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RESEARCH PAPER

An Up-to-date Approach Using Machine Learning Methods in Fish Condition Factor Estimation

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Abstract

The present study aims to estimate the condition factor (CF) of mackerel (*Trachurus mediterraneus*, Steindachner, 1868) by making use of three input parameters (length, weight, and sex) that the CF is related to. For this purpose, data were obtained from 866 mackerel fished in the Eastern Black Sea. In the present study, the estimation performances of Multiple Linear Regression (MLR), Levenberg-Marquardt (LM), and Gaussian Process Regression (GPR) models, among statistical instruments, were compared. Quality levels of the models were compared by making use of the coefficient of determination (R^2), the root mean square of error (RMSE), and the mean absolute percentage error (MAPE) criteria. It was aimed to select the model, which yields the best estimation performance for length-weight relationships, by comparing the verification results. The results showed that the ANN trained with the GPR model yielded the highest accuracy. It was determined that the R^2 of estimation results achieved using the GPR model was higher than 0.99 for all the parameters. Given these results, it can be concluded that the GPR model that is suggested here is a robust instrument to estimate CF at a high level of accuracy.

Introduction

Fish meets min. 15% of the animal protein needs of more than 4.5 billion individuals. The unique nutrient properties of fish make it irreplaceable considering the health of billions of consumers living in developed and developing countries (Béné et al., 2015). Fish is rich in omega-3 fatty acids, vitamins, and minerals for human health. Fish consumption contributes to reducing the risk of heart disease, improves brain function, and promotes healthy skin and hair. It is also a low-fat protein alternative that is low in saturated fat, thus making it an essential part of healthy lifestyles (Shahzad, 2024). Thus, sustainable fish stock management, increasing production quantity, and improving quality are among the urgent necessities.

Monitoring the growth level and behavior of fish is an important part of a healthy aquaculture process (Saberioon et al., 2017; Li & Du, 2022). Including wild fishing and aquaculture production, the average global fish production for the period 2018–2020 was 178 million tons. It is estimated to increase to 201 million tons (with an increase by 12.8%) as of the year 2030 (OECD, 2022; Steenson & Creedon, 2022). Ensuring a sufficient amount of food and a sustainable healthy diet is a necessity for 8 billion individuals living on earth, and it is estimated that it would be required to feed 2 billion more people by the year 2050 and there would be a 1.1% increase annually in the demand for the food (European Union, 2015; Sacchettini et al., 2021).

Length-weight relationships (LWRs) are used in estimating the biomass by making use of length distribution that is obtained more easily, determining the growth models of species, and determining the population status and spatiotemporal change in the adaptation (Froese, 2006). The LWR, growth pattern, and CF are very important in analyzing and managing fish resources (Dinh et al., 2022; Yazıcı et al., 2020; Yazıcı et al., 2024). Similarly, the condition factor (CF) is also a useful parameter when examining the environmental effects on the fish and it indicates the relative health status of fish populations (Froese, 2006).

Various coordination and canonic analysis methods and univariate and multivariate linear, nonlinear, and logistic regressions were utilized when examining how different characteristics of fish are associated with the environment (Laë et al., 1999; Payne & Harvey, 1989; Schlesinger & Regier, 1982). These traditional methods, particularly those based on multiple regression, can resolve many problems but they also have some insufficiencies. Even though relationships between parameters are generally nonlinear in the environmental sciences, methods rely on linear principles. Nonlinear conversion of parameters allows for remarkable (yet insufficient) improvements in results. Besides that, with an error back-propagation procedure, a neural network lays the foundation for a useful technique that can be utilized together with regression analyses, especially in nonlinear relationships (Rumelhart, 1986).

Artificial neural network (ANN) is a robust data mining procedure used in estimating the inclination scores thanks to its robustness against non-normal residual distributions, capacity to reveal complex nonlinear relationships between procedures and confusing variables, and trainability based on observed cases and non-fundamental model specification (Collier et al., 2021; Işık et al., 2024). ANN refers mainly to mathematical structures fulfilling various functions through artificial neurons. Neurons are organized in layers constituting the neural network. The results are obtained by subtracting the weight of neurons that are responsible for errors and it is called the "learning process" (Abdullah et al., 2018). ANN offers a flexible method for identifying the relationship between variables without requiring an assumption in resolving complex structural problems (Özger et al., 2020). In ANNs, neurons are the fundamental components that act as supervisors receiving input data from one or more features to create an output. A typical network has three layers: input, hidden, and output layers. The inputs of the network are matched frequently to the outputs of the network through a diagram directed by weighted nodes (Çepelioğullar et al., 2018). ANNs, are inspired by the brain of humans. These networks are inspired from the human brain. They were constructed and organised to work (think) like it. Since artificial neural networks consist of artificial neurons, they are commonly named ANN. In an ANN, neurons are connected to each other via weights and they operate parallelly in general. Network parameters are fine-adjusted to recall, learn, and generalize the data (Chauhan et al., 2022).

Although traditional statistical methods or mathematical models offer suitable and rapid advantages in establishing a model, they also have disadvantages. A method should ensure a linear relationship between dependent and independent variables and the observations are independent. There are no multiple connections between the variables. In other words, it is a linear model and there is no problem in resolving the correlation and overlapping problems between the independent variables (Wu et al., 2022). ANNs offer many advantages. Developing NN models requires less formal statistical training. These models can indirectly perceive complex nonlinear interactions between independent and dependent variables. They can explore all the possible interactions between predictive variables. Moreover, they can be created using various training procedures (Akkan et al., 2024; Uncuoglu et al., 2022).

The present study aims to compare the reliability, accuracy, and estimation power of ML in estimating CF value by using length, weight, and sex variables. For this purpose, estimations were conducted employing criteria including length, weight, and sex by making use of the MLR, MLP-LM, and GPR methods in algorithm selection.

Material and Method

The samples were randomly selected among the mackerel (*Trachurus mediterraneus*, Steindachner, 1868) fishes brought to the Giresun's fisheries, Türkiye. To determine the biometric characteristics of fish, length and weight measurements were made and sex was determined in the laboratory. The dataset for this study included a total of 866 mackerel samples. Table 1 represents the descriptive statistics for the mackerel samples.

Statistical Calculations and Artificial Neural Networks

Calculation of Condition Factor

At a specific length, the fish having a higher weight has a higher condition factor. The comparison factor is Fulton's condition factor, which is the most widely used one and calculated assuming b=3 in the length-weight relationship (Erkoyuncu, 1995; Ricker, 1975; Sparre & Venema, 1992).

The condition factor was calculated using the formula;

$$CF = (W/L^3)*100 \text{ (Ricker, 1975).}$$

where, W: Weight (g), and L: Total length (cm).

CF examined in the present study was estimated using the ANN in MATLAB 2018 package software. CF data were trained using the ANN and MLR methods. The

Table 1. The descriptive statistics results of mackerel samples

		Length (cm)	Weight (g)
Female	Mean	14.6513	27.3686
	Std. Error of Mean	0.06654	0.37655
	Minimum	11.00	10.00
	Maximum	17.60	53.00
	N	567	567
Male	Mean	14.8519	29.1168
	Std. Error of Mean	0.10099	0.59708
	Minimum	11.00	10.00
	Maximum	18.80	58.00
	N	214	214
Juvenile	Mean	9.5929	7.6000
	Std. Error of Mean	0.14844	0.36098
	Minimum	7.90	4.00
	Maximum	12.30	14.00
	N	85	85
Total	Mean	14.2044	25.8603
	Std. Error of Mean	0.07356	0.35534
	Minimum	7.90	4.00
	Maximum	18.80	58.00
	N	866	866

purpose was to achieve the most accurate CF estimation model. Since it is simple and has been widely used for various problems, linear regression was used in the paper. Moreover, the NN was used for its high performance in identifying and estimating nonlinear relationships. These three models were chosen because they are among the most widely used models.

