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Modeling and Optimization of a Liquid Flow Process using an Artificial Neural Network-Based Flower Pollination Algorithm

https://doi.org/10.1515/jisys-2018-0206
Received April 27, 2018; previously published online July 17, 2018.

Abstract: Controlling liquid flow is one of the most important parameters in the process control industry. It is challenging to optimize the liquid flow rate for its highly nonlinear nature. This paper proposes a model of liquid flow processes using an artificial neural network (NN) and optimizes it using a flower pollination algorithm (FPA) to avoid local minima and improve the accuracy and convergence speed. In the first phase, the NN model was trained by the dataset obtained from the experiments, which were carried out. In these conditions, the liquid flow rate was measured at different sensor output voltages, pipe diameter and liquid conductivity. The model response was cross-verified with the experimental results and found to be satisfactory. In the second phase of work, the optimized conditions of sensor output voltages, pipe diameter and liquid conductivity were found to give the minimum flow rate of the process using FPA. After cross-validation and testing subdatasets, the accuracy was nearly 94.17% and 99.25%, respectively.

Keywords: Process control, optimization, neural network, flower pollination algorithm.

1 Introduction

In most industrial applications, there is a need to calculate the inputs to a process that will drive its outputs in a desired way and thus achieve the optimum (desired) goal. In such applications, a mathematical input–output model for the process is usually derived. Most of the process control systems are at threat due to improper input parameter settings.

To optimize the performance of a multivariable process, control through the classical method is inflexible and time-consuming. The main drawback of classical optimization is getting a response that is influenced by individually independent variables. When a response is measured with respect to the influence of a particular variable, then other input variables should be kept constant. In general, interactiveness between the input variables is absent in classical optimization, that is why it can generate the overall effects on an independent variable with respect to a particular response. A precaution is that the total number of experimental trials, if increased, is time consuming. That is why an alternative approach is adopted wherein mathematical modeling (computational optimization) of the process is designed (input–output relationship) using different computational intelligence (CI) techniques. The model could be based on either physical phenomena or historical input–output data for a given system. Once the model is developed, mathematical techniques can be applied to determine the inputs to the process that will satisfy a certain given criterion. Normally, in a liquid flow control process, flow rate depends on several important factors like sensor output, pipe diameter, liquid conductivity, liquid viscosity, etc. In this present investigation, the authors developed a mathematical model between the abovementioned variables using one of the efficient bio-inspired neural network (NN) model CI techniques such that it can describe the liquid flow control process in an efficient manner.

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Flow rate measurement is one of the high precision operations performed in most of the process control industries; it can suffer from the setback of various effects like the effect of energy associated with a flowing fluid through a pipeline, the Doppler effect and the effect of the speed of the fluid suction pump, which are important causes for rejection of a sensor in the process industry. The liquid flow rate passing through the pipeline can be measured by the various types of flow sensor such as a positive displacement type sensor [13, 14, 16, 21, 24, 29, 34], a mass flow rate sensor such as coriolis, a vane type sensor and anemometer where mass flow rate is relied upon for the product of volume flow rate and liquid density. To overcome all of these problems, an anemometer-type mass flow rate measurement sensor has been described in refs. [11, 12, 17]. The flow rate of the fluid as a function with temperature-sensitive resistance is converted to heat energy. The transducer output of the anemometer flow sensor is nonlinear with flow rate. Therefore, it minimizes the nonlinearity characteristic of transducer output and liquid flow rate. The present investigation proposes an NN model of the flow rate of a process based on an experimental investigation where controlling of this transducer output, pipe diameter and liquid density was also considered. Furthermore, this work found the optimum condition of flow using the flower pollination algorithm (FPA).

