Yarn Unevenness Prediction Using Generalized Regression Neural Network

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Abstract

This study aimed to propose a method to predict yarn unevenness grounded on the generalized regression neural network and traditional neural network model to further improve the prediction accuracy. The yarn unevenness model was constructed. Under this model, a three-layer neural network, a four-layer neural network, a five-layer neural network, and a generalized regression neural network were designed. Finally, Python was used for training and simulation. The training parameters and the three network models data were made consistent to ensure the comparability of the results. The results showed that using the yarn unevenness model, the average relative error of the four-layer neural network to cut down 0.87% compared with that of the three-layer neural network. Compared with the five-layer neural network, the four-layer neural network performance was not much different, but the running speed was increased by 46.05%. Compared with the four-layer neural network, the average relative error of the generalized regression neural network was reduced by 0.57%, the mean square error was reduced by 0.98%, he root mean square error was reduced by 4.76%, and the running speed was increased by 74.70%.

Keywords: Generalized regression neural network, Mean absolute error, Neural network, Running speed, Unevenness

1 Introduction

The yarn quality index prediction is a hotspot in the field of textile research. The quality of yarn determines the final fabric product quality. The yarn quality index prediction can effectively reduce the cost of yarn production. Five different yarn quality indexes are used: strength, nep, evenness, unevenness, and strength CV (coefficient of variation). However, at present, most scholars at home and abroad only pay attention to the prediction of yarn strength, nep, evenness, and strength CV; a few studies have reported about the yarn unevenness prediction. For most researchers in China, finding a method to effectively and accurately predict the yarn unevenness is urgently needed.

The prediction of yarn unevenness is a complex nonlinear a can of worms. The neural networks application to nonlinear problems usually gives better results. Ureyen and Gurkan utilized artificial neural network and linear regression model to forecast the unevenness of ring spinning. The experimental results show that artificial neural network is more effective [1]; Malik et al. applied artificial neural network and multiple linear regression method to predict yarn unevenness index, and the results showed that artificial neural network was better [2]; Zha et al. proposed double-hidden layer BP neural network on the basis of traditional three-layer neural network. The results show that the four-layer BP neural network is superior to the three-layer neural network in all aspects for cotton yarn quality prediction [3]; Majumdar et al. artificial neural network (ANN) and neural-fuzzy system to forecast the unevenness of ring spun yarns [4]; Ghanmi et al. combined fuzzy expert system and artificial neural network to predict and determine rotor spinning quality [5]; Mwasiagi et al. used a neural network combination and an evolutionary algorithm to predict the yarn unevenness index [6].

Although the artificial neural network effectively predicts the yarn unevenness, its prediction effect still does not reach the prediction goal. One of the main reasons about this problem is that artificial neural networks usually require a certain much data to realize their desired goals, and it's hard to gather enough clean data in the spinning factory for the artificial neural network training. Consequently,the results fell short of expectations. The generalized regression neural network (GRNN) proposed by DF (1991) converges to the optimal regression surface with more sample randomization accumulation and also has a good prediction effect when few data samples are present [7]. As a result of that GRNN has been used for many industrial sectors,including predicting water consumption of Populus euphratica seedlings [8], electricity price [9], road accident risk [10], key biological parameters in marine protease fermentation process [11], transformer health indicators [12], response of grade 6 titanium wire-cutting machine tool [13], pearlite layer spacing and mechanical properties related to alloy elements [14], wear AA219 graphite (GR) composites characteristics under diverse opportunities and standards [15], underground evaporation rate in arid areas [16] and others [17-19]. But its application in the textile prediction field is still limited. Therefore, this study aimed to use GRNN to forecast yarn unevenness and compare it with the traditional three-layer, four-layer, and five-layer neural network to prove its effectiveness.

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2 Problem Formulation

2.1 Generalized Regression Neural Network

The theoretical basis of GRNN is nonlinear regression analysis, which is a radial basis function network based on mathematical statistics. The network not only deals with unstable data but also has good universality: when data samples are more in number, the model eventually converges to the optimal regression with more sample size; and when few data samples are present, the prediction effect of the model is good.