Application of Artificial Neural Networks

Multiple Linear Regression (MLR)-Based CF Model

The Multiple Linear Regression method was implemented using MATLAB 2018b. MLR is designed to establish a linear equation based on observed values to clarify the linear relationships between dependent and independent variables (Abba et al., 2017). The MLR equation used in this study is the following (Palabıyık & Akkan, 2024; Said & Khan, 2021):

$$Y=b_0+b_1X_1+b_2X_2........+b_kX_k \quad (1)$$

MLR is one of the popular parametric models thanks to its simplicity and ease of interpretation and is used as a reference to compare the performances of other models (Gkerekos et al., 2019).

Artificial Neural Network (ANN)-Based Levenberg Marquardt (MLP-ANN)

The MLP is a form of ANN, which can be available for solving regression and can also be employed in classification tasks. It has several neurons and it is constructed of three different types of layers. The input layer is the first layer, which contains the input variables to be processed. The output layer is developed to calculate the value of the target parameter or output using the data obtained from hidden layers. The hidden layer must be placed between these two layers (Jin et al., 2022).

A typical three-layer NN is utilised in the MLP method. In this method, the input dataset is fed to input layers and the output layer would contain the output parameter to be achieved through calculations done in the hidden layer. The number of hidden layers can be altered or adjusted with the complexity of the task in order to achieve the most efficient outcomes in the modelling of a process (Isık & Akkan, 2025). There are several ways to train the network. The most popular and practical ones are the gradient descent and the Levenberg-Marquardt (LM). A back-propagation method, which is based on gradient descent, is employed to minimize the square error between reference and target outputs, and the nonlinear functions are optimized using LMA (Dokht Shakibjoo et al., 2022).

LM training algorithm is a data-oriented calculation method that can be utilized more specifically in case of a nonlinear relationship between model input and output parameters (Nguyen-Truong & Le, 2015). The ANN-based LM algorithm considers three process layers or nodes; in other words, there are one input layer, one or more hidden layers, and one output layer (Tarawneh, 2013).

The weights are calculated by identifying the RMSE and optimized by making use of gradient methods. The most known method relying on the steepest descent concept is the back-propagation algorithm. Levenberg Marquardt (LM), a second-degree optimization method, is known to be generally more productive in comparison to the fundamental back-propagation algorithm and it was used in the present study (trainlm function of MATLAB) (Ahmed et al., 2010).

Levenberg Marquardt, one of the most widely used hybrid algorithms, converges a problem to the ideal solution. This algorithm is called hybrid since it incorporates two approaches (the Steepest Descent and the Gauss-Newton) in order to minimize the error function (Chauhan et al., 2022).

By using the 3-layered Levenberg-Marquardt algorithm for the ANN-based CF model, two different training, verification, and testing data were utilized for CF values. The estimations were performed as follows: First of all, the Levenberg Marquardt algorithm was used with the combination of 70% training data, 15% verification data, and 15% testing data; then, the combination of 80% training, 10% verification, and 10% testing data was used for the LM algorithm used for CF values the second time. At least one error result was used in order to reveal the accuracy and optimality of the ANN model. The data was operated by MATLAB R2018b using the nntool function for the ANN model. The input parameters were set as sex, weight and length, and the output parameter was set as CF value. The ANN architecture is shown in Figure 1. The 9-neuron and 15-neuron ANN models used for training, testing and validation of the network are also given in Figure 2.

Gaussian Process Regression

Gaussian Process Regressions **(**GPRs) are employed directly in modeling Gaussian data and as the basis for non-Gaussian models such as generalized linear models. Thus, employing the GPR-based Gaussian process regression is both simple and accurate for small data clusters having a high level of generality (Li et al., 2021; Zhang & Xu, 2021).

GPR is a non-parametric Bayesian nonlinear regression method that offers a good learning performance even for small data clusters of nonlinear regression problems and has a robust theoretical base (Sheng et al., 2021).

GPR has various advantages, including the capacity to analyze uncertainty in estimations and the flexibility to work with limited datasets (Mahmoodzadeh et al., 2021).

GPR operation yields a regression with various Gaussian distributions. This approach determines the function as an example of different Gaussian distributions having average function and joint variance function (Mukesh Kumar & Kavitha, 2021). The variables that should be set to achieve an optimum GPR model include the kernel function, kernel scale, and kernel parameter (Aladwani & Elsharkawy, 2023).

The average and variance of a Gaussian distribution are used for calculating the probability of an input vector. GPR model produces an average and correlation vector rather than a scaler average and variance (Kocijan et al., 2007).

The estimation of CF values calculated using the real measurements was performed using the MATLAB machine learning toolkit.

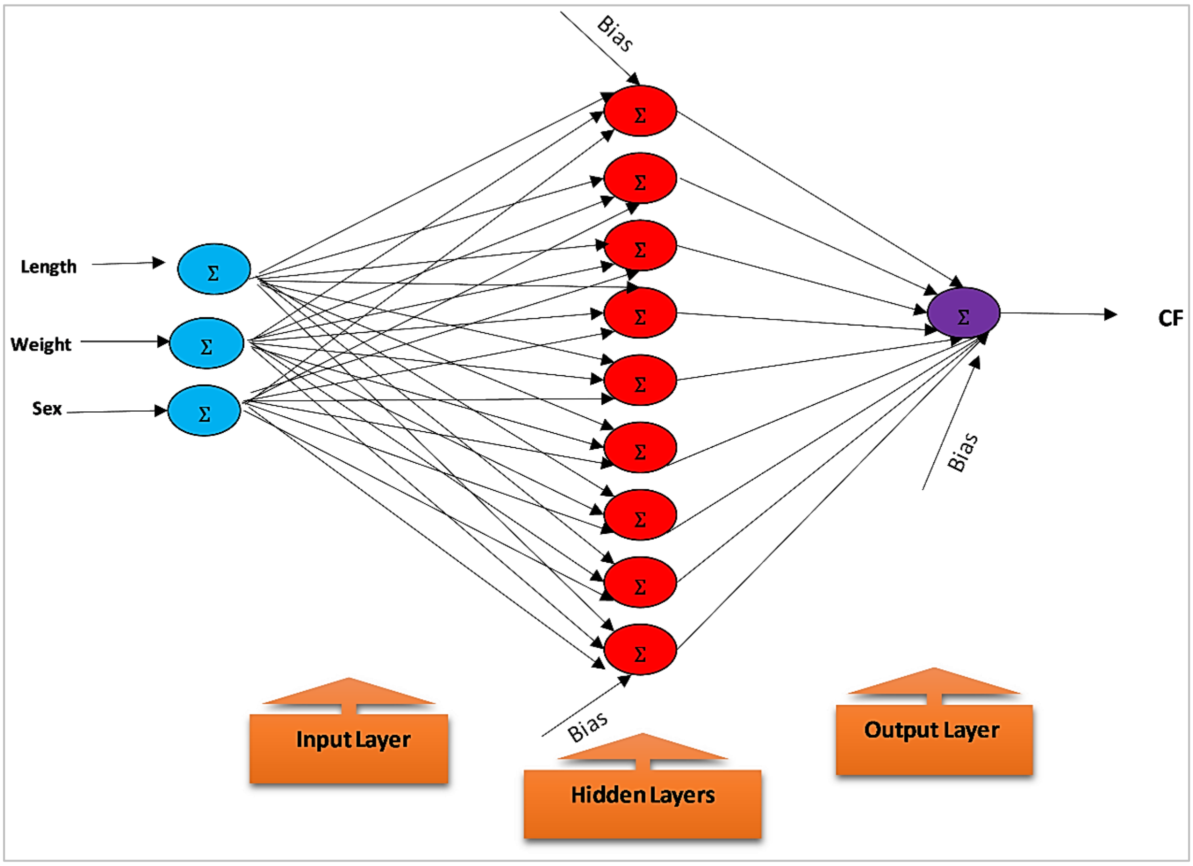

Figure 1. ANN architecture used in this study.

