Design an intelligent calibration technique using optimized GA-ANN for liquid flow control system

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ABSTRACT. *Designing a highly accurate model for liquid flow process industry and controlling the liquid flow rate from experimental data is an important task for engineers due to its non-linear characteristics. Efficient optimization techniques are essential to accomplish this task. In most of the process control industry flow rate depends on a multiple number of parameters like sensor output, pipe diameter, liquid conductivity, liquid viscosity & liquid density etc. In traditional optimization technique its very time consuming for obtaining the optimum flow rate which is manually controlled in the process. Hence the different computational optimization processes are utilized by using different intelligence techniques. In this paper three different selection of hybrid Genetic Algorithm- Neural network model is proposed & tested against the present liquid flow process. Equations for neural network are being used as non-linear model and these models are optimized using the proposed different selection of Genetic optimization techniques which is based on mimic of the genetic evolution of species that allow the consecutive generations in population to adapt their environment. From the numerical result it is observed that among the three different selection rank selected hybrid Genetic Algorithm- Neural network (GA-ANN) model is better than the other two selections (Tournament & Roulette wheel) in terms of the accuracy (98.42%) of final solutions, minimum absolute error (0.6463), computational time, and stability.*

RÉSUMÉ. *En raison de ses caractéristiques non linéaires, la conception d'un modèle extrêmement précis pour l'industrie de supervision de la dynamique des fluides et le contrôle du débit de liquide à partir de données expérimentales est une tâche importante. Des techniques d'optimisation efficaces sont essentielles pour accomplir cette tâche. Dans la plupart des industries de supervision, le débit de liquide dépend de nombreux paramètres tels que la sortie du capteur, le diamètre de la conduite, la conductivité, la viscosité et la densité du liquide, etc. Dans la technique d'optimisation traditionnelle, il prend beaucoup de temps pour obtenir le débit optimal lors du contrôle manuelle. Par conséquent, les différents processus d'optimisation informatique sont utilisés à l'aide de différentes techniques intelligentes. Dans cet article, trois choix différents de modèles hybrides d'algorithme* *génétique et de réseaux neuronaux sont proposés et testés par rapport au processus actuel de la dynamique des fluides. Les équations du réseau de neurones sont utilisées comme modèles non linéaires et ces modèles sont optimisés à l'aide de ces choix différents de techniques d'optimisation génétique proposée, qui repose sur une imitation de l'évolution génétique d'espèces permettant aux générations consécutives de la population d'adapter leur environnement. Le résultat numérique montre que, parmi les trois choix différents, le modèle hybride d'algorithme génétique - réseau de neurones artificiels (GA-ANN en anglais) est meilleur que les deux autres choix (Tournoi et roulette wheel) en termes de précision (98,42%) du résultat final, d'erreur absolue minimale (0,6463), de temps de calcul et de stabilité.*

KEYWORDS: *liquid flow control process, anemometer type flow sensor, modelling, genetic algorithm, neural network model.*

MOTS-CLÉS: *processus de contrôle de la dynamique des fluides, capteur de débit de type anémomètre, la modélisation, algorithme génétique, modèle de réseau de neurones.*

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1. Introduction

In most of the industrial applications to achieve the optimum goal or output there is a need to calculate the inputs to a process that will drive its outputs. In such applications, a mathematical relation is needed between input–output. Due to improper input parameter settings most of the process control systems are lead to mis spend. To optimize the performance of a multivariable process control through the classical method is inflexible and time-consuming. The main drawback of the classical optimization is to get the responses influenced by the individual independent variables. In classical method when a response is measured with respect to the influence of a particular variable, then other input variables should be kept constant thats the interactiveness between the input variables which are absent in classical optimization to state the overall effects on the independent variable with respect to a particular response. This kind of problem in a classical optimization can be solved if the total number of experimental trials increased which is really a time consuming process. Hence the alternative approach is adopted where computational optimization of the process is designed through the input–output relationship using different computational intelligence techniques. The model is designed on the basis of physical phenomena or the historical input–output data for a given system. Once the model is developed, computational optimization 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, liquid density etc. In this present investigation, Author develops a mathematical model between above mentioned variables using one of the efficient hybrid evolutionary algorithm & neural network model computational intelligence techniques such that it can describe the liquid flow control process in efficient manner.