Compared with a neural network, GRNN does not need training, and each network node has no corresponding weight. The final prediction result of GRNN is only related to the given training data. To some extent, GRNN belongs to a probability model. The neural network needs training. Each network node has not only weight but also a corresponding activation function. The prediction result of a neural network is related to not only the given training data but also the number of training programs and the weight obtained by training.

The structure diagram of GRNN network is exhibited in Figure 1. GRNN is generally composed of four layers: input layer, mode layer, summation layer, and output layer. Suppose the input data is X=[$x1$, $x2$, $x3$,…, xm]T and xi=[$xi1$, $xi2$, $xi3$,…, xin], the output data is Y=[$Y1$, $Y2$, …, Ym] Tand $Y1$=[$yi1$, $yi2$, …, yik]. Note: The input data and output data are test data.

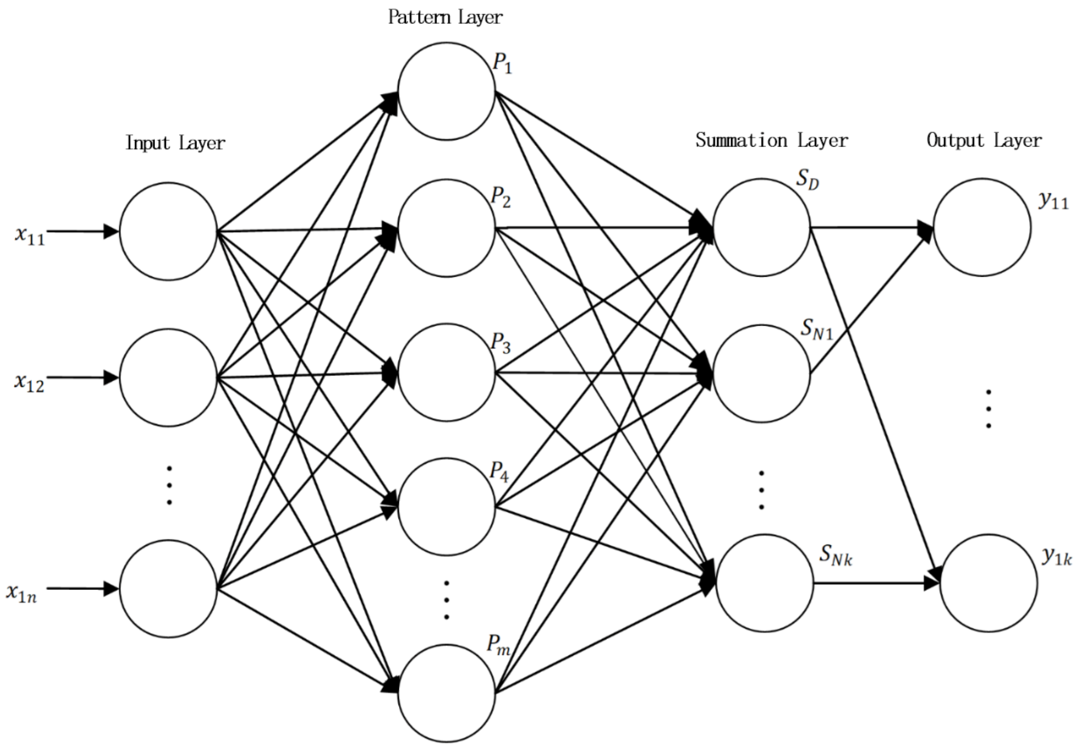


Figure 1. Network structure of GRNN

2.1.1 Input Layer

The dimension of input data is the number of input layers in GRNN, that is, the number of input layers is n.