The FPA is already being utilized in different domains of optimization. A new hybrid optimization method [9] has been described by the FPA with particle swarm optimization to improve the searching accuracy in global optimization. Abdel-Baset and Hezam [1] proposed a new method that was developed based on the FPA combined with chaos theory (IFPCH) used to test several ratio optimization problems' (ROPs) benchmark; a hybrid optimization method called the hybrid FPA with a genetic algorithm (FPA-GA) was described in ref. [2] to improve the searching accuracy in seven benchmark optimization problems. Abdel-Baset and Hezam [4] described – by combining with the features of FPA – an improved simulated annealing algorithm proposed (FPSA) for the optimization of engineering problems. They [3] also proposed a novel technique to solve the ill-conditioned system of linear and nonlinear equations by hybridization and combined the feature of FPA and the conjugate direction (CD) method. A new binary version of flower pollination [5, 8] is proposed for solving the 0-1 knapsack problem. Application of modified FPA is discussed in refs. [6, 7].

Except for FPA, other soft computing techniques are also applied in different fields with real-life applications like a genetic-based NN ensemble applied for the estimation of daily soil temperature [25] by using a sequential genetic-based negative correlation learning algorithm. A comparative study was done between the modular model (MM) and global models (GM) for the prediction of the stream flow [37] by employing the binary coded swarm optimization for the identification of filter parameters and model structure while an extreme learning machine was used to reduce the computation time. How the CI methods investigated hydrogen production [10] and explained the performance in the prediction, assessment and optimization tasks related to different types of hydrogen production methods were also studied. An application of a CI-based survey [22] (single and hybrid methods) in flood management system (FMS) and a comprehensive survey of FMS have been explained. An artificial NN approach was employed [15] to determine the implicit limit-state functions for reliability evaluations in performance-based design and to optimally evaluate a set of design variables under specified performance criteria and corresponding desired reliability levels in design.

The present paper studies a bio-inspired algorithm FPA for the optimization of an NN model to avoid the local minima, improve accuracy and reduce the convergence speed of a liquid flow process. Here FPA advances the performance of NN after optimizing the weights and bias value to explore large search spaces and increases the ability to choose a similar solution. That is why a flower-pollination-based neural network algorithm (FPNN) is more suitable in convergence speed and accuracy than a BAT Cuckoo search algorithm and particle swarm optimization for an optimized NN model.

For a liquid flow control process [14, 29], the relationship between output (i.e. flow rate) and input variables (i.e. sensor output voltage, pipe diameter, liquid conductivity, liquid viscosity, etc.) is assumed to be nonlinear in nature. Several nonlinear models [12] like regression analysis, response surface methods, analysis of variance (ANOVA), etc. are very popular, wherein polynomial, logistic, quadratic, exponential, logarithmic and power equations can be used to represent the behavior of a system [17]. During a numerical extraction method, an efficient optimization technique is required to optimize the model parameters such that the experimental curve fits best with the simulated output. Therefore, accurate modeling of a liquid flow control process is a typical example of a nonlinear optimization problem where we need to identify the optimal parameters for the model. The accuracy of the extracted parameters depends on the selection of a suitable optimization technique.

Unsupervised machine learning method [18], support vector machine (SVM) and K nearest neighbor (KNN) were developed as functional classifiers, which can correctly and automatically classify the actual level of the flow rate from unseen datasets. But it is difficult to choose a better kernel function to construct the model, and other disadvantages are the long training time on large datasets and difficulty in understanding and interpreting the final model, variable weight and individual impact.

This paper is organized as follows: in the Introduction, the design of a flow sensor and the experimental set up are briefly introduced in Sections 2 and 3. Section 4 introduces the modeling and optimization technique. In Section 5, the proposed algorithms NN and FPA are described, while the results are discussed in Section 6, and finally, conclusions are presented in Section 7.

2 Flow Sensor Design

The present research was done by using a semiconductor-based anemometer flow sensor instead of other types of flow sensor, which are used as process control industry alternatives. The present work sensors are an electromagnetic flow sensor, an ultrasonic flow sensor, a hall effect flow sensor, a Venturi meter, an ultrasonic flow sensor, etc. This sensor has the following advantages: low cost, application of the cooling technique, Doppler effect, negligible fluid suction pump and energy association, applicability for a wide range of fluid speeds (up to 600 lpm for the present experiment) by means of the convection method, can be used a long period of time, high resolution and less interference of noise on the output.