Liquid flow rate measurement is one of the high precision operations in most of the process control industries, but most of the cases it suffers from the setback of various effects, like the effect of energy associated with a flowing fluid through a pipe line, Doppler effect and effect of speed of the fluid suction pump etc. which are important causes for rejection of a sensor in process industry. The liquid flow rate passing through the pipeline is measured by the various types of flow sensor like positive displacement type sensor like mass flow rate sensor such as corolis, vane type sensor & anemometer proposed by Bera *et al*. (2012), Ahmed *et al*. (2006), Bera *et al*. (2007; 2001) where mass flowrate is relied upon the product of volume flowrate & liquid density. To overcome all these problems an Anemometer type mass flow rate measurement sensor has been described in Bera *et al*. (2007, 2001) where flow rate of the fluid is the function of temperature sensitive resistance which is converted into heat energy hence transducer output of the anemometer flow sensor is non linear with flowrate. Therefore, researcher needs to minimize the non linearity characteristics of transducer output & liquid flowrate. The present investigation proposed a hybrid evolutionary algorithm along with neural network model where the desired flow rate is obtained by optimizing transducer output, pipe diameter & liquid density considering also.

In 1971, Fu first invented the Intelligent control system by means of beyond the adaptive & learning control process. Later on Saridis defined the intelligent control as the process of autonomous decision making in structured & unstructured environment based on the disciplines of Artificial intelligence, operation research & Automatic control. The main logic behind the intelligent control is that the designer needs not to design the system which ought to be rigidly modelled because intelligent control system stimulates the given input and evaluates the output. This calculated output is approximately close to the experimental result. There are a number of intelligent control systems which are available in process control industry including: Fuzzy logic controller, Artificial neural network, Genetic Algorithm, Support vector machine, Reinforcement learning etc. In present work author finds out the fitness function of five dimensional from Neural network model from train data & in next level for testing purpose three different version of hybrid Genetic Algorithm- Neural network (GA-ANN) intelligent control is applied.

Genetic algorithms (GA) approach, based on natural biological evolution motivated by the Darwinian Principle of evolution through genetic selection. Compared to traditional optimization technique Genetic algorithm is more robust, global and may be applied without recourse to domain-specific heuristics. It can be used not only for general optimization problems, but also in indifferent optimization and unconventional optimization problems. GAs are widely used for machine learning, function optimizing and system modelling. Goldberg (1989) proposed an optimized Genetic Algorithm for describing an energy saving building system in modern building project. Sardinas *et al*. (2006) Describing the application of Genetic Algorithm for an optimization model of a linear laminated elastic plate. Genetic Algorithms have been shown to be an effective tool to use in data mining and pattern recognition. De Jong *et al*. (1993) describe the application of Genetic Algorithm to the optimization of Hybrid Rockets where both the continuous & discrete variables are optimized.

Artificial Neural Network is the part of the Artificial intelligence which is applicable for the different fields effectively for example, Pattern recognization, process control, Optimization and clustering. The concept of the Neural Network is similar to the Human brain neuron where signal transmission of the nodes is stimulated from human neurons. Althrough the mathematical model of the Artificial neural network is a dynamic weighted of sum by using the optimization technique we determine the weighted value of the non linear equation. Among all the different techniques in Artificial neural network, least square method is one of the best model in NN extensively used in a statistics where fitting the parameters in a linear & non linear function to a set of data points describe by Batesand (1988), Philip (1978) & Griva (2009). Other application like Predicting the total stream flow discharge, baseflow & excess flow components by Taromina *et al*. (2015), design a lagging free rainfall run off model by Nu *et al*. (2011), determine implicit limit state functions for reliability evaluations in performance-based design and optimal set of design variables also explained by Chau *et al*. (2007).