2.1.2 Pattern Layer

The number of nodes in the input layer in GRNN is the number of input data, that is, the number of nodes in the pattern layer is m. The transfer function of the mode layer is shown in Formula (1):

$$P_i = exp(-\frac{(X-x_i)^T(X-x_i)}{2\sigma^2})i = 1, 2, \ldots, m. \quad \textbf{(1)}$$

Here P_i represents the output of neuron i; X represents the sample corresponding to the ith node (i.e., the ith data of the training sample); x_i represents the test data of article i; and σ represents the smoothing factor, it is an unknown number.

2.1.3 Summation Layer

The dimension of the output data plus 1 is the node number of the summation layer in GRNN, that is, the number of nodes in the summation layer is K + 1. In the summation layer of GRNN, two types of neurons are used for summation operations:

(1) Arithmetic summation

Only the first neuron is arithmetic summation neuron in the summation layer, and its neuron output value is the value of arithmetic summation output by neurons in all mode layers. The arithmetic summation neuron calculation formula is shown in Formula (2):

$$S_D = \sum_{i=1}^{m} \mathrm{p}_i, \quad \textbf{(2)}$$

where S_D represents the arithmetic summation result.

(2) Weighted summation

The weighted summation neurons quantities in the summation layer is equivalent to the output data dimension, and its neuron output value is the weighted summation value of the outputs of neurons in all mode layers. The link weight between the ith summation neuron in the summation layer and the ith neuron in the pattern layer is the jth element y_{ij} in the ith output sample y_i. The weighted summation neuron calculation formula is exhibited in Formula (3):

$$S_{(N_j)} = \sum_{i=1}^{m} \mathrm{y}_{\mathrm{ij}} \mathrm{P}_{\mathrm{i}} = 1,2,\ldots,k, \tag{3}$$

where S_{N_j} represents the weighted summation result of the jth neuron; And y_{ij} represents the connection weight between the jth summation neuron in the summation layer and the ith neuron in the mode layer.

2.1.4 Output Layer

The number of output layer nodes in GRNN is the dimension of output data, that is, the number of output layer nodes is K. The jth neuron output value in the output layer is the jth weighted summation neuron output ratio in the summation layer to the arithmetic summation neuron output. The formula is exhibited in Formula (4):

$$\mathrm{y}_i - \frac{S_{N_i}}{S_D} = 1,2,\ldots,k, \tag{4}$$

where y_j represents the jth neuron output in the output layer.

2.2 Evaluation Index of the Model

In this study, the evaluation indexes of the model included the precision index and speed index. Among them, the speed index included the operation time and the percentage of operation speed increase. Accuracy indicators included mean absolute error (MAE), determination coefficient (R2), root mean square error (RMSE) and mean square error (MSE). Their calculation formulas are shown in formula (5), (6), (7) and (8) respectively:

$$MAE = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{actual_i - predict_i}{actual_i}\right|. \tag{5}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}\left(actual_i - predict_i\right)^2}{\sum_{\mathrm{i}=1}^{\mathrm{N}}\left(actual_i - \frac{1}{N}\left(\sum_{i=1}^{N} predict_i\right)\right)^2}. \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(actual_i - predict_i\right)^2}. \tag{7}$$

$$MSE = \frac{1}{N}\left(actual_i - predict_i\right)^2, \tag{8}$$

where $actual_i$ represents the measured value of article I data, $predict_i$ represents the ith data forecast value, and N represents the test sets quantities.

3 Data Preparation

The experimental data used in the experiment part of this paper come from the actual production data of a textile factory in Anhui, China. The yarn produced in this experiment belongs to combed compact spinning yarn (5.9Tex).

3.1 Parameter Setting

The parameters in this research data mainly included input parameters and output parameters. The input parameters were further divided into three parts: raw cotton parameters (data before production), raw cotton parameters (data detected during production) and parameters during machine operation. The output parameter was the produced yarn unevenness (%), which was recorded as y. The parameters of each part and their corresponding units and abbreviations are exhibited in Table 1 to Table 3.