Determination of Model Effectiveness

Models were compared by making use of the specification R^2, RMSE, and MAPE criteria. RMSE, MAPE, and R^2 were obtained utilizing Equations (1), (2), and (3), respectively. Model training, statistical analysis of parameters, correlation coefficient calculations, error analysis, etc. were performed mainly on MATLAB 2018b.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(output_t - target_t)^2} \tag{1}$$

$$MAPE = \frac{1}{n}\sum\nolimits_{t=1}^{n}\left|\frac{output_t - target_t}{target_t}\right| \tag{2}$$

$$R^2 = 1 - (\sum\nolimits_{t=1}^{n}(output_t - target_t)^2 / (output_t - \bar{target_t} \tag{3}$$

Results and Discussion

In this section, the estimation performances of three ML algorithms including GPR, MLR, and MLP-ANN were compared. All these algorithms were programmed in MATLAB. Then, the accuracies of their CF estimation results were comparatively analyzed.

CF Data Description

A total of eight hundred sixty-six fish species in the mackerel were collected during the study period. The highest total length of 18.8 cm and weight of 58 g were recorded from samples. The mean length and weight of the collected samples were 14.20 cm and 25.86 g for mackerel. The calculated mean CF values were 0.906 (±0.118) for females, 0.943 (±0.213) for males, and 0.809 (±0.0744) for juveniles indicating variations among the mackerel (Figure 3). Also, the calculated CFs were lowest in juveniles (0.4009) and highest in males (2.6267). Moreover, there was no significant difference in mean CF values between sexes (t-test, $P=0.1396$). However, differences between CF values of females, males, and juveniles were detected using the covariance analysis (ANCOVA, $P<0.05$).

Gaussian Process Regression

GPR model's CF estimation performances, comparison between real CF vs. estimated values, R^2 diagrams, and the residual errors between estimated CF values and real values are illustrated in Figure 4.

Among all ML algorithms examined, the GPR algorithm yielded the best estimation performance with the lowest MAE, MSE, and RMSE (0.00017, 2.97, and 0.0017) and the highest R^2 (1) values. This result is supported by a high R^2 determination coefficient and low residual errors seen in Figure 4. The estimation data, which are perfectly close to the estimation line, and the proximity of residual errors to the "zero" line can be clearly seen. The GPR used in the present study showed the highest estimation performance.

MLR-Based CF Model

In the MLR-based CF model, estimations were performed by using the same training dataset as the one used in the ANN model. The robustness of MLR models was examined by using the determination coefficient (R^2).

The results of MLR estimations and performances are presented in Table 2. In general, MLR modeling was determined to have accuracy values $R^2=0.5554$, RMSE=0.0027762, and MAPE=0.0472363. Given these results, it can be concluded that MLR is not a suitable method for estimating the CF.

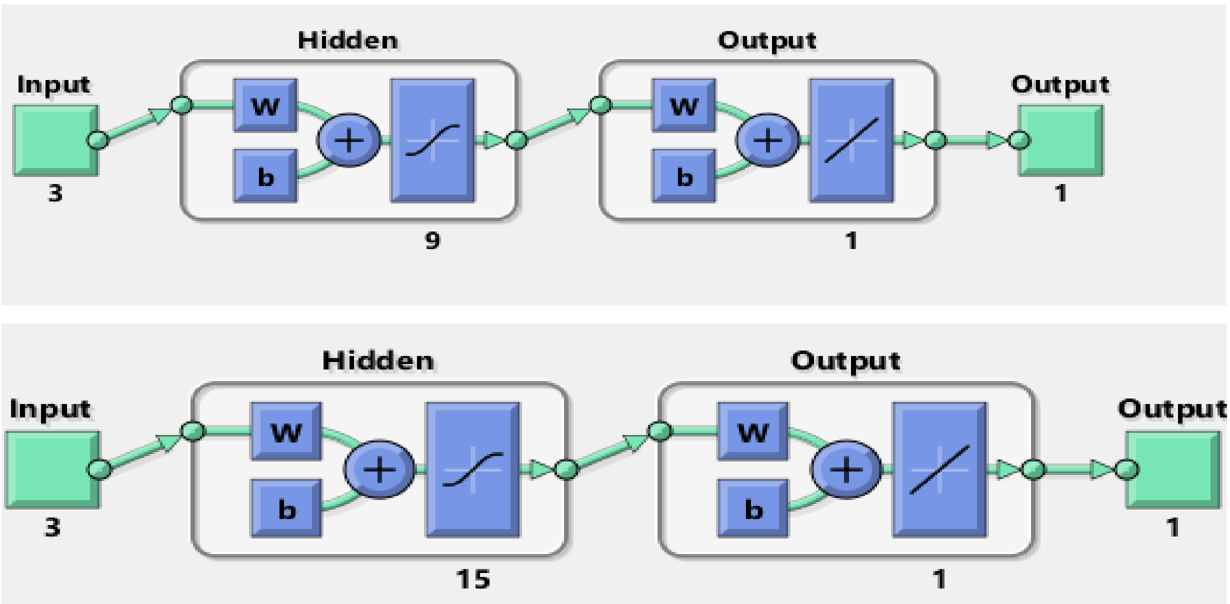

Figure 2. ANN model used in this study.

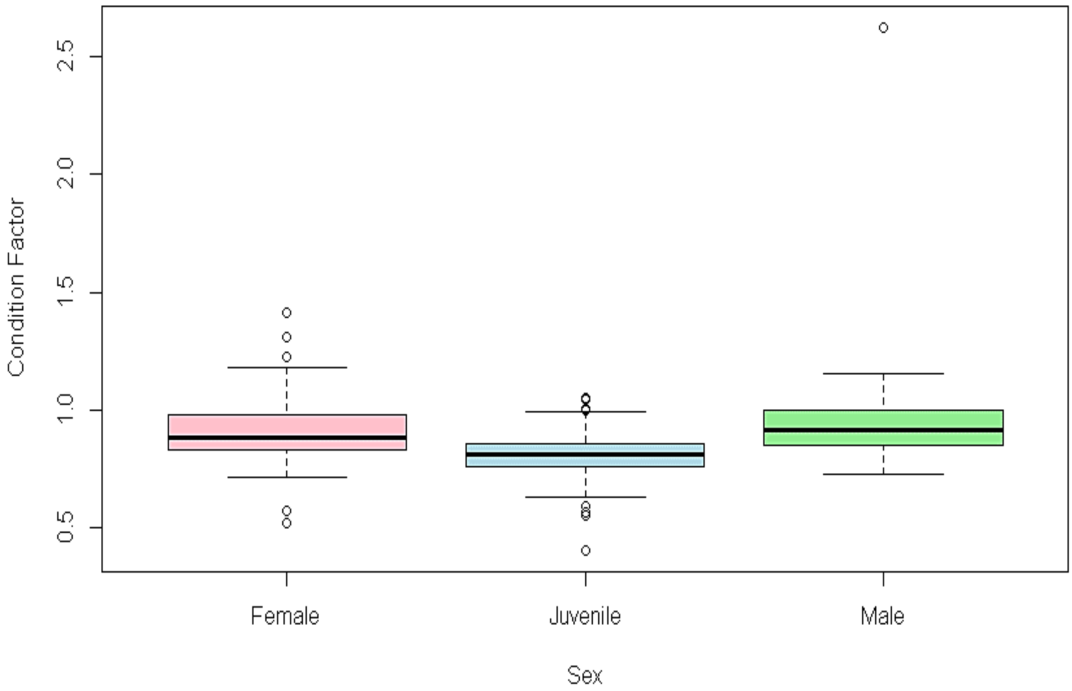

Figure 3. The boxplots of CF values in the mackerel.

