Novel Evolutionary-Optimized Neural Network for Predicting Fresh Concrete Slump

Hamed Safayenikoo 1,*, Mohammad Khajehzadeh 2 and Moncef L. Nehdi 3,*

1 Department of Civil Engineering, Chabahar Maritime University, Chabahar 99717-78631, Iran
2 Department of Civil Engineering, Anar Branch, Islamic Azad University, Anar 77419-43615, Iran; mohammad.khajehzadeh@anariau.ac.ir
3 Department of Civil Engineering, McMaster University, Hamilton, ON L8S 4M6, Canada
* Correspondence: h.safayenikoo@cmu.ac.ir (H.S.); nehdim@mcmaster.ca (M.L.N.);
Tel.: +1-905-525-9140 (ext. 23824) (M.L.N.)

Abstract: Accurate prediction of fresh concrete slumps is a complex non-linear problem that depends on several parameters including time, temperature, and shear history. It is also affected by the mixture design and various concrete ingredients. This study investigates the efficiency of three novel integrative approaches for predicting this parameter. To this end, the vortex search algorithm (VSA), multi-verse optimizer (MVO), and shuffled complex evolution (SCE) are used to optimize the configuration of multi-layer perceptron (MLP) neural network. The optimal complexity of each model was appraised via sensitivity analysis. Various statistical metrics revealed that the accuracy of the MLP was increased after coupling it with the above metaheuristic algorithms. Based on the obtained results, the prediction error of the MLP was decreased by up to 17%, 10%, and 33% after applying the VSA, MVO, and SCE, respectively. Moreover, the SCE emerged as the fastest optimizer. Accordingly, the novel explicit formulation of the SCE-MLP was introduced as a capable model for the practical estimation of fresh concrete slump, which can assist in project planning and management.

Keywords: neural network; metaheuristic optimization; shuffled complex evolution; concrete; slump; prediction

1. Introduction

Concrete is the world’s most consumed commodity after water and the most used construction material on earth. It is widely used in different construction sectors such as buildings, bridges, dams, roads, and infrastructure systems [1–4]. For this reason, investigating the mechanical characteristics of this material has been frequently considered in the literature [5–7]. Since concrete is a mixture of various components and behavior is influenced by several environmental parameters, an approximation of concrete’s key parameters (e.g., compressive strength and slump) is a complex non-linear problem. Traditional regression methods have often attained poor performance in predicting the engineering properties of concrete as a function of its mixture design. Hence, several studies have been dedicated to testing new predictive models for estimating these parameters [8–10]. Regression-based equations such as Scheffe’s [11] and Ibearugbulem’s regression models [12] have been widely used for optimizing concrete mixtures. Different numerical and analytical approaches have also been applied to analyze the relationship between concrete performance and mixture ingredients [13,14]. More recently, machine learning models have emerged as promising data-driven and intelligent tools in this field [15,16].

From a more general perspective, recent advances in mathematics and programming enabled experts to develop new methodologies towards facilitating laborious engineering analysis [17–19]. In the field of civil engineering, efforts such as slope stability analysis [20], risk assessment of natural disasters [21], material strength evaluation [22], etc. represent successful examples in this domain. Among these methodologies, artificial intelligence has
created valuable models which are designed based on natural behaviors such as biological systems and genetic evolution [23,24]. Some popular fields for applying different artificial intelligence models are environmental simulations [25], fault diagnosis [26], structural identification [27], strength estimation [28], etc.

Structural simulations, and more particularly, concrete-related analysis have been another target for utilizing machine learning models. For instance, Hoang and Pham [29] found that least squares support vector regression (LS-SVR) was a capable tool for modeling the concrete workability based on the slump test. Nguyen, et al. [30] indicated the potential of artificial neural network (ANN) for predicting the workability parameters of self-compacting concrete. Fan, et al. [31] suggested the use of fuzzy weighted relative error support vector machines (RE-SVMs) for estimating concrete components. Amlashi, et al. [32] used ANN, multivariate adaptive regression splines, and the M5 model tree to simulate the slump, compressive strength, and elastic modulus of bentonite plastic concrete. They found that ANN was more effective and identified the variables having the largest and least influence on the slump of BPC, respectively. Also, the superiority of the ANN (over response surface methodology) was revealed by Hammoudi, et al. [33] for compressive strength modeling. Onikeku, et al. [34] examined the efficiency of ANN and multiple linear regression in simulating the compressive strength and slump of two blended Agro-industrial waste materials concrete.