An anemometer flow sensor is designed by placing four transistors in diametrical plane of a polyvinyl chloride (PVC) pipe at right angles to each other to form a bridge circuit. The base and emitter terminal of each transistor are shortened to form a P terminal, while the collector terminal is considered as an N terminal so that the transistor can be considered as a conventional PN junction diode. After forming a Wheatstone bridge circuit, one pair of transistor operates in a forward biased mode while the opposite arm transistor operates in a reverse bias. Due to the cooling technique, the change in resistance for the forward biased transistor and reverse biased transistor will be different. The resulting bridge output voltage is the sum of the positive and negative half cycle output voltage, which again linearly depends on the change in forward biased resistance. As the change in resistance is linearly proportional to the flow rate, the sensor output produces a linear voltage corresponding to the flow rate.

3 Experimental Setup for the Liquid Flow Process

The experimental work was carried out with the flow and level measurement and control setup. The setup was used along with the flowing parts, which are given in Table 1.

The experimental work was done in a process control setup with flow and level measurement and control (model no. WFT-20-I), as shown in Figure 1. In the present investigation, the liquid velocities measured were in the range of 0 lpm–600 lpm. Flow sensor voltages were calibrated against liquid flow velocities, which

Table 1: Experimental Setup.

Machine/Tools	Specification/Description
Process control setup flow and level measurement and control	Model no. WFT-20-I
Anemometer flow sensor	Designed by the SL 100 transistor
PVC pipe	Diameter with 20 mm, 25 mm and 30 mm
Digital multimeter	3 1/2
Rotameter	Taking the reading of the flow rate ranging 0–600 lpm

Figure 1: Semiconductor-based Anemometer.

were determined by a special mass flow control unit to have an inaccuracy of 1% from the reading. Overall temperature variation of the liquid was typically less than ±0.5°C during the course of the entire experiment at room temperature. The purpose of water flow control process is to keep the water flow in the tube at a desired rate and track the reference trajectory. In this paper, water is considered as the liquid to check the nonlinearity of the cylindrical tank. A reservoir tank collects the water that is pumped to the cylindrical tank. The flow is calculated by using an anemometer-type flow sensor. In this experimental setup, water is pumped into in a PVC pipe from the reservoir tank (see Figure 2). A DC motor is connected in the reservoir to drive the system. The rate of change of the water flow is measured by using a rotameter indicator. A nonlinear electrical signal is achieved across the noncontact type liquid flow sensor connected at the end of the PVC pipe. Here, we used a transistor-based flow sensor wherein four transistors were connected in a diametrical plane of the PVC pipe to form a bridge-type full wave rectifier. A change in water flow affected the output of the sensor signal. Water from the sensor fell into the cylindrical tank, which was again connected to the main water reservoir through a pipe so that a cyclic process is formed. A pneumatic control valve allowed water to flow into the tube from the tank and caused a flow rate change in the tube. The operation was repeated throughout the control process until the water flow rate in the tube was set to a reference. A reference trajectory or flow rate was first set to be followed by the system. From the above experimental setup, we obtained a sensor output voltage with respect to the variation of the water flow rate under the different combination of pipe diameter and water parameters [19].

Experiments were carried out at different flow rates, sensor output, pipe diameter and liquid density. The output variable was considered as the liquid flow rate predicted by the optimization technique defined by the function of input parameter sensor output, pipe diameter and liquid density. The experimental conditions are shown in Table 2.