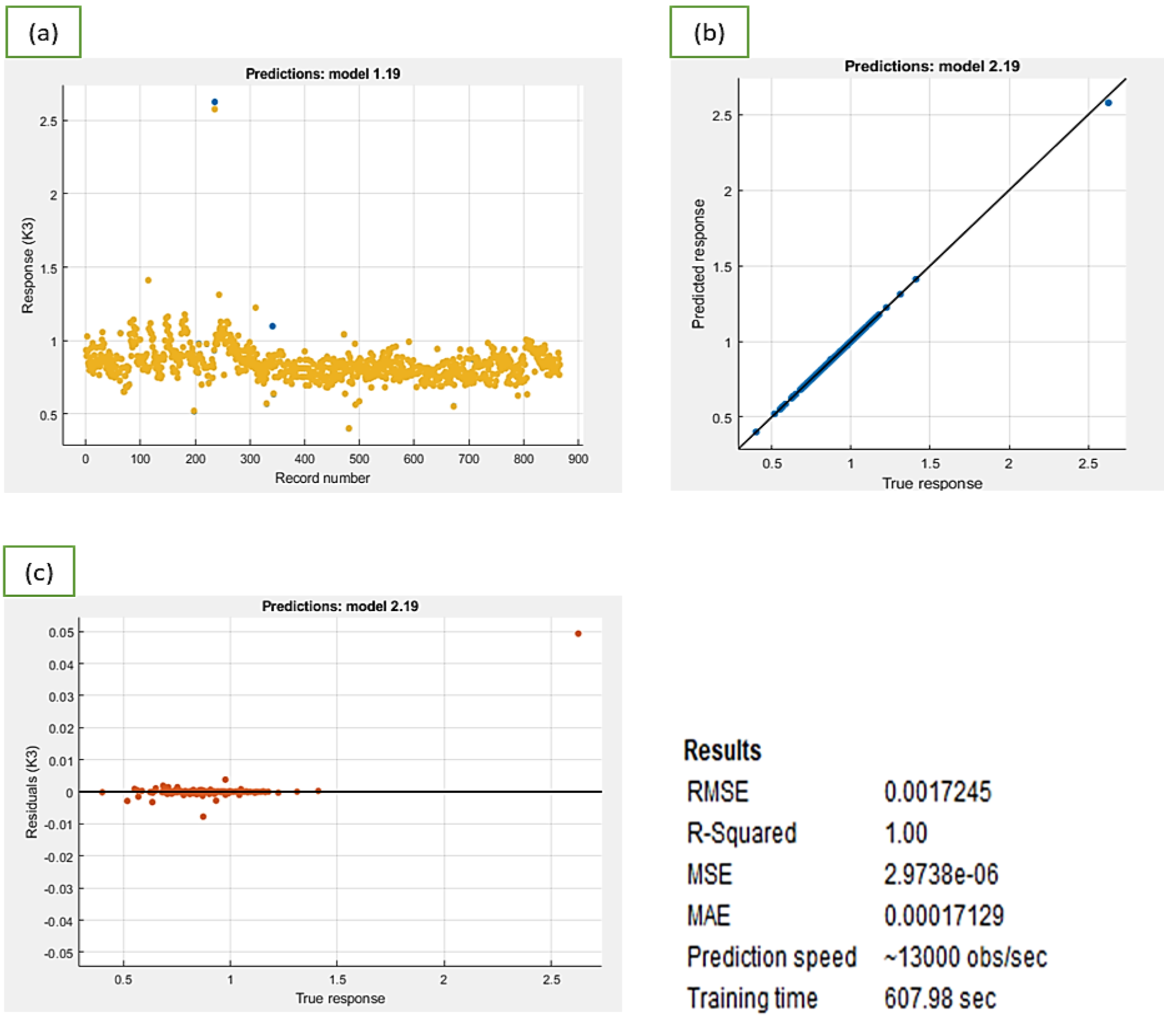

Figure 4. CF prediction performance of the GPR model (a), results comparing predicted values against actual CF (b), residual results between predicted CF values and actual values (c).

CF Estimation by MLP-ANN Model

Parity diagrams and regression models of MLP-ANN estimation of condition factor indices are presented in Figure 5. MLP-ANN's modeling errors were determined using the sum of the squared errors. In general, low modeling errors were found in all MLP-ANN models. This finding suggests that MLP-ANN has the capacity to accurately and reliably estimate CF.

In Figure 5, the dataset regression by 70% training, 15% verification, and 15% testing for the Levenberg-Marquardt algorithm in the first application is presented both separately and as a whole. In these diagrams, the function presented with the dotted line is the target function that was determined to be the best mode by the neural network. In this case, there will be a correlation coefficient that equals 1 (R^2=1); otherwise, it would be lower than 1. The function through the vertical line represents a function adapted to the data points by the neural network. This figure illustrates each one of the three data clusters named training, verification, and test. Moreover, it was determined that the regression of each data category was higher than 0.91 for each number. The diagram of calculated CF values vs. those estimated using ANN is presented in Figure 5.

As seen in Figure 5, given the R^2 values (R^2= training (0.93), testing (0.91), validation (0.92), and total (0.92)), ANN was found to be an effective method for CF modeling.

The performance analysis of the datasets used in LM algorithm is presented in Figure 6. LM method would perform infinite iterations and not finish the training without achieving the best result. If the error value meets the determined criterion, then the iteration process will be ended. In the present study, the best verification result was found to be lower than 0.5. Epoch was found to be 0.0018303 after 18 iterations. The best verification result is presented in Figure 6.