Moreover, more recent attempts have demonstrated the applicability of metaheuristic algorithms in approximating different engineering parameters [35,36], particularly concrete parameters including creep strain [37], workability [38], compressive strength [39], and other performance parameters [40,41]. Chandwani, et al. [42] employed genetic algorithms for training an ANN for predicting the slump of ready-mix concrete. Their results showed that the used metaheuristic techniques reduced the prediction error of the ANN and increased the model correlation. Nguyen, et al. [43] employed particle swarm optimization for fine-tuning an LS-SVR model for predicting the plastic viscosity and yield stress of concrete. Javid, et al. [44] used metaheuristic algorithms (including interior-point optimizer) for the optimal design of concrete mixtures. Aydogmus, et al. [45] applied a bagging optimization approach to four well-known predictive models of SVM, radial basis function, classification and regression trees, and MLP and reported the corresponding improvement of their performance in predicting the concrete slump flow, respectively. Moayedi, et al. [46] suggested two nature-inspired optimizers that work based on the foraging behavior of ant lion and grasshopper, as well as biogeography-based optimization for creating metaheuristic slump predictors. Their findings showed that the mentioned algorithms could properly accompany the ANN for this task. Based on the respective root mean square errors (RMSEs) of 3.7788, 4.9553, and 4.1859, the superiority of the ant lion optimization was deduced.

Referring to the suitability of metaheuristic techniques in analyzing the relationship between concrete-related parameters, the main focus of this study is evaluating three novel optimization techniques, namely the vortex search algorithm (VSA), multi-verse optimizer (MVO), and shuffled complex evolution (SCE) for the objective of accurately predicting fresh concrete workability. The algorithms can assist an ANN model in finding optimal computational parameters. The results of the hybrid models are compared to the typically trained ANN to examine and the effectiveness of these algorithms is compared.

2. Data and Modeling Methodology

2.1. Data Provision

Based on study by Yeh [47], information for various concrete specimens was collected. In these tests, the slump was measured for 103 specimens and their concrete mixture ingredients including cement (X1), slag (X2), water (X3), fly ash (X4), superplasticizer (X5), fine aggregate (X6), and coarse aggregate (X7) were considered as the independent (i.e., input) variables. Notably, standards for preparing the concrete specimens and determining the concrete consistency were considered from the American Society for Testing and Materials (ASTM), including the conventional slump test (ASTM C143/C143M-00) [48].
Considering the data (a partition ratio of 0.8:0.2, which is well-accepted for splitting datasets into training and testing groups, respectively [46,49]), the intelligent models were trained using 82 samples. It is worth noting that these data were randomly selected for analyzing the relationship between the slump and input variables. Subsequently, information of the remaining 21 samples was provided to the trained networks to validate their generalization robustness. Table 1 gives descriptive statistics of the dataset (in terms of minimum, maximum, average, and standard deviation values).

Table 1. Statistical analysis of the used dataset.

| Slump (cm) | Cement (kg/m$^3$) | Slag (kg/m$^3$) | Water (kg/m$^3$) | Fly Ash (kg/m$^3$) | SP (kg/m$^3$) | FA (kg/m$^3$) | CA (kg/m$^3$) |
|------------|-------------------|----------------|-----------------|-------------------|-------------|-------------|-------------|
| Minimum    | 0.0               | 137.0          | 0.0             | 160.0             | 4.4         | 640.6       | 708.0       |
| Maximum    | 29.0              | 374.0          | 260.0           | 240.0             | 193.0       | 902.0       | 1049.9      |
| Mean       | 18.0              | 229.9          | 149.0           | 197.2             | 78.0        | 739.6       | 884.0       |
| Standard deviation | 8.7     | 78.9           | 85.4            | 20.2              | 60.5        | 2.8         | 63.3        |

Moreover, Figure 1 depicts the correlation matrix of the dataset. The scatter plots of each two variables are depicted along with their histogram. The last row of this matrix shows the slump (on the y-axis) versus the input parameters (on the x-axis). It can be observed that slump was more correlated to the water content (correlation index = 0.47).

Figure 1. Correlation matrix of the dataset (points are data and purple lines show their trend and column charts are histogram).

2.2. Methodology

2.2.1. Shuffled Complex Evolution

The SCE was first suggested by Duan, et al. [50] and connotes a three-tier architecture which comprises population, complex, and simplex. Therefore, as a basic rule, this tech-
nique treats the universal search as a bottom-up population evolution. The SCE combines the advantages of various techniques including competitive evolution, controlled random search, complex shuffling and a simplified version of Nelder-Mead algorithm [51]. Figure 2 illustrates the flowchart of the SCE algorithm.