Yun *et al*. proposed a hybrid ANN-GA optimization technique to control the operation of parameters of a new dry-process cement kiln to predict and optimise the nitrogen oxide emissions. The result shows that this optimization process offers 98% accuracy. Grzesiak *et al*. (2007) used GA –ANN specialized hybrid controller for potential adaptive and robust control skills. Cook *et al*. (2007) proposed an integrated GA-NN model to predict the value of a critical strength parameter in a particleboard manufacturing process based on current operating conditions and the stage of manufacturing process. A hybrid model of an Artificial Neural Network and Genetic Algorithm describe by Ghosal *et al*. (2015) in modeling of a hybrid laser welding process to achieve the prediction and optimization of penetration depth with corresponding process parameters in CO_2 laser–MIG hybrid welding. Istadi *et al*. (2006) proposed a hybrid artificial neural network−genetic algorithm to model, simulate, and optimize a dielectric barrier discharge (DBD) plasma reactor without catalyst and heating. Erlich *et al*. (2009) proposed an optimized GA-ANN to solve the optimal power flow (OPF) problem for reactive power dispatch and result of the Simulation reveal that the proposed method can speed up the computing procedure 5 time faster than the conventional OPF. Ramazan *et al*. (2012) designed a maximum power point tracking (MPPT) algorithms by the GA-ANN to force photovoltaic (PV) modules to operate at their maximum power points for all environmental conditions.

For a non linear process control system several non-linear models like Regression Analysis, Response Surface Methods, Analysis of Variance (ANOVA) etc are very popular where polynomial, logistic, quadratic, exponential, logarithmic, power etc. equations can be used to represent behaviour of a system proposed by Leung *et al*. (1994) & Griva *et al*. (2009). Accurate modelling of liquid flow control process is a typical example of non-linear optimization problem where we need to identify optimal parameters for the model. The accuracy of the extracted parameters depends on the selection of suitable optimization technique. In present research a non linear model of a liquid flow sustem is designed by ANN, the it is GA optimization technique is utilized to optimize the model parameters such that experimental curve fits best with the simulated output.

This paper is organized as follows: after introduction, design of a flow sensor & the experimental set up is briefly introduce in section 2 & 3. Section 4 describes the methods & optimization process, mathematical description is presented in a section 6, results & discussion and finally conclusions are presented in section 6.

2. Flow sensor

Figure 1. Semiconductor based Anemometer

Present research done by the semiconductor based Anemometer flow sensor instead of the other type of flowsensor which are used in process control industry alternatives of present work sensors are electromagnetic flow sensor, Ultrasonic flow sensor, Hall effect flow sensor, Venturi meter, Ultrasonic flow sensor etc. This sensor has the following advantages: low cost, apply the cooling technique, Dopller effect, fluid suction pump & energy association are neglected, can be applicable for wide range of fluid speed (upto 600 lpm for the present experiment) by means of convection method, long time research tool & provides high resolution and less interference of noise on output. Anemometer flowsensor designed by placing four transistor in diametrical plane of a pvc pipe at right angles to each other to form a bridge circuit. Base & emitter terminal of each transistor are shorted to form P terminal while collector terminal considers as N terminal so that transistor can be considered as 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 & reverse biased transistor will be different. The resulting bridge output voltage is sum of the positive & negative half cycle output voltage which are again linearly depends on the change in forward biased resistance. As the change in resistance is linearly propotional to the flow rate. Hence sensor output produces a linear voltage corresponding to the flowrate.

3. Experimental setup

The experimental work is carried out with the Flow & level measurement & control set up. The set up is used along with the flowing parts which are given in Table 1.

Table 1. Experimental setup

Machine/tools	Specification/Description
process control setup Flow & Level measurement and Control	Model no. WFT -20-I
Anemometer Flow sensor	Designed by the SL 100 transistor
PVC pipe	Diameter with 20mm,25mm & 30mm
Digital Multimeter	3 1/2
Rota meter	Taking the reading of the Flow rate ranging 0-600 lpm