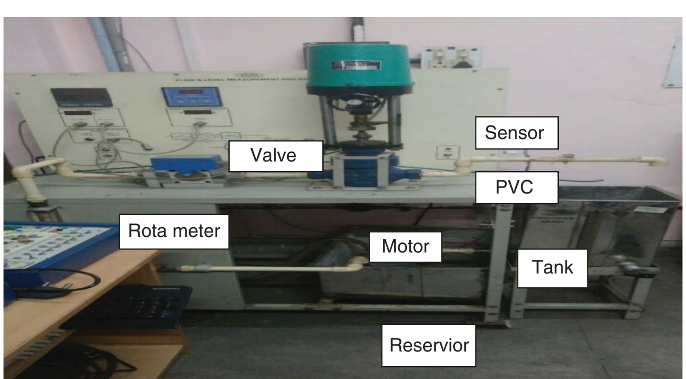

Figure 2: Experimental Setup for Liquid Flow Rate Measurement [19].

Table 2: Ranges of the Process Parameters.

Process conditions (input parameters)	Range of the parameters
Sensor output voltage	210 mv–285 mv
Pipe diameter (mm)	20, 25 and 30
Water conductivity (W/m.k)	606, 615 and 622

4 Proposed Methods for Modeling and Optimization of Liquid Flow Process

Before going through the detailed process for NN-based modeling and optimization using FPA, some preliminary concepts about NN and FPA are discussed here.

4.1 Preliminary details of an Artificial Neural Network (ANN)

An ANN is one of the models of AI that are inspired by the human neuron topology applied to overcome the nonlinearity problem between input and output data (see Figure 3). This model constructs the complex structure for the datasets for which we predict output for the unknown input variable that lies in a domain [14]. An ANN has great potential to predict and determine more practical results compared with the traditional methods [29]. The sole goal of an ANN is to make a computer learn something so that the network would adapt to a given dataset. Like human beings, ANN can learn by example and apply these into a training purpose, that is why it is suitable for pattern recognition, speech recognition or data classification problems [23].

The construction of an NN involves three different layers with feed forward architecture. This is the most popular network architecture in use today. The input layer of this network is a set of input units that accept the elements of input feature vectors. The input units (neurons) are fully connected to the hidden layer with the hidden units. The hidden units (neurons) are also fully connected to the output layer. The output layer supplies the response of the NN to the activation pattern applied to the input layer. The information given to a neural net is propagated layer by layer from the input layer to the output layer through (none) one or more hidden layers. The following is the simplest NN model.

The factors $W_1,W_2,\ldots,W_n$ are weights to determine the strength of input vectors $I = [I_1,I_2,\ldots, I_n]^T$. Each input is multiplied by the associated neuron connection $I^T W$, which can be given as the following equation. The positive weights excite and the negative weights inhibit the node output.

$$I = I^T \cdot W = I_1 W_1 + I_2 W_2 + \ldots + I_n W_n = \sum_{i=1}^{n} I_i W_i \qquad (1)$$

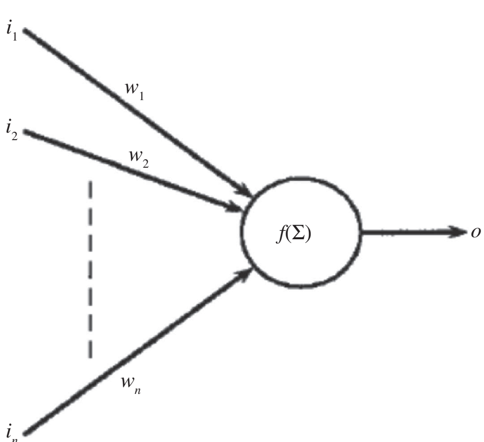

Figure 3: A Simple Neuron.

