17	Case-4	Training	19	300	0.95	31.5871	5.6202	0.96867
Run-18	Case-4	Training	14	250	0.55	37.0580	6.0875	0.96877
Run-19	Case-5	Training	18	100	0.95	27.6297	5.2564	0.97985
Run-20	Case-5	Training	19	500	0.90	27.9931	5.2909	0.98186

4. CONCLUSIONS

In this study, artificial neural network (ANN), which is an artificial intelligence technique was considered to obtain predictions of volumetric water flow rate of downstream Maritsa river. The water volumetric flow rate of the river was defined using the measurements captured at İpsala water measurement station found on Maritsa river. Accordingly, the volumetric water flow rate of Maritsa river on İpsala water measurement station was linked with a mathematical functional relation defined on four different rivers including Arda, upstream and midstream Meriç (Maritsa), Tunca, and Ergene; as well as, ten different water measurement stations found on these rivers consisting of Ivoylovgrad on Arda, Harmanlı, Svilengrad, and Kirişhane on upstream and midstream of Maritsa, Elhova, Suakacağı, and Değirmenyeni on Tunca, İnanlı, Lüleburgaz, and Yenicegörece on Ergene. Five different approaches of ANN were implemented in creation of the models, in which those are extensively specified in the text.

In other words, as output, the estimated values of the volumetric flow rate of İpsala water measurement station on the Maritsa River were obtained with the created models; and as input, the volumetric water flow rates of the four different rivers at the mentioned ten different stations were used as the algorithm input. In this way, a mathematical relationship was created between the input and output volumetric water flow rates. Large volumetric water flow rate data sets were taken into account in the ANN computations to form those mathematical algorithmic relations between 11 water measurement stations. Accordingly, the volumetric water flow rate values of four rivers, defined on 11 different water measurement stations were initially stored as 11 distinct data column matrices and kept in the computer. Next, the computations were started to include 2,000 different simulations for each applied approach of ANN, constituting a cumulative of 10,000 models. The variation of the models was executed due to alterations of the values of the equation number, epoch number, as well as the training percentage. The large number of the model formation depended on implementation of further programming as well as relies on the use of a large number of computers. In this regards, possibility of scanning all space with rapid and more alteration of the cited three adjustment parameters of ANN was acquired.

The output results of ANN were compared in terms of three statistical accuracy parameters including mean absolute error (MAE), root mean square error (RMSE), as well as the correlation coefficient (R). The approach of MAE and RMSE towards zero, as well as approach

of R towards one have indicated the higher quality of the models. In this way, all models were compared with each other. The training and testing stages of ANN algorithm were reported differently in terms of the quality of ANN simulations. As soon as the computations were completed, the models were reported in terms of the ones giving the highest R , as well as the ones generating the lowest MAE and RMSE. In this context, at the testing stage, Run-2 of 1st implemented ANN method, which had 8 equation number, 100 epoch number, as well as 0.55 training percentage have generated the highest correlation coefficient corresponding to the magnitude of 0.96469 R , at the testing stage. At the training stage, Run-20 of 5th applied ANN method, which was adjusted to 19 equation number, 500 epoch number, and 0.90 training percentage have produced the highest value of the correlation coefficient at 0.98186 R . Therefore, these two models were reported to have the two ones having the highest correlation coefficient (R) values. But, the evaluation was further conducted on the MAE and RMSE statistical error reports. One model at testing stage, and one another at training stage have procreated the lowest values of both error results. Since two models have turned the lowest values of MAE and RMSE, namely, best values of two statistical error magnitudes among the total of three; those two models were concluded to be better than the other cited two models which gave the highest and best, however one statistical error value, i.e., the R , for the testing and training stages. To summarize, at the testing stage, Run-5 of 3rd implemented ANN approach, which was created at 15 equation number, 350 epoch number, and 0.95 training percentage has procured 9.8476 m³/s MAE and 3.1381 m³/s RMSE. Besides, at the training stage, Run-19 of 5th applied ANN approach, which was brought about at 18 equation number, 100 epoch number, and 0.95 training percentage has resulted 27.6297 m³/s MAE as well as 5.2564 m³/s RMSE. In conclusion, the two models that were generated at the 3rd implemented ANN approach and 5th applied ANN approach, as Run-5 and Run-19 of testing and training stages, respectively, were concluded to be the best models among the total of 10,000 models, considering all of the ANN computations.

5. REFERENCES

- Ay, M., Kisi, O., 2014. Modelling of chemical oxygen demand by using ANNs, ANFIS and k-means clustering techniques. *J. Hydrol.* 511, 279-289.
<https://doi.org/10.1016/j.jhydrol.2014.01.054>.
- Bilgili, M., 2010. Prediction of soil temperature using regression and artificial neural network models. *Meteorol. Atmos. Phys.* 110, 59-70. <https://doi.org/10.1007/s00703-010-0104-x>.
- Bilgili, M., Ozgoren, M., 2011. Daily total global solar radiation modeling from several meteorological data. *Meteorol. Atmos. Phys.* 112, 125-138.
<https://doi.org/10.1007/s00703-011-0137-9>.
- Cobaner, M., Citakoglu, H., Kisi, O., Haktanir, T., 2014. Estimation of mean monthly air temperatures in Turkey. *Comput. Electron. Agric.* 109, 71-79.
<https://doi.org/10.1016/j.compag.2014.09.007>.
- Devlet Su Isleri (DSI), 2026. 11th regional directorate of DSI of Türkiye.
<http://edirnenehir.dsi.gov.tr/> (accessed 10 August 2026).
- Farhadi, H., Zahiri, A., Hashemi, M.R., Esmaili, K., 2019. Incorporating a machine learning technique to improve open-channel flow computations. *Neural Comput. Appl.* 31, 909-921. [10.1007/s00521-017-3120-7](https://doi.org/10.1007/s00521-017-3120-7).
- Flake, J.T., 2007. Application of the relevance vector machine to canal flow prediction in the Sevier River basin. Dissertation, Utah State University, Utah, USA.
- Graupe, D., 2007. Principles of Artificial Neural Networks, second ed. World Scientific Publishing Co. Pte. Ltd., USA.
- Han, S., Qiao, Y.H., Yan, J., Liu, Y.Q., Li, L., Wang, Z., 2019. Mid-to-long term wind and photovoltaic power generation prediction based on copula function and long short