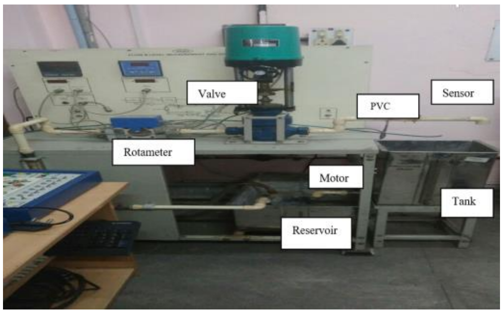

Figure 2. Experimental set up for liquid flow rate measurement

The experimental work is done in a process control setup Flow & Level measurement and Control (model no. WFT -20-I) shown in figure 1. In the present investigation, the liquid velocities measured were in the range of 0lpm-600lpm. Flow sensor voltages were calibrated against Liquid flow velocities which was determined by a special mass flow control unit, to 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 non-linearity of the cylindrical tank. Reservoir tank collects the water which is pumped to the cylindrical tank. Flow is calculated by using anemometer type flow sensor. In this experimental set up water is pumped up in poly vinyl chloride (PVC) pipe from reservoir tank. A DC motor is connected in reservoir to drive the system. the rate of change of the water flow is measured in Rota meter indicator. Non linear electrical signal is achieved across the non contact type liquid flow sensor connected at the end of the PVC pipe. Here we use Transistor based Flow sensor where four transistor connected in a diametrical plane of the PVC pipe to form a Bridge type full wave rectifier. Change in water flow affects the output of the sensor signal. Water from the sensor is fall into the cylindrical tank which is again connected to the main water reservoir through a pipe so that cyclic process is formed. Pneumatic control valve allows water flow into the tube from the tank and causes flow rate change in the tube. The operation is repeated throughout the control process till the water flow rate in the tube is set to reference. A reference trajectory or flow rate is first set to be followed by the system. From the above experimental setup we get sensor output voltage with respect to the variation of the water flow rate under the different combination of pipe diameter & water parameters. Experiments are carried out at different flow rates, sensor output, pipe diameter & liquid density. The output variable is considered as liquid flow rate predicted by the optimization technique defined by the function of input parameter sensor output, pipe diameter & liquid density. The experimental conditions are shown in Table 2.

Table 2. Ranges of the process parameters

Process Conditions (Input parameters)	Range of the parameters
Sensor output voltage	210 mv to 285 mv
Pipe diameter (mm)	20mm, 25mm & 30mm
Water conductivity (W/m.k)	606,615 & 622 (W/m.k)
Water Viscosity	725.4,779.7 &898.2 µpas.sec
Water Density	993.9,995.6&996.9kg/m3

For this work, total 134 sample data have been observed which consist of four independent variables sensor output voltage, pipe diameter, liquid (water) conductivity & viscosity. Among these 134 datasets 17 number of datasets are used for the testing purpose shown in table 3. To conduct this research, we had taken the 3 different set of pipe diameter i.e. 20mm, 25mm and 30 mm. For each of the cases we collect data of the flow rate as an experimental output data for different sensor output voltage, pipe diameter, liquid conductivity & viscosity. Liquid density is assumed to be constant as overall temperature variation of the liquid was typically less than ±0.5°C during the course of the entire experiment at room temperature. Experimental data are shown in table 3.

Table 3. Experimental datasets for liquid flow control process

Sensor output	Diameter	Conductivity	Viscosity	Flow rate
0.218	0.024	0.606	0.8982	0.0008
0.221	0.025	0.616	0.7797	0.0008
0.225	0.025	0.616	0.8982	0.0016

0.232	0.025	0.597	0.7797	0.0016
0.234	0.02	0.615	0.8982	0.0024
0.237	0.027	0.622	0.7797	0.0024
0.238	0.03	0.6065	0.7254	0.0024
0.239	0.025	0.616	0.8982	0.0032
0.241	0.027	0.622	0.7797	0.0032
0.245	0.024	0.6065	0.7254	0.0032
0.247	0.024	0.616	0.8982	0.004
0.247	0.025	0.622	0.7797	0.004
0.25	0.025	0.6065	0.7254	0.0048
0.256	0.025	0.616	0.8982	0.0048
0.254	0.024	0.622	0.7797	0.0056
0.259	0.03	0.606	0.7254	0.0064
0.265	0.027	0.622	0.7797	0.0072

4. Proposed methods for modeling and optimization

Before going through the detailed process for Neural Network (NN) based modeling and optimization using Genetic Algorithm (GA), some preliminary concepts about NN and GA are discussed here.