The nodes interval or threshold F is the magnitude offset. It affects the activation of node output O as follows:

$$O = f(I) = f\left\{\sum_{i=1}^{n} I_i W_i - \Phi_k\right\} \tag{2}$$

For the classification task, the ANN needs to be trained for the networks to be able to produce the desired input–output mapping. For training purposes, a set of examples or data is fed into the network, and connection weights, which are also called the synaptic weight, are adjusted by using a learning algorithm. The objective of the NN system is to give a desired output in response to some input signals. Before the training of the NN, the system is initialized to its default or random values. While the network is being trained, the weights that define the connection between the nodes can be modified, and depending on the input and hidden values, the structure can also be changed using some conventional learning algorithms like the back propagation algorithm [27, 32]. This implies that it is possible to optimize the NNs modifying the structure of the solution and modifying the way that the weights are calculated. However, recently, different evolutionary optimization techniques or metaheuristics [28, 31, 33, 36] were successfully employed to learn the weights of an NN.

4.2 Preliminaries of an FPA

A FPA is typically associated with the transfer of pollen [38] for the reproduction or flowering of plants, and pollinators such as insects, birds and bats are mainly responsible for such transfer. An FPA [39–41] was recently proposed metaheuristic optimization that is based on some simplified rules for pollination. Biotic cross-pollination can be assumed as a process of global pollination, and pollen-carrying pollinators follow Levy flights during transport (Rule 1). For local pollination, abiotic pollination and self-pollination are used (Rule 2). Pollinators may develop flower reliability, which is proportional to the resemblance of two flowers, i.e. reproduction probability (Rule 3). The switching of local to global pollination can be controlled by a switch probability $p \in [0, 1]$, slightly biased towards local pollination (Rule 4). Here, each pollen or flower corresponds to a solution of the optimization problem being considered. Global and local pollinations (i.e. search) are done according to the following two equations [36], respectively.

$$x_i^{t+1} = x_i^t + \gamma \text{ Lêvy}(\lambda)\left(g_* - x_i^t\right) \tag{3}$$

$$x_i^{t+1} = x_i^t + \varepsilon\left(x_j^t - x_k^t\right) \tag{4}$$

Here, x_i^t is the pollen i or solution vector x_i at iteration t, γ is the scaling factor to control the step, g_* is the current best solution found among all solutions at the current iteration, x_j^t and x_k^t are pollens from the different flowers of the same plant species, and ε stands for random walk step size within a uniform distribution in [0, 1]. The reason behind selecting an FPA as an optimization method is that it gives better convergence and accuracy than do other popular metaheuristic techniques.

5 Proposed Approach for Modeling

The objective of this work was to find an optimal point during a flow process control where flow rate will be at minimum, i.e. the most suitable condition for grinding. Three conditions or constraints of the process are chosen on which different flow rates are obtained. These conditions are flow sensor output, pipe diameter and liquid (water) conductivity. To obtain the optimal condition, NN modeling of a liquid flow process is proposed here. The proposed method has two stages: in the first phase, a single NN model for flow rate was developed by assuming a linear relationship between inputs (conditions during flow process) and outputs (flow rate). These neural models were then optimized using an FPA, which was used to find out the optimal value of weight and bias parameters of the NN model by minimizing the training error. In the second phase, a search or optimization was carried out to find the best value of the flow sensor output, pipe diameter and liquid (water conductivity) so that the combined function of derived neural models for flow rate is minimized. For this optimization, FPA is used again.

5.1 Finding NN Model for the Flow Rate

In this work, it is considered that flow rate (F) is the linear function of output of sensor voltage (E), pipe diameter (D) and water conductivity (k). A simple neuron without any hidden layer is used to represent a linear function. So, it can be written as follows:

$$F = f_1\,(E,\ D,\ k) \tag{5}$$

For each of these neurons, nodes of the input layer are sensor output, pipe diameter and conductivity, whereas the flow rate is the node of the output layer. There are three weights, i.e. $w_{1,}$ w_2, w_3, which are associated with the three inputs, respectively, and the bias term β is associated with the output node. Here, we do not consider any activation function, as this work is not a classification problem. So, according to the NN model, temperature or force can be expressed as follows:

$$F = E * w_{1,F} + D * w_{2,F} + k * w_{3,F} + \beta_F \tag{6}$$

Now, these weights and bias parameters are unknown, and their optimal values are needed to be derived. For this optimization purpose, an FPA is introduced to find out the NN structure, i.e. function F. For learning the NN, the experimental data that were obtained from the experiments are used for training. This training dataset consists of a set of values of output of the flow sensor, pipe diameter and fluid conductivity (water) as inputs and corresponding values of the flow rate as outputs. A total of 20 such types of data are generated by experimentation. However, 80% of these data, i.e. 17 cases, are used for training, and the rests or the three data are used for testing of a new case for the purpose of validation. Initially, the FPA generates some random populations; those can be considered as the initial solutions for the problem. A set of w_1, w_2, w_3, β is considered as the populations. For m number of training data, the squared error can be given as follows:

$$E = \sum_{i=1}^{m} (t_i - o_i)^2, \tag{7}$$

where t is the target output and o is the calculated output from the training data. This training error E is used as a fitness or objective function of the FPA, which needs to be minimized. Based on the training error, the best and optimal solution is obtained after completion of all iterations. For the implementation of the FPA, the following parameter setting is considered for optimizing the weights and bias of the NN (Table 3).

After implementation of the FPA, the flow rate (F) can be written as follows:

$$F = E * 0.13719 + D * (-0.0166) + k * (-1.0519e - 05) + (-0.03575) \tag{8}$$

To observe the effectiveness of these models, one validation technique is utilized. First, these models are tested against a training dataset, i.e. cross-validation. Next, these models are validated for three new data, or

Table 3: Parameter Setting for FPA for NN Modeling of Flow Rate.

Parameter of FPA	Value
No of parameter to be optimized	3
Range of E	0.180–0.265
Range of D	0.20–0.30
Range of k	550–650
Number of initial solution	20
Maximum iteration	2000
probabibility switch	0.8

those that were not used for training. So, for cross-validation, the values of flow rate are found out using the mentioned equations for 17 training conditions, and the calculated values are compared with the experimental values, which are shown in a flowchart in Figure 6. From Tables 4 and 5, it can be seen that these models can predict the flow rate for different training conditions with a very satisfactory accuracy of 94.17%. Thus, this process validates our proposed approach.

Figure 4 shows a comparative study between the experimental and calculated values of the outputs with respect to the number of instances; both the experimental and calculated flow rate are increased proportionally to the instances. Figure 5 represents the graph between deviation $\left(=\frac{X_{\exp}-X_{\mathrm{Cal}}}{X_{\exp}}\right)$ and experimental flow

Table 4: RMSE for Cross-validation.

Parameters	RMSE	Accuracy
Flow rate	5.83%	94.17%

Table 5: Results for Testing New Data.

Parameters	Experimental value	Calculated value	RMSE	Accuracy
Flow rate (*F*)	0.0056	0.005236926	0.75%	99.25%
	0.0064	0.005659794		
	0.0072	0.006695997		

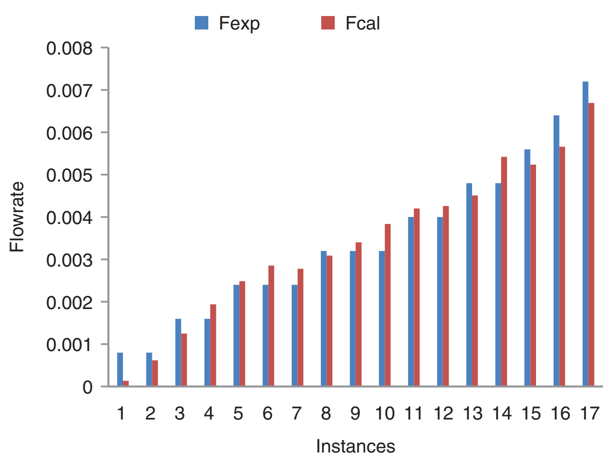

Figure 4: Calculated Flow Rate vs. Experimental Flow Rate.