![Flowchart of SCE algorithm](image)

**Figure 2.** Illustration of SCE flowchart.

After generating the initial random population, the agents are partitioned into complexes. In each of these units, a so-called strategy competitive complex evolution (CCE) is applied to do the evolution. In other words, it is the main component of this algorithm. The CCE uses the steps of Nelder-Mead algorithm to produce offspring. The worst vertex of the simplex is then replaced by a new offspring. This work leads the simplex to a local optimum. This process is expressed as follows [50]:

I. Initialize: three parameters of $q$, $\alpha$, and $\beta$ are selected where $m \geq q \geq 2$, $\beta \geq 1$, and $\alpha \geq 1$.

II. Weight assignment: a triangular probability distribution is assigned to the complex, as expressed in Equation (1):

$$P_i = \frac{2(m + 1 - i)}{m(m + 1)} \quad i = 1, 2, \ldots, m$$

(1)
III. Selecting parents: based on the above equation, \( q \) different points (i.e., \( u_1, u_2, \ldots, u_q \)) are chosen from the proposed complex. They are then stored in an array, as expressed in Equation (2).

\[
B = \{u_j, F_j, i = 1, 2, \ldots, q\}
\]

in which, the function \((FV)\) is the value of the corresponding point. The locations of the complex, which are used for constructing the simplex \( B \), are also stored in \( L \).

IV. Generating the offspring: based on the function values, the points are sorted and the centroid \( c \) is calculated as follows:

\[
c = \frac{1}{q - 1} \sum_{j=1}^{q-1} u_j
\]

Then, the new point is computed as \( u_r = 2c - u_q \). There are two possibilities for the next step:

(a) If the new point is within the existing space, the \( FV \) is calculated and the number of evaluations (\( NFEs \)) is changed to \( NFEs + 1 \).

(b) Otherwise, the smallest hypercube \( H \) (which contains the proposed complex) is computed. The point \( u_z \) is randomly produced within \( H \). The \( NFEs \) is changed to \( NFEs + 1 \), and in the mutation stage, \( u_r \) and \( F_r \) will equate \( u_z \) and \( F_z \).

Here, \( u_q \) is replaced by \( u_r \), if \( F_r < F_q \). Otherwise, \( u_{ic} = (c + u_q)/2 \) and its \( FV \) (i.e., \( F_{ic} \)) is calculated and \( NFEs \) is changed to \( NFEs + 1 \). Similarly, \( u_q \) is replaced by \( u_{ic} \), if \( F_{ic} < F_q \). Otherwise, \( u_z \) is randomly generated within \( H \) and \( F_z \) is computed, \( NFEs \) is changed to \( NFEs + 1 \), and \( u_q \) is replaced by \( u_z \). This process continues for \( \alpha \) times.

V. In the last step, the parents are replaced by offspring and the complex is sorted regarding the obtained \( FVs \).

VI. Steps a to e are repeated \( \beta \) times [52].

2.2.2. Benchmark Optimization Models

The vortex search algorithm is a single-solution-based metaheuristic scheme that was proposed by Do˘gan and Ölmez [53] for numerical function optimization. The basis of the VSA is the vortical flow patterns of stirred fluids. In order to have a balance between the explorative and exploitative search phases, the VSA benefits from an adaptive step size adjustment strategy. Hence, the algorithm conducts explorative behavior in the initial search stages. This process results in increasing the global search ability of the VSA. Once the algorithm approaches the best-fitted solution, the exploitative is considered for tuning the found solution based on the optimal one [54]. More details about the mathematical procedure of the VSA can be found in earlier studies such as [55–57].

The second benchmark optimizer is the multi-verse optimizer. As a recently-designed metaheuristic technique, the MVO was proposed by Mirjalili, et al. [58]. Despite most of the metaheuristic schemes that mimic the foraging (and social) behavior of animals in nature, the MVO is based on the multi-verse theories. The relationship between cosmological masses (i.e., worm holes, black holes, and white holes) with multiple universes is the main idea of this algorithm. Two parameters including the traveling distance rate (\( TDR \)) and wormhole existence probability (\( WEP \)) are essential parameters of the MVO. The \( TDR \) and \( WEP \) define the amount and the period of the change in the response. As with other optimization techniques, updating the members’ position leads to finding the most proper solution. This task is carried out by increasing the \( WEP \) [59]. The MVO is mathematically detailed in similar studies such as [60–62].