Moreover, Figure 7 illustrates the histogram of 20-division estimation error. It can be seen in Figure 7 that most of the data points fall into a smaller error range. It can also be seen that the error, which is defined as the difference between target and output values, generally concentrated on a single zone although it did not cluster

Table 2. MLR accuracy values

		Confidence Intervals for Beta		Performance for the Test Set		R^2	F	p-value for F Test	Std. Error Est.
Variables	**Beta**	**Lower Bound**	**Upper Bound**	**Test Values**	**Predicted Values**	**0.5554**	3.26E+02	0.0000	6.55E-03
Constant	2.466781	2.201643	2.731919	0.7513	0.7830				
X1	-0.010451	-0.013633	-0.007270	0.8117	0.8631			**RMSE**	**0.0027762**
X2	-0.108618	-0.116310	-0.100925	0.6244	0.7934			**MAPE**	**0.0472363**
X3	0.023212	0.021751	0.024672	0.8061	0.8009				
				0.7153	0.7904				
				0.8385	0.8705				
				0.7738	0.7387				
				0.7391	0.7387				
				0.8746	0.8547				
				0.7951	0.7979				
				0.7156	0.7514				
				0.8945	0.8779				
				0.8752	0.8779				
				0.7230	0.7746				
				0.7230	0.7851				
				0.8371	0.8547				
				0.9513	0.9244				
				1.0054	0.9708				
				0.7447	0.8083				
				0.6330	0.7387				
				0.9840	0.8622				
				0.9840	0.8622				
				0.9989	0.8749				
				0.9430	0.8517				
				0.9779	0.8854				
				0.9430	0.8517				
				0.9430	0.8517				
				0.9917	0.9086				
				0.9512	0.9086				
				0.9184	0.8854				
				0.9318	0.9086				
				0.9318	0.9086				
				0.9129	0.8981				
				0.7870	0.8053				
				0.9444	0.9318				
				0.9129	0.9086				
				0.9444	0.9318				
				0.8815	0.8854				
				0.8946	0.8981				
				0.8946	0.9086				
				0.8637	0.8854				
				0.9069	0.9214				
				0.8464	0.8854				
				0.8464	0.8854				

Table 2. *Continued*

		Confidence Intervals for Beta		Performance for the Test Set		R^2	F	p-value for F Test	Std. Error Est.
Variables	**Beta**	**Lower Bound**	**Upper Bound**	**Test Values**	**Predicted Values**	**0.5554**	3.26E+02	0.0000	6.55E-03
				0.9481	0.8696				
				0.8296	0.7768				
				0.8593	0.8000				
				0.8133	0.7663				
				0.9397	0.8928				
				0.9112	0.8592				
				0.9397	0.8824				
				0.9682	0.9160				
				0.9397	0.8928				
				0.8655	0.8464				
				0.8376	0.8232				
				0.8214	0.8232				
				0.7666	0.7768				
				0.8762	0.8696				
				0.7666	0.7768				
				0.8593	0.8696				
				0.8956	0.9160				
				0.7639	0.8000				
				0.8269	0.8592				
				0.8545	0.8306				
				0.7997	0.7970				
				0.8468	0.8538				
				0.8468	0.8538				
				0.8468	0.8538				
				0.8703	0.8771				
				0.7851	0.8074				
				0.8082	0.8306				
				0.7851	0.8074				
				0.8082	0.8306				
				0.7935	0.8306				
				0.7944	0.8771				
				0.8159	0.9003				
				0.9159	0.9541				
				0.8752	0.9077				
				0.7664	0.8149				
				0.8352	0.9205				

in a very narrow region. This observation applies to training, testing, and verification. Thus, it suggests that the current neural network can effectively learn the relationship between input parameters and final output.

RMSE, MAPE, and R^2 used in analyzing the verification of CF via an artificial neural network by implementing the Levenberg Marquardt algorithm are presented in Table 3. The error between the modeled output and the simulated dataset was employed in assessing the effectiveness of this algorithm. Given the previous experiences, an optimal network generally includes 2 to 15 hidden networks (Najjar et al., 1996; Sinshaw et al., 2019; Chauhan & Trivedi, 2022).

The number of neurons in the hidden layer was set to range between 2 and 15 and the tests were performed. However, the best performance was achieved with the ANN model with 9 hidden neurons. Thus, the number of hidden neurons was set to be 9 in this study. The model 3–9–1–1 was determined to be the best model in terms of R^2.

In the second application, the dataset regression performed for the Levenberg Marquardt algorithm by using 80% training, 10% verification, and 10% testing combination is presented in Figure 8 both separately and in total.

As shown in Figure 8, R^2 (R^2= training (0.93), testing (0.92), validation (0.91), and total (0.93)) values of the second ANN application showed that it yielded better performance in CF modeling in comparison to the application performed using 70% training, 15% testing, and 15% verification.

Epoch was met with the value 0.0018938 after 17 iterations. The best verification result is presented in Figure 9.

Figure 10 illustrates the result data of the 20-division estimation error histogram. It can be seen in this figure that most of the data points fall into smaller error range boxes.

ANN-based verification assessment of CF by using the Levenberg Marquardt algorithm (80%-10%-10%) is presented in Table 4 by using RMSE, MAPE, and R^2. The best RMSE, MAPE, and R^2 values were obtained from the algorithm performing the estimations by using 15 hidden neurons. Thus, more accurate CF results were achieved by making use of 15 hidden neurons. The model 3–15–1–1 was determined to be the best model in terms of R^2 value.

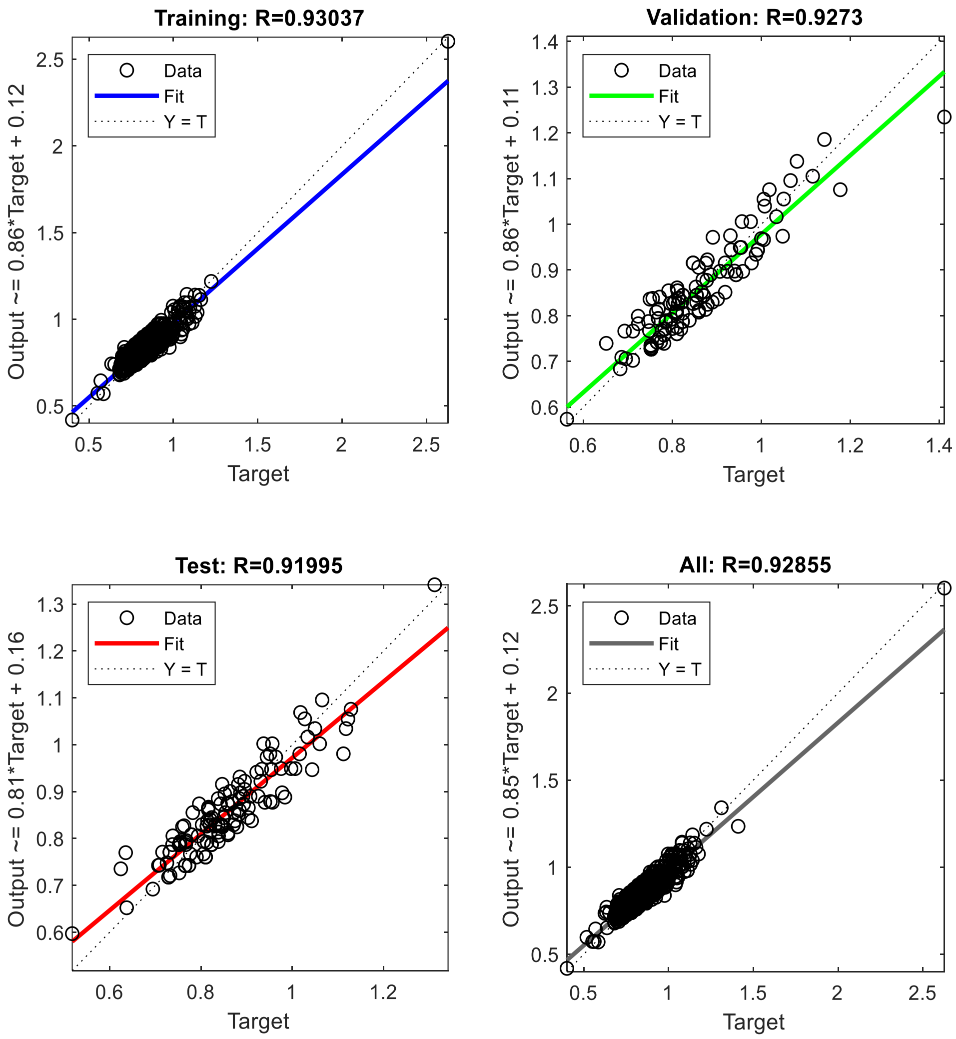

Figure 5. Regression coefficients of training, validation, testing and all in the neural network model as indicated.