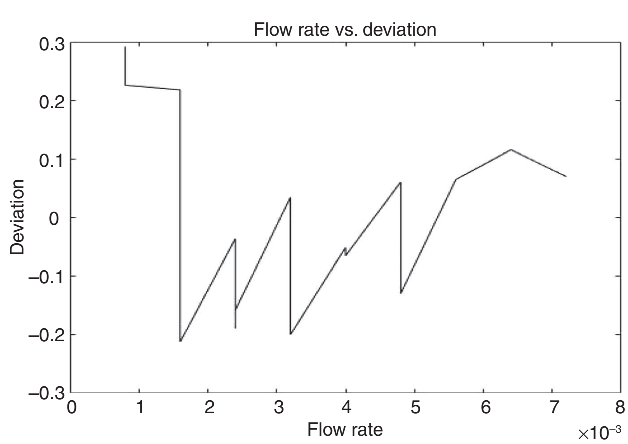

Figure 5: Deviation vs. Experimental Flow Rate.

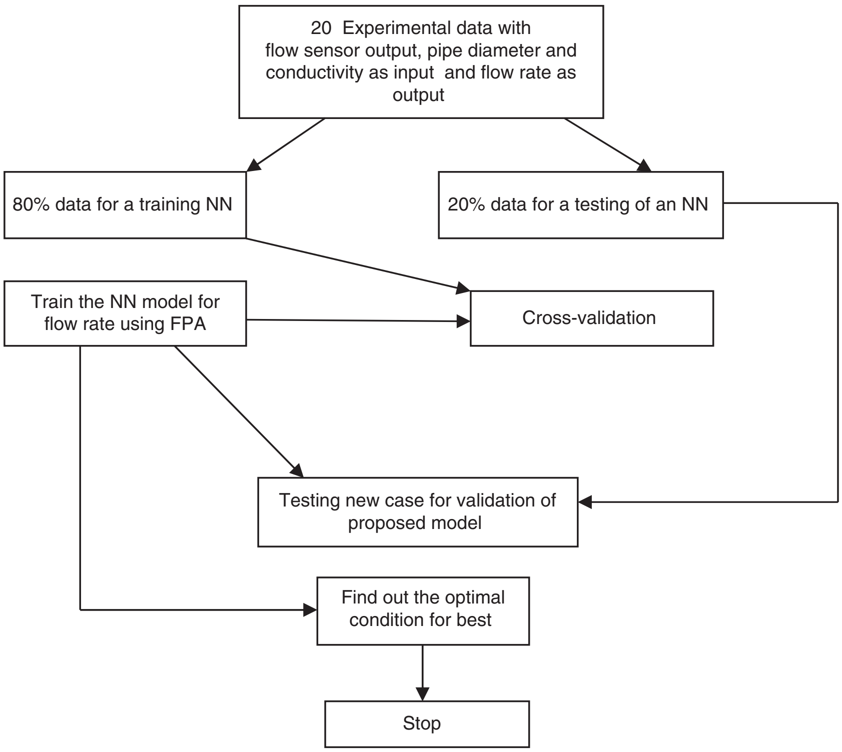

Figure 6: Flowchart of the Proposed Methodology.

rate, where deviation is minimum between the flow rate of 100 lpm and 400 lpm. The prediction error can be calculated using the root mean square error (RMSE), which can be defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(\frac{X_{\text{exp}} - X_{\text{Cal}}}{X_{\text{exp}}}\right)^2} * 100\% \tag{9}$$

$$\text{Accuracy} = (100 - \text{RMSE})\,\%, \tag{10}$$

where X_{exp} is the experimental value, X_{cal} is the calculated value and m is the number of training data.