3. Results and Discussion

3.1. Accuracy Indices

In this work, the performance of the models is evaluated by two well-known accuracy indices. The RMSE and mean absolute error (MAE) are used to measure the error during
the learning and prediction processes. Assuming $K$ as the number of samples, these indices are defined as Equations (4) and (5).

\[
\text{RMSE} = \sqrt{\frac{1}{K} \sum_{i=1}^{K} [(Z_{i,\text{observed}} - Z_{i,\text{predicted}})^2]}
\]

(4)

\[
\text{MAE} = \frac{1}{K} \sum_{i=1}^{K} |Z_{i,\text{observed}} - Z_{i,\text{predicted}}|
\]

(5)

where $Z_{i,\text{predicted}}$ and $Z_{i,\text{observed}}$ stand for the forecasted and expected slumps, respectively.

3.2. Improving ANN Using VSA, MVO, and SCE

A multi-layer perceptron (MLP) model is selected as the basic ANN tool for this study. This model is conventionally trained by the Levenberg–Marquardt (LM) algorithm [63]. The VSA, MVO, and SCE metaheuristic algorithms are applied to this network for optimizing its performance. Achieving this objective requires adjusting the weights and biases of the MLP. Therefore, these parameters are considered as the variables of the problem. After creating the VSA-MLP, MVO-MLP, and SCE-MLP hybrid models, the models were fed by the training data. Since the VSA, MVO, and SCE are population-based algorithms, a sensitivity analysis is carried out to find the best population size for each algorithm. To this end, nine different values, namely 10, 25, 50, 75, 100, 200, 300, 400, and 500 were tested for this parameter. Meanwhile, the objective function was set to be the RMSE to measure the error at each iteration. The models were implemented for 1000 iterations. The objective functions obtained for each population size are shown in Figure 3. According to Figure 3, the best accuracy of the VSA-MLP, MVO-MLP, and SCE-MLP was yielded for the population sizes of 300, 200, and 75, respectively. Figure 4a–c illustrate the convergence behavior of these models.

![Figure 3. Obtained objective functions for different complexities of the ensembles.](image-url)
Figure 4. Convergence behavior of the elite models of (a) VSA-MLP, (b) MVO-MLP, and (c) SCE-MLP.

3.3. Efficiency Assessment

Figure 5 depicts the error values (= expected slump − forecasted slump) for the training phase. The error values of the LM-MLP, VSA-MLP, MVO-MLP, and SCE-MLP predictors ranged within $[−11.0232, 14.1187]$, $[−9.4983, 13.5624]$, $[−9.4937, 12.4816]$, and $[−12.4852, 14.1505]$, respectively.
SCE-MLP, respectively, which indicates that the hybrid ANNs acquired a more reliable understanding of the relationship between the slump and concrete effective factors.

Figure 5. Training errors obtained for (a) LM-MLP, (b) VSA-MLP, (c) MVO-MLP, and (d) SCE-MLP, respectively.

In this phase, the RMSE of the typical ANN (i.e., the LM-MLP) was 5.5533. This value was decreased to 5.0287, 4.6631, and 5.2971 for the VSA-MLP, MVO-MLP, and SCE-MLP, respectively. This demonstrates the efficiency of the used metaheuristic algorithms in optimizing the performance of the ANN. In addition, the reduction of the MAE ranged from 4.4964 for the LM-MLP to 4.0273, 3.8046, and 4.2097 for the VSA-MLP, MVO-MLP, and SCE-MLP, respectively, which indicates that the hybrid ANNs acquired a more reliable understanding of the relationship between the slump and concrete effective factors.

In the testing phase, the models attained high accuracy in predicting the slump. The prediction errors, along with the histogram chart of these values are shown in Figure 6. In this regard, the RMSE of the LM-MLP experienced considerable reductions from 4.9689 to 4.0331, 4.3158, and 3.1798 for the VSA-MLP, MVO-MLP, and SCE-MLP, respectively. From these changes, it can be deduced that the weights and biases adjusted by the metaheuristic algorithms are more promising than the LM. The lower MAEs of the MLPs trained by the VSA, MVO, and SCE (i.e., 3.1398, 3.4039, and 2.5385, respectively) compared to the MAE of the LM-MLP (i.e., 3.7831) can support this observation.
Figure 6. Cont.
As was inferred, utilizing the VSA, MVO, and SCE metaheuristic techniques for training the ANN resulted in better accuracy for both the training (9.45, 16.03, and 4.61% reduction of RMSE and 10.43, 15.39, and 6.38% reduction of MAE, respectively) and testing (18.83, 13.14, and 36.01% reduction of RMSE and 17.00, 10.02, and 32.90% reduction of MAE) phases. A comparison between the potential of these algorithms reveals that the MVO outperformed the VSA and SCE in training the ANN. This is while the SCE presented the best prediction accuracy, followed by the VSA and MVO. Also, Figure 7 compares the computation time taken for implementing the proposed hybrid algorithms (on the operating system at 2.5 GHz and 6 Gigs of RAM). Based on Figure 7, the VSA-MLP took the largest time (around 4686 s), followed by the MVO, which took around 2801 s. The fastest ensemble was the SCE-MLP with about 867 s.