4.1. Preliminary of artificial neural network (ANN)

Artificial Neural Network (ANN) is one of the models of AI which is inspired by the human neuron topology applied to overcome the nonlinearity problem between input & output data. This model constructs the complex structure for the datasets for which we predict output for the unknown input variable lies in a domain. ANN has a great potential to predict & determine more practical result than the traditional methods. The sole goal of ANN is to make a computer learn something so that network would adapt to a given dataset. Like human beings, ANN can learn by example & applying these into the training purpose that’s why it make suitable for pattern recognition, speech recognition or data classification problems proposed by Chen *et al*. (2007). The construction of the neural network 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, which 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 neural network to the activation pattern applied to the input layer. The information given to a neural net is propagated layer-by-layer from input layer to output layer through (none) one or more hidden layers. Following is the simplest NN model.

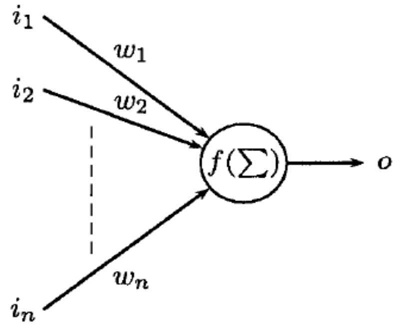

Figure 3. A simple Neuron

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 of the neuron connection $I^T W$ which can be given as following equation. The positive weights excite and the negative weights inhibit the node output.

$$I=I^T.\, W=I_1W_1 + I_2W_2+, \ldots, +I_nW_n = \sum_{i=1}^{n} I_i\, W_i \quad (1)$$

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

$$O=f(I)=f\{\sum_{i=1}^{n} I_i W_i - \phi_k\} \quad (2)$$

For the classification a desired input –output mapping is done by the trained the neural network model. For training purpose, a set of examples or data are fed to the network and connection weights, which is also called synaptic weight which is adjusted by using a learning algorithm. The objective of a neural network system is to give a desired output in response to some input signals. Before the training of the neural network, 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 algorithm like Back Propagation Algorithm proposed by Leung *et al.* (1994) etc. So by applying the proper optimization technique we can evaluate the solution of the modifying structure and weights of the Neural network model. However, recently different evolutionary optimization techniques or metaheuristics were successfully employed to learn the weights of a NN.

4.2. Preliminaries of genetic algorithm (GA)

GAs belongs to a population-based stochastic search algorithm inspired by the principles of Evolutionary Algorithms described by Mohd *et al*. (2006). GA is based on the principle of "survival of fittest", as in the natural phenomena of genetic inheritance Proposed by Charles Darwin. GA produce the potential solution to a particular problem by operates on a population.by using the biological principle in nature, a single individual of a population usually is affected the other individuals in its environment. Better an individual performs under these competitive conditions, has a greater chance to survive and reproduce. After several generations, the bad individual will be automatically removed and better individuals will be survived.

Initially GA is to optimally solve the sequential decision processes more optimized the function but last couple of years it is seen that GA has been used widely in both learning and optimization problems described by Aaron *et al*. (2015). There are two important issues in searching strategies for optimization: exploiting the best solution and exploring the search space proposed by Santosh *et al*. (2012). GA makes a balance between the exploitation and exploration of the searching strategies for optimization. It reduces the converging to a local minimum. The exploitation in the neighbourhood of possible solutions will perform as the high fittest solutions to be developed. Performance of weights evolution using GA depended on the number of populations and generations. For the very low value of these the evolution may converge to immature solution again for the very large value of populations and generations it would require longer computation time for convergence.

5. Mathematical description of the problem

Due to the non linear characteristics of the semiconductor based Anemometer flow sensor we get a variation of sensor output voltage with the change in liquid flow rate by considering the different values of the experimental pipe diameter where the sensor is placed in a diametrical plane. Again sensor output voltage depends on the pipe diameter, liquid water viscosity & conductivity & partially depends upon the liquid density which is ignored when we construct the fitness function of flowrate. So, any change in pipe diameter it is very difficult to recalibrate the conventional controller circuit each time to predict the output and it is also a time consuming process. To overcome such type of drawbacks (i.e. manual recalibration) we need to develop a mathematical model using some computational intelligence tools which may help us to establish a relationship between liquid flow rate, sensor voltage and pipe diameter, experimental liquid (water) conductivity & viscosity. These models will also help to find out the optimal operating condition and to predict the flow rate under certain condition (i.e. for particular values of diameter, sensor output voltage, water viscosity & conductivity) without recalibration. However, in this work, we have considered a basic model neural network where the output flowrate is the function of sensor output (E), pipe diameter (D), water conductivity (k) & viscosity (n) i.e