Table 1. Raw cotton parameters (before production)

Parameter	Symbol
Short staple rate(%)	x_1
Neps per-gram	x_2
Micronaire value	x_3
Strength (cN/tex)	x_4
	x_5
Length uniformity (%)	x_6
Impurities rate (%)	x_7

Table 2. Raw cotton parameters (during production)

Parameter	Symbol
Neps detected before cotton passes the carding machine (Neps/g)	x_8
Neps detected after cotton passes the carding machine (Neps/g)	x_9
Short staple rate detected before cotton passes through the carding machine (%)	x_{10}
Short staple rate detected after cotton passes through the carding machine (%)	x_{11}
The drop rate of cotton through the carding machine (%)	x_{12}
Neps detected before cotton passes through the comber (Neps/g)	x_{13}
Neps detected after cotton passes through the comber (Neps/g)	x_{14}
Cotton short staple rate detected before cotton passes the comber (%)	x_{15}
Cotton short staple rate detected after cotton passes the comber (%)	x_{16}
The cotton drop rate through the comber (%)	x_{17}

Table 3. Machine operating parameters

Parameter	Symbol
Carding speed (m/min)	x_{18}
Pre-parallel strip linear speed (m/min)	x_{19}
Comber clamp time (nips/min)	x_{20}
Roving twist shrinkage (%)	x_{21}
Spinning twist shrinkage (%)	x_{22}
Average spindle speed (r/min)	x_{23}
Draft multiple	x_{24}
Spinning number (tex)	x_{25}

3.2 Quality Index of Raw Cotton

(1) Short staple rate

Short staple ratio of raw cotton refers to the ratio of fiber weight less than specified length to total fiber weight. The lower the staple rate of raw cotton, the higher the yarn strength.When the staple rate of raw cotton increases,the yarn breakage rate will increase and the yarn production efficiency will decrease.

(2) Nep

A raw cotton nep is a knot formed by entanglement of cotton fibers.

(3) Micronaire value

The Micronaire value is an indicator of cotton fiber measured with a Micronaire airflow meter and is related to maturity and linear density.It has been proved by experience that when cotton's micronaire value is between 3.7 ～ 4.3, the yarn strength is higher and the uneverness is smaller.

(4) Strength

Raw cotton strength refers to the maximum load that cotton fibers can bear when they break. The stronger the raw cotton, the higher the yarn quality.Raw cotton strength is low, easy to lead to yarn breakage, yam breakage rate increases, production efficiency decreases, increase the unevenness.

(5) The right half average length

The average length of the right half refers to the weighted average length of each group of fibers longer than the body length, also known as the quality length.Where in the body length refers to the length of the group of fibers with the largest weight in the sample.

(6) Length uniformity

Length uniformity refers to the degree of uniform or neat distribution of cotton fiber length,which has an important influence on yam unevenness, cotton drop rate,and yarn strength.

(7) Impurity rate

The impurity ratio of raw cotton refers to the ratio of impurity weight to sample cotton weight.The more impurities in raw cotton, the higher the impurity rate, the easier to produce short fiber.

3.3 Process Parameters and Indicators

Carding linear speed

Carding line speed refers to the speed of carding machine. The impurities in raw cotton are difficult to be removed and the quality of sliver becomes worse with the increase of carding line speed.

(2)Pre-parallel line speed

Pre-parallel drawing line speed refers to the speed of drawing frame.The speed of pre-paralle1 drawing increases and the quality of yarn decreases.

(3) Combing forceps

Combing pliers refers to the size of the car speed of combing machine. Comber can eliminate the short lint in cotton yarn, improve the strength of yarn, reduce yarn unevenness.

(4)Roving twist coefficient

The roving twist coefficient is an important parameter in the roving process. The reasonable selection of roving twist coefficient can effectively reduce the yarn unevenness.

(5) Twist coefficient of yarn

The twist coefficient of roving is an significant parameter in roving process. Reasonable selection of spinning twist coefficient can not only improve spinning machine output, but also improve yarn quality.

(6) Average spindle speed

Average spindle speed means the average spindle speed of the spinning frame. The spindle speed will affect the twist shrinkage and thus the yarn quality.