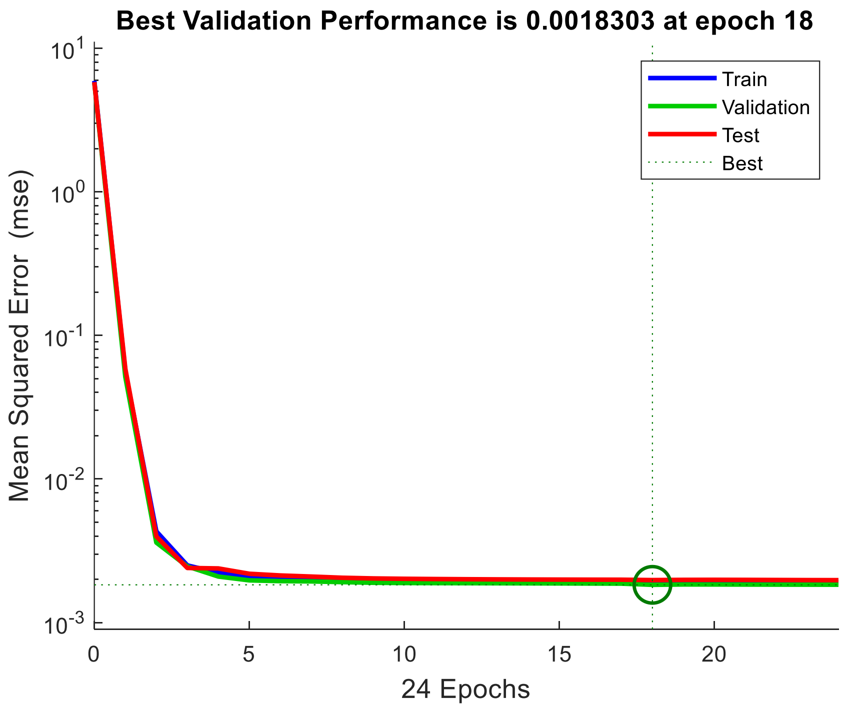

Figure 6. Best validation performance model based on the Levenberg-Marquardt algorithm.

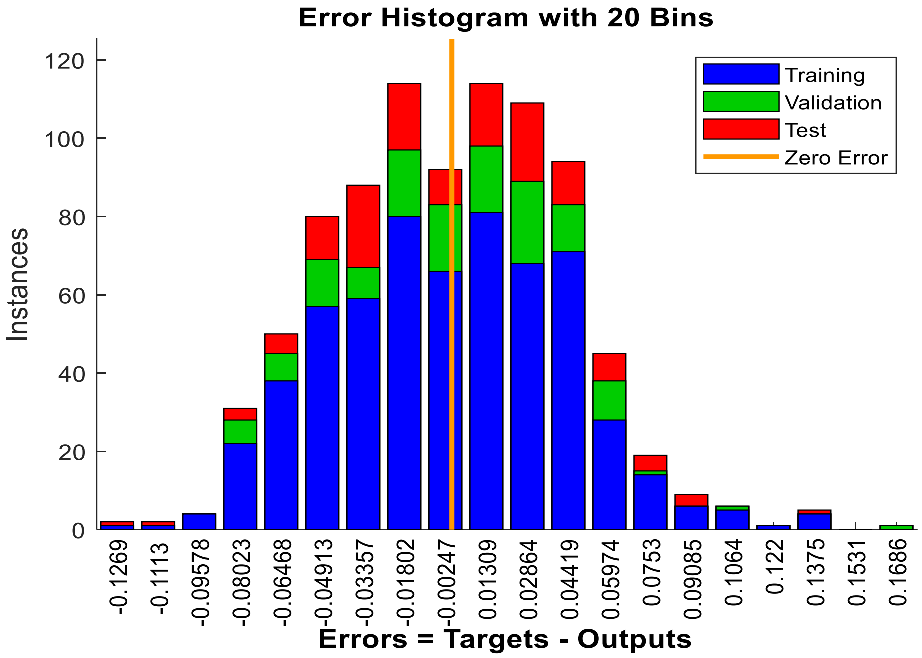

Figure 7. Error histogram for training, testing, and validation.

Table 3. Performance statistical results of the model in training, validation and testing for MLP-ANN (Levenberg-Marquardt 70%-15%-15%)

	MLP-ANN (Levenberg-Marquardt)			
Number of hidden nodes	**Dataset**	**RMSE**	**MAPE**	**R^2**
	Validation	0.0442	4.4799	0.8692
3–2–1-1	Training	0.0454	4.3524	0.9300
	Testing	0.0453	4.5555	0.9226
	Validation	0.0463	4.2973	0.9159
3–3–1-1	Training	0.0453	4.4146	0.9281
	Testing	0.0454	4.3350	0.9005
	Validation	0.0436	4.3797	0.9048
3–4–1-1	Training	0.0462	4.4120	0.9279
	Testing	0.0442	4.0597	0.9117
	Validation	0.0481	4.4998	0.9010
3–5–1-1	Training	0.0434	4.2265	0.9061
	Testing	0.0529	4.5668	0.9619
	Validation	0.0411	4.0148	0.9129
3–6–1-1	Training	0.0441	4.2172	0.9338
	Testing	0.0472	4.4204	0.9025
	Validation	0.0412	3.7775	0.9200
3–7–1-1	Training	0.0444	4.2759	0.9317
	Testing	0.0460	4.3436	0.9130
	Validation	0.0415	4.0162	0.9358
3–8–1-1	Training	0.0466	4.4589	0.9242
	Testing	0.0442	4.3454	0.9013
	Validation	**0.0428**	**3.9578**	**0.9273**
3–9–1-1	**Training**	**0.0440**	**4.2598**	**0.9303**
	Testing	**0.0444**	**4.2983**	**0.9199**
	Validation	0.0424	4.1910	0.9063
3–10–1-1	Training	0.0454	4.3033	0.9319
	Testing	0.0431	4.1942	0.9017
	Validation	0.0460	4.4873	0.9039
3–11–1-1	Training	0.0426	4.1127	0.9375
	Testing	0.0453	4.2678	0.9078
	Validation	0.0376	3.7629	0.9104
3–12–1-1	Training	0.0436	4.1560	0.9348
	Testing	0.0484	4.7750	0.9184
	Validation	0.0407	4.0339	0.9143
3–13–1-1	Training	0.0446	4.2204	0.9331
	Testing	0.0435	4.1420	0.9117
	Validation	0.0442	4.2569	0.9109
3–14–1-1	Training	0.0433	4.1776	0.9350
	Testing	0.0471	4.4192	0.9062
	Validation	0.0437	4.1258	0.9138
3–15–1-1	Training	0.0426	4.0600	0.9353
	Testing	0.0457	4.1195	0.9244

Comparison of ML Models

It was determined that the GPR model yielded the most accurate estimation among the models examined here. Comparative results of the models are presented in Table 5.