$$F = f_1(E, D, k, n) \tag{3}$$

For each of these neurons, nodes of input layer are sensor output, pipe diameter and conductivity whereas flow rate is the node of output layer. There are 4 weights i.e. $w_{1\,,} w_2, w_{3,}\, w_4$ are associated with the three inputs respectively and bias term β is associated with the output node. Here, we don't consider any activation function as this work is not a classification problem. So, according to neural network model, temperature or force can be expressed as follows:

$$F = E * w_1 + D * w_2 + k * w_3 + n * w_4 + \beta \tag{4}$$

Now, these weights and bias parameters are unknown and optimal values of those are needed to be derived. For this optimization purpose Genetic Algorithm is introduced to find out the neural network structure i.e. function F. For learning of NN, the experimental data that were obtained from the experiments are used for training. This training dataset consist of a set of values of output of the flow sensor, pipe diameter fluid conductivity (water) and viscosity are considered as inputs; and corresponding values of flowrate as outputs. Initially, GA generates some random populations those can be considered as initial solutions for the problem. A set of $w_{1\,,} w_2, w_3, w_4, \beta\ are$ considered as population. Values of the coefficients are needed to be estimated using some computational intelligence techniques from the experimental dataset.

5.1. Optimization of the mathematical model

Finding out the values of coefficients of nonlinear model (i.e. Eqn.4) of liquid flow rate is essentially a nonlinear optimization process. Normally, Evolutionary algorithm is used to fit the calculated characteristic of liquid flow control process to the experimental one. The estimation task aims to seek the most optimal values for the unknown parameters so as to minimize the error between the measured and simulated flow rate. The root mean square of the error is defined as Eq. (5) can be used as the objective function for the metaheuristic which is used for modelling of liquid flow control process.

$$\text{RMSE}\ (X) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f(E_i\,, D_i\,, K_i\ \ , n_i, X)^2} \tag{5}$$

where N is the number of the experimental data, X is the set of the estimated parameters. For ANN based modelling, the error function $(E_i\,, D_i\,, K_i\ \ , n_i, X)$ and set of parameters X can be written as

$$f(E_i\,, D_i\,, K_i\ \ , n_i, X) = E * w_1 + D * w_2 + k * w_3 + n * w_4 + \tag{6}$$

$$X = \{\ w_{1\,,} w_2, w_3, w_4, \beta\ \} \tag{7}$$

Obviously, smaller objective function value gives better solution which corresponds to superior set of estimated model parameters or coefficients.

5.2. GA–ANN hybrid model for predction and optimization

The GA–ANN hybrid model developed in the present work can be employed for training, prediction and optimization of the operational parameters of an experiment by running a single program in the MATLAB 2015B environment. Two separate data files are used for storing training and testing data of ANN. The program first employs a user defined ANN training algorithm to perform the task of training and subsequent testing to assess the function approximation and prediction capability of a particular ANN architecture. A number of ANN architectures are studied in this way by randomly varying the number of hidden layer neurons, and the architecture with the maximum prediction accuracy is considered as the best ANN. Next, the program calls the subroutine of GA and starts iteration with the initial population. As the objective function (theoretically connecting input parameters and output) exists for the experimental dataset which is shown in eqn. 4 the program control switches from the GA subroutine to the ANN module in the main program and employs the best coefficient of ANN so that testing datasets obtained maximum accuracy corresponding to the experimental datasets. The program control then switches back to the GA subroutine and the cycle continues up to the point of appropriate convergence. The program completes the training, prediction and optimization in a single run. A schematic diagram for the present method is given in Figure 4. The working of ANN and GA for the present problem is furnished in some detail as follows.

Table 4. Parameter setting for GA modeling of flow rate

Parameter of Genetic Algorithm	Value
No of decision variables to be optimized	5
Search range for the optimization	[-75,75]
No of Iteration	100 to 5000
Population size	100
Cross over percentage	0.7
Extra range factor for crossover	0.4
Mutation rate	0.1
Length of the chromosome	6bit

6. Results and discussion

The overall optimization is done by the 134 experimental datasets with Flow sensor output, pipe diameter and conductivity as input and Flow rate as output. Among the 100% datasets 85% (117 datasets) datasets are used for the training purpose & cross validated by the optimization technique to determine range of the coefficient of the NN model the NN models are validated for rest of 20% data (17 new datasets) those were not used for training previously.