3.4 Yarn Quality Index

Unevenness

Unevenness is a measure of the uniformity of yarn linear density. High inhomogeneity will lead to a decrease in yarn strength, affecting normal use.

3.5 Division of Training Set and Test Set

There are 61 pieces of data were collected from textile mills. The values of the first 5 pieces of data are shown in Table 4 and Table 5. The data set is split by the train_test_split function in the Sklearn library package in Python. The train_te st_ split function was used on the basis of dissimilar random_Seed, and dissimilar test_Size divided data sets into training set and test set with dissimilar sizes and dissimilar sample distribution. Order test_size = 0.1; the random_training data set was divided into seven sets and seed = 1 set.

Table 4. The first half of the first five data bars parameters

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}
6.6	203	4.33	34.7	32.45	84.4	2.11	311.5	43.88	6.64	6.31	8	33.38	7.1
5.9	188	4.35	37.3	33.73	85.2	2.44	285.25	37.13	6.75	6.05	8	33.5	6.85
5.7	176	4.24	38.5	34.48	85.7	2.45	285.25	37.13	6.75	6.05	8	33.5	6.85
5.5	174	4.21	39.2	34.87	85.9	2.46	285.25	37.13	6.75	6.05	8	33.5	6.85
5.4	171	4.2	39.4	34.99	85.9	2.42	285.25	37.13	6.75	6.05	8	33.5	6.85

Table 5. The second half of the first five data bars Parameters

x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}	y
6.19	2.24	20	100.2	420	300	96.33	390.34	16500	108.5	5.9	13.86
6.16	2.24	20	100.2	420	300	96.33	380.87	17000	107.8	5.9	13.74
6.16	2.24	20	100.2	420	300	96.33	380.87	17000	107.8	5.9	13.66
6.16	2.24	20	100.2	420	300	96.33	380.87	17000	107.8	5.9	13.74
6.16	2.24	20	100.2	420	300	96.33	380.87	17000	107.8	5.9	13.64

4 Case Analysis

The focus of this case study was to verify through experimental comparison that GRNN had faster speed and higher accuracy in predicting yarn unevenness than the three-layer, four-layer, and five-layer neural networks. The algorithms used in this experiment were performed in Python (3.7), NumPy (1.18.1) , Pandas (1.0.1), Matplotlib (3.1.3) , Neupy (0.8.2), Sklearn (0.0), and Tensorflow (1.13.2).

4.1 Neural Network

In the present paper,the commonly used three-layer (25*32*1, 25, 10, 1 are the neurons number in the inputlayer, hidden layer, and output layer, respectively), four-layer (25*32*32*1, 25, 32, 32, 1 are the neurons number in the inputlayer, hidden layer, hidden layer, and output layer, respectively), and five-layer (25*32*32*32*1, 25, 32, 32, 32, 1 are the neurons number in the inputlayer, hidden layer, hidden layer, hidden layer, and output layer, respectively). The hidden layer activation functions are all relu functions, and the output layers activation functions are sigmoid functions. neural networks were used for comparative simulation experiments to prevent the depth of the network from causing deviation of the experimental results. The results are exhibited in Table 6.

Summarizing the data shown in Table 6, it was observed that the overall performance of the four-layer neural network was the best among all neural networks. At the same time, by analyzing the changes in the number of network layers under various indicators, it was concluded that when the hidden layers quantities was greater than 2, the increase in the network layers quantities did not cause a significant improvement in performance, and when the number of iterations of the model changed little, increasing the number of layers of the model led to a sharp increase in the running time, this makes model less efficient in actual production.

Table 6. Neural network simulation results

Evaluating indicator	Three-layer neural network	Four-layer neural network	Five-layer neural network
	25*32*1	25*32*32*1	25*32*32*32*1
RMSE (%)	19.85	18.24	18.47
R^2	0.14	0.28	0.26
Number of iterations	26	24	28
Running time (s)	3.91	3.28	6.08

4.2 Generalized Regression Neural Network

Considering the performance and smoothing factor of GRNN, the MSE was taken as the evaluation index and the incremental iterative method was used to solve the minimum MSE. Let the initial value be 0; 1000 iterations were carried out in increments of 0.001. The results are exhibited in Figure 2.