Among the fish condition factor estimation methods above, the Levenberg- Marquardt method yielded the worst performance, and the MLR method yielded the second-worst performance. In the literature, it was confirmed that the performance of the method recommended here is superior in all the assessment criteria. Examining different studies, it was reported that, in comparison to other estimation models, the GPR model yielded better results in terms of MAE, RMSE, and R values which are the performance criteria (Benzer & Benzer, 2018; Huan et al., 2020; L. Zhang et al., 2020; Guo et al., 2022).

Finally, in comparison to the other two models, the GPR model yielded a perfect R^2 value and a very low RMSE value. Comparing the models examined here, the GPR model showed a perfect estimation capacity in all the parameters. Table 5 represents the superior regression and generalization capacity of the GPR model.

Conclusion and Suggestions

In this study, the performances of three ML-based models in the estimation of CF by using the data obtained from mackerel samples were determined and compared. The CF estimations performed using the MLR model were found to not have a very strong relationship with the observed results. Thus, it was not preferred due to its poor performance in estimating the CF values.

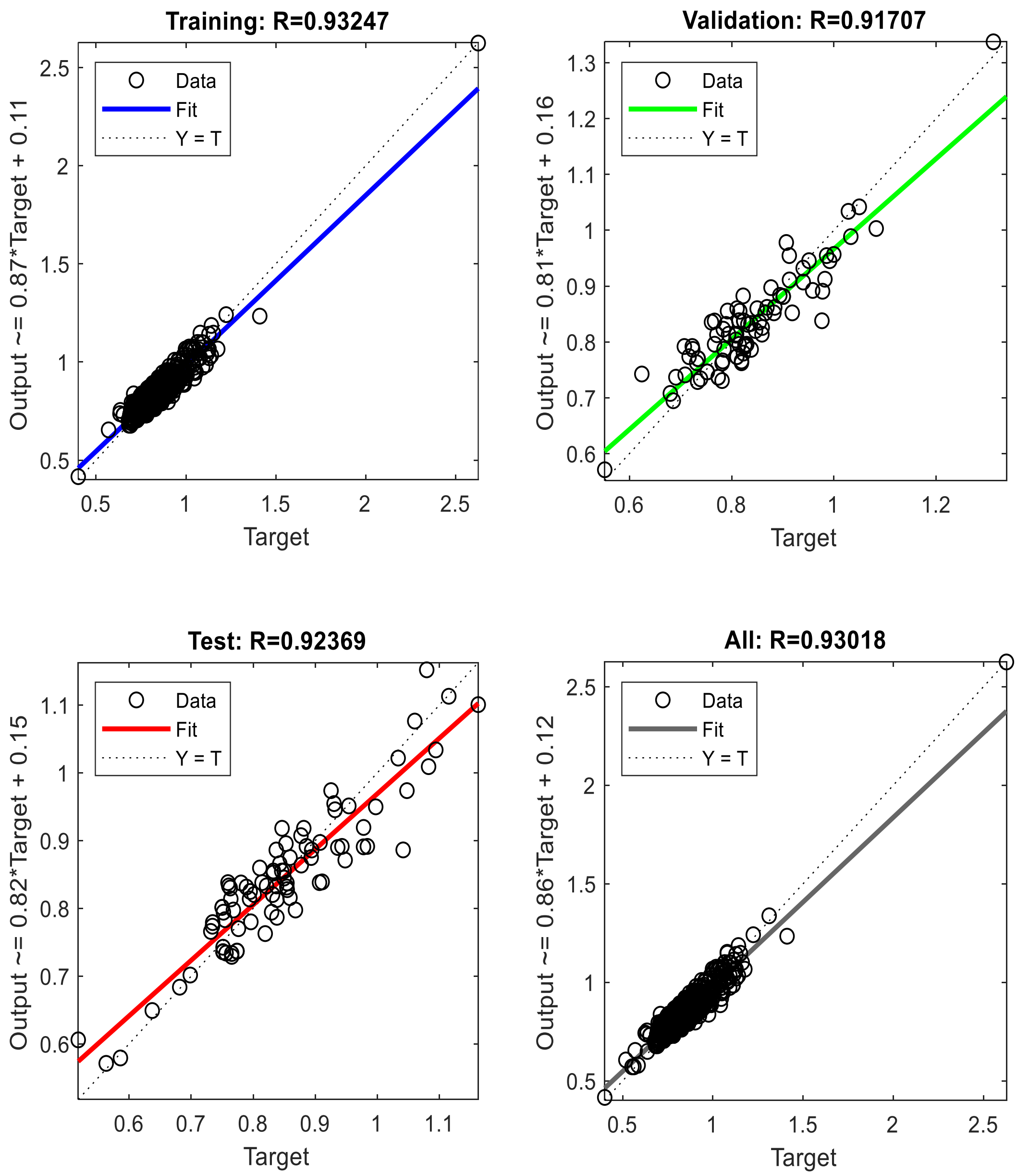

Figure 8. Regression coefficients of training, validation, testing and all in the neural network.

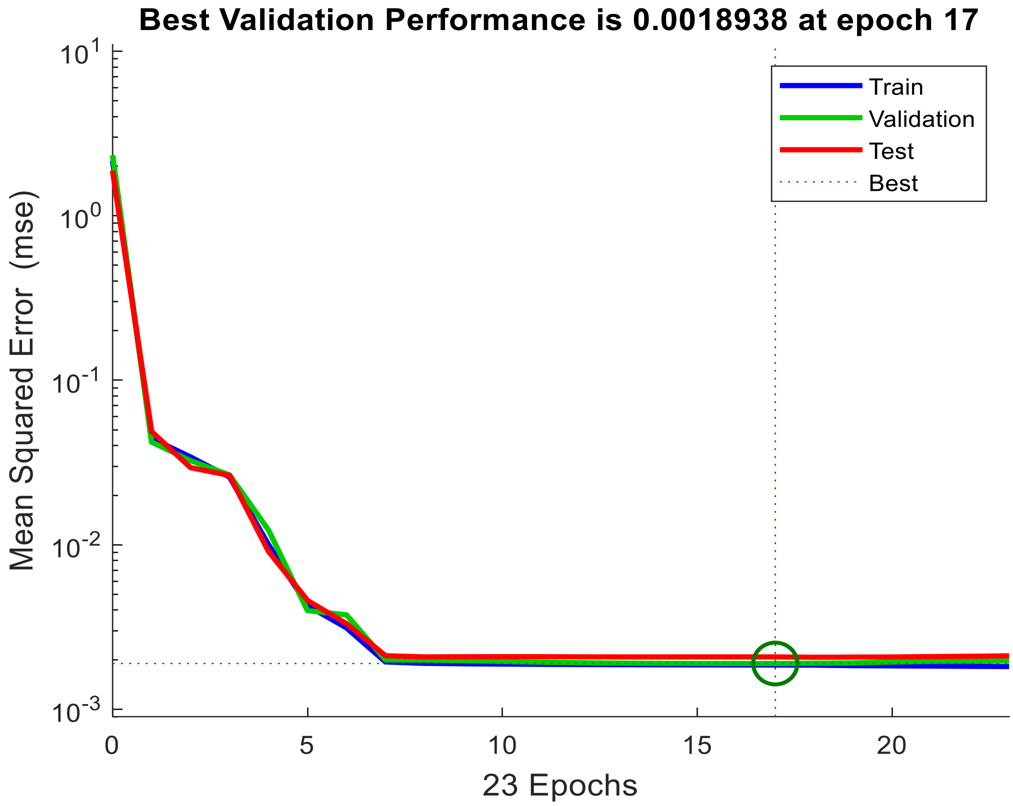

Figure 9. Best validation performance model based on Levenberg-Marquardt algorithm.