5.2 Finding Optimal Condition for Flow Rate

In the next phase of this work, the best condition for the proper flow rate is found by searching optimal values of sensor output voltage, pipe diameter and water conductivity so that, at that point, the liquid flow rate is minimized. Now, a new fitness or objective function (*OF*) is defined where the numerical values are only considered and not their unit. Again, FPA is implemented to minimize this combined function of derived neural models for temperature and force. It is clear that *OF* will have minimum value when the flow rate will have a minimum value. In this case, a set of random values of E, D and k is used as initial solutions or populations. So, these three parameters are needed to be optimized by the FPA such that the value of the *OF* is minimized. The search ranges of these parameters are selected so that they match with the experimental conditions.

6 Result Analysis

The overall optimization is done by 20 experimental data with flow sensor output, pipe diameter and conductivity as input and flow rate as the output. Among the 100% datasets, 80% (17) datasets are used for training purposes and cross-validated by the optimization technique to determine the RMSE and the accuracy of the predicted flow rate, as shown in Table 4.

Next, the NN models are validated using the remaining 20% data (here, three new cases); those were not used for training previously. It can be observed that the model is able to predict a flow rate for new conditions with good accuracy. Table 5 shows a comparison between predicted and experimental values of the flow rate. This proves the effectiveness of the proposed model, as shown in Figure 6.

After the completion of iteration, it is found that the optimal condition is found as 0.200, 0.3 and 590, respectively, for sensor output voltage, pipe diameter and water conductivity and minimum error is at −0.006718.

As the sensor output voltage increases, the semiconductor-based anemometer flow sensor allows the increment of the liquid flow rates. This flow rate is very much affected by the primary input parameter, sensor output. When pipe diameter is increased for the same sensor output, the flow rate is also proportionally increased. Although the sensor is placed in a diametrical plane of the PVC pipe, the change in pipe diameter also has an impact on the liquid flow of the process control. Irrespective of the liquid density, conductivity also proportionally affects the flow. The FPA analysis also shows that minimum sensor output with the application of large pipe diameter and least liquid conductivity is the optimized condition for the process flow. Therefore, an FPA can be a perfect tool to optimize the liquid flow process.

7 Conclusion

Modeling of liquid flow control in a process industry is an interesting task for the researchers. Generally, liquid flow and level measurement control unit depends on the voltage output of a sensor (anemometer), diameter of the pipe, liquid viscosity and liquid conductivity. Initially, 118 Measurements (i.e. liquid flow rate) were observed in a laboratory at different experimental conditions (i.e. for different values of pipe diameter and sensor voltage). In this study, our aim was to model the liquid flow control process so that we could find a relationship between liquid flow rate, pipe diameter and sensor voltage output by keeping the liquid viscosity and conductivity at a constant level. For mathematical modeling purposes, we used analysis of variance (ANOVA) as a nonlinear model to establish the relationship between variables of the liquid flow control process.

Now, in finding the suitable ANOVA-based model for a nonlinear optimization problem, we need to find the optimal values of the coefficient of the models using some suitable metaheuristic optimization techniques so that the estimated liquid flow rate best fits with the experimental results. For this purpose, we have proposed FPNN and observed its efficiency for the modeling of liquid flow control process.

Both the NN and flower pollination are theoretically very simple and relatively easy to implement due to the very few parameters that need to be adjusted during the optimization process. An ANN-based FPA can deal with the continuous optimization problem as well as has a great potential to solve real-time problems with great accuracy. Here, this algorithm was successful in solving the optimization problem with a higher degree of accuracy of 94.17% for cross-validation and 99.25% for three subtesting data. The result of the experiment shows that this unimodal optimization technique is very successful in finding one solution for a multiple number of runs. Two of the main advantages of this hybrid optimization technique are that it quickly yields the optimal solution and it does not require any additional input parameters for optimization purposes.

In future applications, this hybrid optimization technique can be used for multimodal process control optimization purposes; more detailed and accurate modeling of the liquid flow control process (including liquid viscosity and conductivity as the input variable) could be a future aspect of this work. Moreover, further tunings of the metaheuristics are necessary to achieve more efficiency, accuracy, convergence speed and stability.

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