The optimal solution obtained by the iterative method was 0.367, that is, when the number of iterations was 367, the MSE was the smallest and the running time (given smoothing factor) was 0.34 s.. The values under each evaluation index are calculated as shown in Table 7.

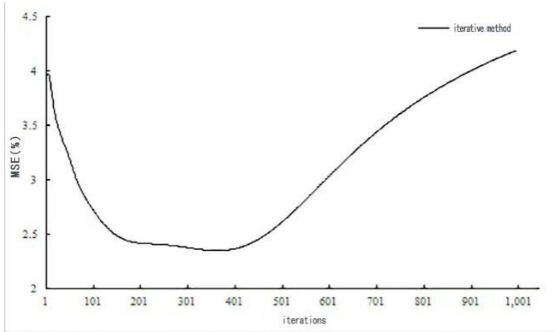


Figure 2. Simulation result graph of the iterative method

Table 7. Four-layer neural network and generalized regression neural network results

Evaluating indicator	Four-layer neural network	Generalized neural network
MAE (%)	15.89	15.32
MSE (%)	3.33	2.35
RMSE (%)	18.24	13.48
R2	0.28	0.49
Running time (s)	3.28	0.83

4.3 Comparative Analysis

Comparing the four-layer neural network simulation results and generalized neural network, accuracy, fitting effect, and running time of the generalized neural network were found to be improved. The accuracy included the following: the performance was improved by 0.57% under the MAE evaluation index, 0.98% under the MSE index, and 4.76% under the RMSE index. In terms of fitting effect, R2 coefficient was increased from 0.28 of the four-layer neural network to 0.49. In terms of running time, although the number of iterations increased from 24 to 1000, the running time decreased from 3.28 s to 0.83 s, and the running speed increased by 74.70%. This proves that the generalized regression neural network has a good effect in predicting small scale yarn unevenness.

5 Conclusion

In this study, three-layer, four-layer, five-layer neural networks and GRNNs were designed to predict the yarn unevenness, and the simulation results were analyzed and compared. The following conclusions were obtained: the deeper the neural network, the better. Compared with the four-layer neural network, the five-layer neural network accuracy was not improved, but it caused wastage of time. Compared with the neural network, GRNN had smaller test error, better fitting effect, and faster running speed. Therefore, the GRNN had a higher effect on addressing the problem of yarn unevenness than the neural network and could be of guiding significance in practical production activities. However, the algorithm in this paper still has limitations, which is not considered when using neural network to predict yarn quality, the accuracy of neural network is a reliable index to measure the model, another important index is whether it conforms to the actual production law, only the model in line with the actual production law can guide production better.

References

[1] M. E. Üreyen, P. Gürkan, Comparison of artificial neural network and linear regression models for prediction of ring spun yarn properties. II. Prediction of yarn hairiness and unevenness, *Fibers and Polymers*, Vol. 9, No. 1, pp. 92-96, February, 2008.

[2] S. A. Malik, A. Farooq, T. Gereke, C. Cherif, Prediction of blended yarn evenness and tensile properties by using artificial neural network and multiple linear regression, *Autex Research Journal*, Vol. 16, No. 2, pp. 43-50, June, 2016.

[3] L. Zha, C. Xie, Prediction of cotton yarn quality based on four-layer BP neural network, *Journal of Textile Research*, Vol. 40, No. 1, pp. 52-56, January, 2019.

[4] A. Majumdar, M. Ciocoiu, M. Blaga, Modelling of ring yarn unevenness by soft computing approach, *Fibers and Polymers*, Vol. 9, No. 2, pp. 210-216, April, 2008.

[5] H. Ghanmi, A. Ghith, T. Benameur, Prediction of rotor-spun yarn quality using hybrid artificial neural network-fuzzy expert system model, *Indian Journal of Fibre & Textile Research (IJFTR)*, Vol. 44, No. 1, pp. 31-38, March, 2019.