- term memory network. *Appl. Energy* 239, 181-191.
<https://doi.org/10.1016/j.apenergy.2019.01.193>.
- Hewett, R., Leuchner, J., Carvalho, M., 2001. From climate history to prediction of regional water flows with machine learning. *IEEE*, 292-297. 10.1109/ICSMC.2001.969827.
- Ilhan, A., 2022. Forecasting of river water flow rate with machine learning. *Neural Comput. Appl.* 34, 20341-20363. <https://doi.org/10.1007/s00521-022-07576-9>.
- Ilhan, A., Bilgili, M., Sahin, B., Akilli, H., 2015. Estimation of aerodynamic characteristics for a horizontal axis wind turbine. *Int. J. Nat. Eng. Sci.* 9(2), 51-57.
<https://ijnes.org/index.php/ijnes/article/view/232/211>.
- International Renewable Energy Agency (IEA), 2025. Renewable energy statistics.
<https://www.irena.org/> (accessed 10 August 2026).
- Jung, J., Broadwater, R.P., 2014. Current status and future advances for wind speed and power forecasting. *Renew. Sust. Energ. Rev.* 31, 762-777.
<https://doi.org/10.1016/j.rser.2013.12.054>.
- Kavasseri, R.G., Seetharaman, K., 2009. Day-ahead wind speed forecasting using f-ARIMA models. *Renew. Energy* 34(5), 1388-1393.
<https://doi.org/10.1016/j.renene.2008.09.006>.
- Khosravi, A., Koury, R.N.N., Machado, L., Pabon, J.J.G., 2018. Prediction of hourly solar radiation in Abu Musa Island using machine learning algorithms. *J. Clean. Prod.* 176, 63-75. <https://doi.org/10.1016/j.jclepro.2017.12.065>.
- Liang, S., Nguyen, L., Jin, F., 2018. A multi-variable stacked long-short term memory network for wind speed forecasting. 2018 IEEE International Conference on Big Data (Big Data), Seattle, WA, USA, 4561-4564.

- Liu, H., Tian, H., Li, Y., 2015. An EMD-recursive ARIMA method to predict wind speed for railway strong wind warning system. *J. Wind Eng. Ind. Aerodyn.* 141, 27-38.
<https://doi.org/10.1016/j.jweia.2015.02.004>.
- N-Sci Technologies, 2025. The importance of hydropower. <https://nsci.ca/2019/08/14/the-importance-of-hydro-power/> (accessed 10 August 2026).
- Renewable Energy Policy Network for the 21st Century (REN21), 2025. Global status report. <https://www.ren21.net/> (accessed 10 August 2026).
- Sahraei, A., Chamorro, A., Kraft, P., Breuer, L., 2021. Application of machine learning models to predict maximum event water fractions in streamflow. *Front. Water* 3, 652100. 10.3389/frwa.2021.652100.
- Shi, X., Lei, X., Huang, Q., Huang, S., Ren, K., Hu, Y., 2018. Hourly day-ahead wind power prediction using the hybrid model of variational model decomposition and long short-term memory. *Energies* 11(11), 3227. <https://doi.org/10.3390/en11113227>.
- Tascikaraoglu, A., Uzunoglu, M., 2014. A review of combined approaches for prediction of short-term wind speed and power. *Renew. Sust. Energ. Rev.* 34, 243-254.
<https://doi.org/10.1016/j.rser.2014.03.033>.
- Tayfur, G., Singh, V.P., Moramarco, T., Barbetta, S., 2018. Flood hydrograph prediction using machine learning methods. *Water* 10(8), 968. 10.3390/w10080968.
- Yu, C., Li, Y., Bao, Y., Tang, H., Zhai, G., 2018. A novel framework for wind speed prediction based on recurrent neural networks and support vector machine. *Energy Convers. Manag.* 178, 137-145. <https://doi.org/10.1016/j.enconman.2018.10.008>.
- Zaytar, M.A., Amrani, C.E., 2016. Sequence to sequence weather forecasting with long short-term memory recurrent neural networks. *Int. J. Comput. Appl.* 143(11), 7-11.
<http://dx.doi.org/10.5120/ijca2016910497>.

- Zhang, J., Yan, J., Infield, D., Liu, Y., Lien, F., 2019a. Short-term forecasting and uncertainty analysis of wind turbine power based on long short-term memory network and Gaussian mixture model. *Appl. Energy*. 241, 229-244.
<https://doi.org/10.1016/j.apenergy.2019.03.044>.
- Zhang, Z., Qin, H., Liu, Y., Wang, Y., Yao, L., Li, Q., Li, J., Pei, S., 2019b. Long short-term memory network based on neighborhood gates for processing complex causality in wind speed prediction. *Energy Convers. Manag.* 192, 37-51.
<https://doi.org/10.1016/j.enconman.2019.04.006>.
- Zhang, Z., Ye, L., Qin, H., Liu, Y., Wang, C., Yu, X., Yin, X., Li, J., 2019c. Wind speed prediction method using shared weight long short-term memory network and Gaussian process regression. *Appl. Energy* 247, 270-284.
<https://doi.org/10.1016/j.apenergy.2019.04.047>.