![Figure 6](image1.png)
**Figure 6.** Results obtained for the testing samples by (a,b) LM-MLP, (c,d) VSA-MLP, (e,f) MVO-MLP, and (g,h) SCE-MLP.

![Figure 7](image2.png)
**Figure 7.** Computation time required for implementing the hybrid models.

### 3.4. Slump Predictive Model

Considering that the proposed SCE-MLP model achieved the largest prediction accuracy, as well as the least convergence time, the neural-metaheuristic equation of this algorithm is presented as the slump predictive model. Equation (6) yields the slump con-
considering six middle parameters of $U$, $V$, $W$, $X$, $Y$, and $Z$. These values can be obtained from Equations (7)–(12). The numbers of these two equations are the weights and biases of the ANN that were optimized by the SCE search scheme. Equation (13) expresses the activation function (i.e., $\text{Tansig}$) that is used in Equations (7)–(12) [64].

$$\text{Slump}_{\text{SCE-MLP}} = 0.5471 \times U + 0.9176 \times V + 0.7795 \times W + 0.9107 \times X + 0.4345 \times Y - 0.2611$$  \hspace{1cm} (6)

$$U = \text{Tansig} (-0.9383 \times \text{Cement} - 0.7470 \times \text{Slag} + 0.9905 \times \text{Water} - 0.2547 \times \text{Fly Ash} + 0.6181 \times \text{SP} - 0.3819 \times \text{FA} - 0.5080 \times \text{CA} + 1.8084)$$  \hspace{1cm} (7)

$$V = \text{Tansig} (-0.6945 \times \text{Cement} + 0.5322 \times \text{Slag} + 1.1251 \times \text{Water} - 0.7992 \times \text{Fly Ash} + 0.1705 \times \text{SP} - 0.5337 \times \text{FA} + 0.5351 \times \text{CA} - 0.3617)$$  \hspace{1cm} (8)

$$W = \text{Tansig} (0.4975 \times \text{Cement} + 0.8389 \times \text{Slag} - 1.0838 \times \text{Water} + 0.1539 \times \text{Fly Ash} + 0.8597 \times \text{SP} + 0.2027 \times \text{FA} + 0.5836 \times \text{CA} - 0.3617)$$  \hspace{1cm} (9)

$$X = \text{Tansig} (-0.4501 \times \text{Cement} - 0.8732 \times \text{Slag} + 0.8080 \times \text{Water} + 0.4132 \times \text{Fly Ash} - 0.1829 \times \text{SP} + 0.9119 \times \text{FA} + 0.7853 \times \text{CA} - 0.3617)$$  \hspace{1cm} (10)

$$Y = \text{Tansig} (-0.1632 \times \text{Cement} + 0.8335 \times \text{Slag} - 0.7284 \times \text{Water} - 0.8634 \times \text{Fly Ash} - 0.8463 \times \text{SP} - 0.7455 \times \text{FA} - 0.0316 \times \text{CA} - 1.0850)$$  \hspace{1cm} (11)

$$Z = \text{Tansig} (0.1347 \times \text{Cement} + 0.6765 \times \text{Slag} + 0.8667 \times \text{Water} + 0.4763 \times \text{Fly Ash} - 0.8368 \times \text{SP} + 0.9431 \times \text{FA} + 0.4761 \times \text{CA} + 1.8084)$$  \hspace{1cm} (12)

$$\text{Tansig} (x) = \frac{2}{1 + e^{-2x}} - 1$$  \hspace{1cm} (13)

3.5. Importance Analysis

This section statically investigates the influence of each input parameter on the concrete slump. For this objective, an importance assessment is executed using the random forest model in a MATLAB environment (a bagged ensemble of 200 regression trees), which is a well-known machine learning algorithm. This approach evaluates the change in the target parameter when each input is permuted and, accordingly, calculates an importance value [65].