As the sensor output voltage increases, due to 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 a same sensor output flowrate is also proportionally increased. Althrough Sensor is placed in a diametrical plane of the PVC pipe. So change in pipe diameter also impact on the liquid flow of the process control. Irrespective of the liquid density, viscosity & conductivity also proportionally affects the flow. As the experiment is conduct between 25-35 degree centigrade so there is no significant change in water density that's why we ignore water density as a one of the optimization parameters. The GA analysis also shows that minimum sensor output with the application of large pipe diameter & least liquid conductivity is the optimized condition for process flow. Therefore, GA can be a perfect tool to optimize the liquid flow process.

To verify its performance of the proposed the Three different selection of hybrid Genetic - neural network algorithm is tested on parameters or coefficients estimation problems for modelling of liquid flow control process. Here, the algorithms are tested against Neural network based model as described earlier section where 117 number of data sets are used to train the data & construct the objective function of liquid Flowrate using ANN model. The experimental dataset has been obtained from the laboratory experimentation as mentioned in earlier section. The dataset consists of 17 data points of sensor output voltage (E), pipe diameter (D) and liquid flow rate (F) liquid conductivity (K) & liquid viscosity (n). This experimental dataset has been used a test dataset for the parametric optimization of Genetic Algorithm based model of liquid flow control process. Objective functions for this case which is already discussed in earlier section. After optimization, best set of coefficients can be obtained. In this section, we present the numerical simulation results of GA-ANN and Three different selection of Genetic Algorithm on liquid flow control process problem. Moreover, we also perform comparison among them and give statistical analysis of the evaluated results. For all algorithms, population and maximum iteration number are set to 100 and 5000 respectively. For ANN based model, search space is restricted to 5 i.e. we have considered 5 dimensional function optimization problems to search optimal values of the coefficients $\{ w_{1}, w_2, w_3, w_4, \beta \}$.

The search range for the optimization of liquid flow control process model is set to [-75, 75] for all of the coefficients for both types of modelling. All the techniques were simulated using Matlab 2015b in a computer with 4 GB RAM, Intel (R) core (TM) i3 processor and Windows7 operating System. Due to stochastic nature of Evolutionary algorithm so they may give different output depending different random initialization. Therefore, each algorithm is executed for 20 times for each case and the statistical analysis has been carried out from the obtained simulated results. During these numerical experimentations, we have tested and compared the efficiency of the proposed algorithm on the basis of some criterions such fitness test, reliability test, computational efficiency test, convergence test and accuracy test which are described in following subsection one by one.

6.1. Fitness test

Final output or fitness value of an optimization algorithm is the most important criterion to prove its efficiency. Using above mentioned parameters setting, we optimized benchmark function by using three different selection method in Genetic Algorithm in the cases of ANN method. Here, we have considered 3 important criterions (output) namely worst (maximum) fitness, best (minimum) fitness and mean (average) fitness values which are obtained after 20 times program run. An evolutionary Genetic algorithm should give smaller values of maximum, minimum and mean of fitness as much $RMSE$ as possible for better performances. In this work, the fitness is calculated from the $RMSE$ of the algorithms. Comparative studies based on these criterions are shown in Table 5. From following Table 5, it can be seen that proposed Rank selection can reach best fitness value (minimum RMSE i.e.4.31E-05) & mean RMSE value in ANN based modelling (i.e. 4.37E-05). It is interesting to observe that for all the three different categories of RMSE for GA based ANN based modelling of liquid flow process (obtained by all algorithms) Rank selection is far better than the rest of the two different selection of GA -ANN.