[6] J. I. Mwasiagi, X. B. Huang, X. H. Wang, The use of hybrid algorithms to improve the performance of yarn parameters prediction models, *Fibers and Polymers*, Vol. 13, No. 9, pp. 1201-1208, November, 2012.

[7] D. F. Specht, A general regression neural network, *IEEE transactions on neural networks*, Vol. 2, No. 6, pp. 568-576, November, 1991.

[8] W. Gao, L. Ma, Z. Jia, Y. Ning, Comparison of the GRNN and BP neural network for the prediction of populus (P.× euramericana cv.“74/76”) seedlings’ water consumption, *2010 3rd International Conference on Advanced Computer Theory and Engineering (ICACTE)*, Chengdu, China, 2010, pp. V2-389-V2-392.

[9] S. Anbazhagan, N. Kumarappan, Day-ahead price forecasting in Asia’s first liberalized electricity market using artificial neural networks, *International Journal of Computational Intelligence Systems*, Vol. 4, No. 4, pp. 476-485, August, 2011.

[10] N. K. Charandabi, A. Gholami, A. A. Bina, Road accident risk prediction using generalized regression neural network optimized with self-organizing map, *Neural Computing and Applications*, Vol. 34, No. 11, pp. 8511-8524, June, 2022.

[11] J. Wu, Y. Sun, Y. Huang, L. Sun, Soft sensor modeling based on GRNN for biological parameters of marine protease fermentation process, *Proceedings of the 33rd Chinese Control Conference*, Nanjing, China, 2014 pp. 5102-5106.

[12] M. Islam, G. Lee, S. N. Hettiwatte, L. Williams, Calculating a health index for power transformers using a subsystem-based GRNN approach, *IEEE Transactions on Power Delivery*, Vol. 33, No. 4, pp. 1903-1902, August, 2018.

[13] H. Majumder, K. P. Maity, Predictive analysis on responses in WEDM of titanium grade 6 using general regression neural network (GRNN) and multiple regression analysis (MRA), *Silicon*, Vol. 10, No. 4, pp. 1763-1776, July, 2018.

[14] L. Qiao, Z. Wang, J. Zhu, Application of improved GRNN model to predict interlamellar spacing and mechanical properties of hypereutectoid steel, *Materials Science and Engineering: A*, Vol. 792, Article No. 139845, August, 2020.

[15] A. Saravanakumar, L. Rajeshkumar, D. Balaji, M. P. Karunan, Prediction of Wear Characteristics of AA2219-Gr Matrix Composites Using GRNN and Taguchi-Based Approach, *Arabian Journal for Science and Engineering*, Vol. 45, No. 11, pp. 9549-9557, November, 2020.

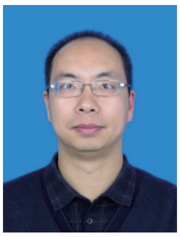
[16] A. H. Kamel, H. A. Afan, M. Sherif, A. N. Ahmed, A. E. Shafie, RBFNN versus GRNN modeling approach for sub-surface evaporation rate prediction in arid region, *Sustainable Computing: Informatics and Systems*, Vol. 30, Article No. 100514, June, 2021.

[17] M. Mansoor, A. F. Mirza, Q. Ling, Harris hawk optimization-based MPPT control for PV systems under partial shading conditions, *Journal of Cleaner Production*, Vol. 274, Article No. 122857, November, 2020.

[18] S. Yu, H. Lan, X. Li, H. Zhang, Y. Zeng, H. Niu, X. Niu, A. Xiao, Y. Liu, Prediction method of shelf life of damaged Korla fragrant pears, *Journal of Food Process Engineering*, Vol. 44, No. 12, Article No. e13902, December, 2021.

[19] M. Wu, W. Chen, Forecast of electric vehicle sales in the world and China based on PCA-GRNN, *Sustainability-Basel*, Vol. 14, No. 4, Article No. 2206, February, 2022.

Biographies



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