The results of this process are shown in the column chart in Figure 8. Based on this chart, water, slag, and CA play a considerably more important role compared to the other ingredients. The large contribution of water to the slump of concrete mixtures was earlier demonstrated in Figure 1, and is in agreement with theoretical expectations. This analysis can be considered for the optimal design of concrete mixtures with respect to a desired slump.

3.6. Further Comparison

Referring to the above results, the models suggested in this work can predict the slump of concrete with a satisfying accuracy. Above all, the SCE-MLP outperformed other benchmarks with a notable difference. Furthermore, this model was considerably faster than other hybrids (i.e., VSA-MLP and MVO-MLP). Hence, it is considered as a reliable alternative to traditional approaches.
This model is also more effective than some similar models applied in earlier literature. Notably, the following studies have used the same data as in this work. A single adaptive neuro-fuzzy inference system (ANFIS) employed by Qiu, Gong, and Gao [49] was superior to single MLP and radial basis function (RBF) neural networks in estimating the slump. The testing RMSE of ANFIS, MLP, and RBF were 3.4896, 4.9479, and 4.7601 which are all larger than the SCE-MLP of this work (testing RMSE = 3.1798). Likewise, Moayedi, Kalantar, Foong, Tien Bui and Motevalli [46] used a combination of MLP with ant lion optimization (ALO), biogeography-based optimization (BBO), and grasshopper optimization algorithm (GOA) for the same purpose. In that study, the ALO-NN could yield the most accurate estimation of slump (testing RMSE = 3.7788). This is while the SCE-MLP of the present study is comparably more accurate, owing to the lower error of prediction (testing RMSE = 3.1798). Therefore, it is also more potent than BBO-MLP and GOA-MLP.

Considering the time-efficiency, the SCE is classified as a quick optimizer. This algorithm is much faster than both the VSA and MVO used in this study, and the BBO and ALO used in the discussed research (optimization times of BBO and ALO were around 32,785 and 4273 s, respectively).

4. Conclusions

In this work, the efficiency of three novel optimizers including the vortex search algorithm, multi-verse optimizer, and shuffled complex evolution was investigated for a highly non-linear civil engineering problem. The algorithms were coupled with artificial neural network for the proper prediction of fresh concrete slump. From sensitivity analysis, it was derived that the SCE enjoys less complexity and, consequently, less computation time for training the ANN. Evaluation of the results, however, showed that the MVO is the most powerful algorithm in analyzing the relationship between the slump and concrete mixture ingredients. In the testing phase, the SCE emerged as the most accurate model. This indicates that the SCE-MLP can predict the slump of fresh concrete mixtures unseen to the model more reliably than the VSA-MLP and MVO-MLP. Overall, the results proved the efficiency of the tested algorithms for enhancing the accuracy of the ANN. The combination of the SCE and ANN can also be a rapid and promising approach for the early prediction of the concrete slump in civil engineering projects and could therefore provide contractors with a project planning advantage. However, there are interesting aspects that should be explored in future research. Trying a reduced dataset (after feature selection) and performing a comprehensive comparison among more recent metaheuristic optimizers coupled with benchmarks such as ANFIS and SVM could be of great interest.

Figure 8. Importance analysis of the dataset.

Equations (7)–(12). The numbers of these two equations are the weights and biases of the equation function (i.e., $\text{Tansig}$).

\begin{align*}
U &= 0.13274 + 0.6765 \times V + 0.9176 \times Z \\
X &= 0.89653 + 0.5836 \times V + 0.4345 \times Z \\
Y &= 0.17887 + 0.3617 \times V + 0.7992 \times Z \\
W &= 0.14203 + 0.1829 \times V + 0.5337 \times Z \\
Z &= 0.7422 + 0.7853 \times V + 0.8634 \times Z \\
V &= 0.8667 + 0.4761 \times V + 1.8084 \times Z \\
W &= 0.5322 + 0.7284 \times V + 0.9905 \times Z \\
W &= 0.8335 + 1.1251 \times V + 0.9107 \times Z \\
Y &= 0.8368 + 0.5836 \times V + 0.4132 \times Z \\
X &= 1.245 + 0.9176 \times V + 0.3617 \times Z
\end{align*}
Author Contributions: H.S.: methodology, writing—original draft preparation, resources, investigation. M.K.: software, investigation, data curation. M.L.N.: supervision, project administration, validation, funding acquisition; writing of final version. All authors have read and agreed to the published version of the manuscript.

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