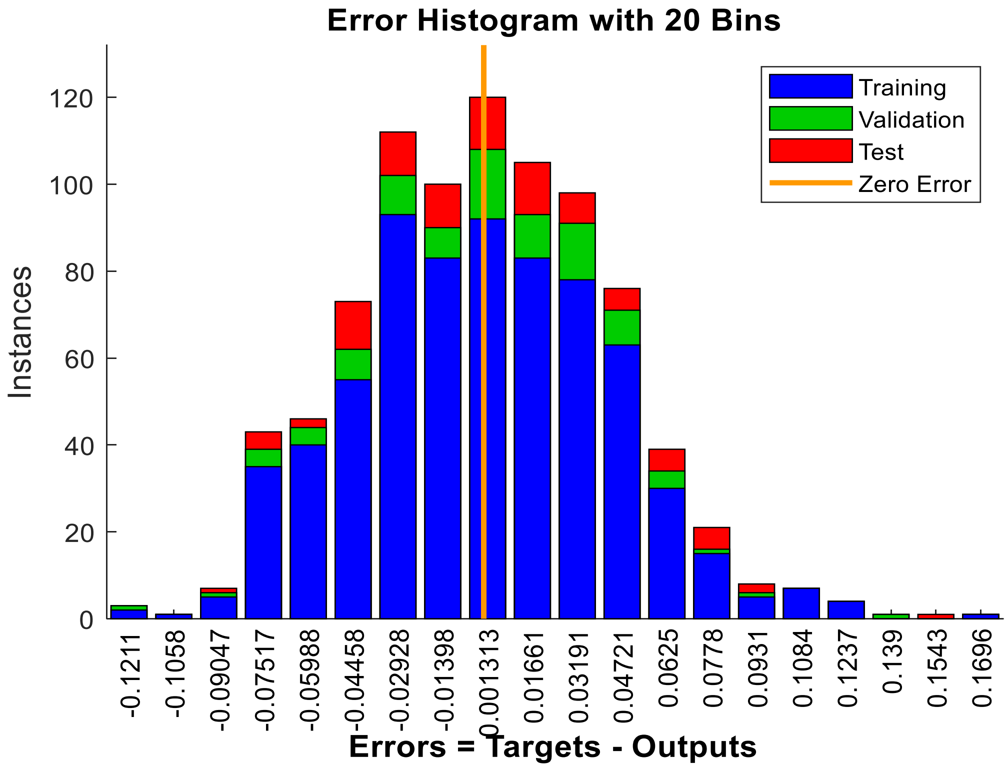

Figure 10. Error histogram for training, testing, and validation.

Table 4. Statistical results of model performance in training, validation and testing for MLP-ANN (Levenberg-Marquardt 80%-10%-10%)

	MLP-ANN (Levenberg-Marquardt)			
Number of hidden nodes	**Dataset**	**RMSE**	**MAPE**	**R^2**
	Validation	0.0445	4.2243	0.9030
3–2–1-1	Training	0.0447	4.4245	0.9273
	Testing	0.5000	4.2954	0.9159
	Validation	0.0442	4.1836	0.9027
3–3–1-1	Training	0.0538	4.8548	0.9094
	Testing	0.0503	4.3380	0.9042
	Validation	0.0366	3.5438	0.9312
3–4–1-1	Training	0.0455	4.4055	0.9279
	Testing	0.0433	4.2470	0.9074
	Validation	0.0456	4.0209	0.9337
3–5–1-1	Training	0.0468	4.3897	0.9185
	Testing	0.0467	4.3547	0.9161
	Validation	0.0375	3.6681	0.9276
3–6–1-1	Training	0.0459	4.4392	0.9254
	Testing	0.0427	4.1590	0.9231
	Validation	0.0404	3.8286	0.9085
3–7–1-1	Training	0.0449	4.3221	0.9299
	Testing	0.0418	3.8258	0.9207
	Validation	0.0452	4.0188	0.9301
3–8–1-1	Training	0.0448	4.3272	0.9275
	Testing	0.0440	4.0836	0.9132
	Validation	0.0458	4.4682	0.9111
3–9–1-1	Training	0.0428	4.0618	0.9338
	Testing	0.0463	4.5877	0.9141
	Validation	0.0376	3.8075	0.9208
3–10–1-1	Training	0.0445	4.2588	0.9310
	Testing	0.0437	3.9083	0.9234
	Validation	0.0493	4.5144	0.9101
3–11–1-1	Training	0.0431	4.1484	0.9316
	Testing	0.0450	4.1897	0.9200
	Validation	0.0475	4.1226	0.9237
3–12–1-1	Training	0.0426	4.1229	0.9333
	Testing	0.0454	4.4564	0.9159
	Validation	0.0389	3.8664	0.9217
3–13–1-1	Training	0.0439	4.2277	0.9332
	Testing	0.0403	3.8880	0.9161
	Validation	0.0488	4.7238	0.9141
3–14–1-1	Training	0.0435	4.1531	0.9331
	Testing	0.0395	3.9831	0.9040
	Validation	**0.0435**	**4.1993**	**0.9170**
3–15–1-1	**Training**	**0.0431**	**4.1153**	**0.9324**
	Testing	**0.0456**	**4.3153**	**0.9236**

Table 5. Final results for all models

	Methods							
	Levenberg-Marquardt %70-%15-%15			Levenberg-Marquardt %80-%10-%10			Gaussian Process Regression	MLR
	Validation	Training	Testing	Validation	Training	Testing		
RMSE	0.0428	0.0440	0.0444	0.0435	0.0431	0.0456	**0.0017240**	0.0028
MAPE	3.9578	4.2598	4.2983	4.1993	4.1153	4.3153	**MAE=0.0001712**	0.0472
R^2	0.9273	0.9303	0.9199	0.9170	0.9324	0.9236	**1.000000**	0.5554

Moreover, in the present study, the structure consisting of 70% training, 15% verification, and 15% testing was used in estimating the CF values first. Then, the estimation was performed using the Levenberg-Marquardt algorithm with training (80%), verification (10%), and testing (10%) data. For both models, the estimations were performed using the number of hidden neurons between 2 and 15. Considering the results, the ANN model having 15 hidden neurons and using 80% training, 10% verification, and 10% testing data yielded the best performance. This result suggests that the increases in the number of hidden neurons and the data used in training would offer better estimation results. In other words, it suggests that increasing the sample size will result in efficient forecasting results. Given the CF values calculated in the present study, GP yielded superior and more reliable results in comparison to other models. R^2 values of GP were found to be 1.000, and GP showed much better performance in comparison to the other three models. This might be because GP is based on a robust stochastic model (Ahmed et al., 2010). Examining these findings, it can be stated that GP was the one yielding the best estimation.

Thus, the GPR model was preferred to estimate the condition factor thanks to its optimum regression performance. In the present study, it was determined that GP is a usable methodology for condition factor estimation. Further studies need to simplify the modeling method and focus on accelerating the training process.

Ethical Statement

The authors declare that they have no ethical statement.

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Author Contribution

Cengiz Mutlu: Conceptualization, Methodology, Investigation, Analysis, Validation, Writing–reviewing and editing.

Buse Eraslan Akkan: Methodology, Investigation, Analysis, Software, Validation, Writing–original draft.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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