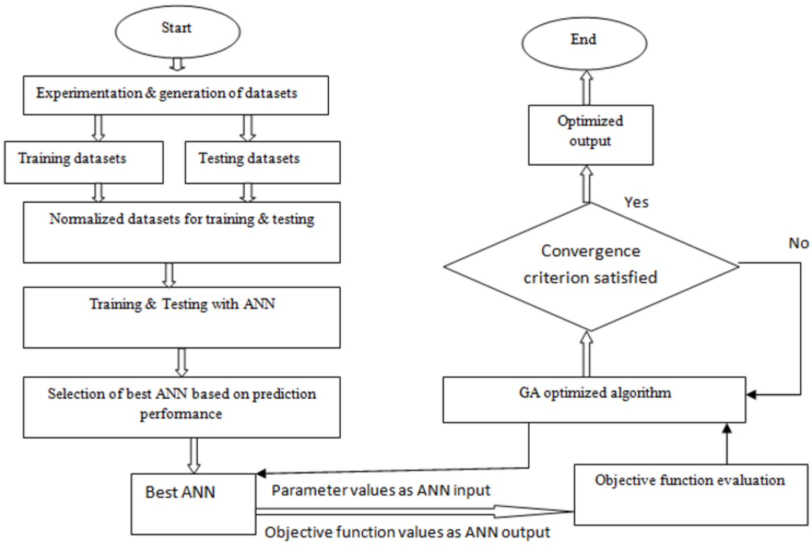

Figure 4. Logical flow diagram of the GA -ANN hybrid model in process control

Table 5. Comparative study based on maximum, minimum and mean of fitness

Fitness test				
case	Method	Maximum	Minimum	mean
	Roulette wheel	5.41E-5	5.31E-5	5.36E-5
	Tournament	5.46E-5	4.33E-5	4.44E-5
	Rank	5.40E-5	4.31E-5	4.37E-5

6.2. Reliability test

It is desirable that an Evolutionary Genetic algorithm must always able to reach nearer to the global minima or maxima point as close as possible in every single run. It indicates that the output of the metaheuristic must be reliable for every single run. But due to random initialization and stochastic process of the evolutionary algorithm, the output of the optimization process may vary in different run. However, the variation should be minimal. Therefore, in this subsection, we have tested the reliability of proposed algorithms on the basis of some median & standard deviation. Median is the measurement of central tendency of the sample or population. The standard deviation is an important statistical parameter which denotes variability or consistency of the data set. Thus, a less value of standard deviation implies a more reliable algorithm. Table 6 shows the comparative study based on median &standard deviation. It can be clearly shown that Roulette wheel & Rank both Genetic Algorithm selection get the smallest values of median (i.e. 2.70E-02) & standard deviation (1.64E-03) for ANN based model. So, regarding standard deviation & median Roulette wheel & Rank selection are the best for the 5 dimensional search space liquid flow model than the Tournament selection GA.

Table 6. Comparative study based on median, standard deviation and success rate

Case	method	median	SD
GA-ANN	Roulette	2.70E-02	1.64E-03
	Tournament	2.75E-02	1.66E-03
	Rank	2.70E-02	1.64E-03

6.3. Computational efficiency test

Besides the previous tests, the computational time is also a major factor for evaluating the efficiency of an evolutionary algorithm. For this purpose, we have observed average execution time taken by each algorithm for each of the problems of liquid flow control process which in turn denotes the computational efficiency of the algorithm. Table 7 shows a comparative study based on average execution time.

It has been observed that Rank selection Genetic Algorithm required least computational time for ANN based modelling so Rank based modelling, computational efficiency is also best for Rank selection.

Table 7. Comparative study based on computational time

Case	Method	Average computational time
GA-ANN	Roulette Wheel	21.8673sec
	Tournament	25.5410 sec
	Rank	14.5106sec

6.4. Convergence test

The above mentioned result and comparisons cannot completely illustrate the performance and the efficiency of the proposed optimization techniques. Therefore, a convergence test has been conducted on liquid flow control process modelling and where we observed the change of best-found fitness values along with the iteration number. So,convergence speeds of the proposed algorithms have been observed to see how the best-found fitness values decrease with the iteration number. For this purpose, we have chosen the output corresponding to the run where we found minimum or best fitness ($RMSE$) amongst all 20 times run and observe the fitness value at each iteration index. Table 8 shows the convergence test for different selection of GA-ANN with respect to the no of iteration 100 to 5000. From the table it is seen that fitness value of Roulette wheel selected GA-ANN model has least value. Fig. 5 shows the convergence of different selection of GA-ANN with respect to no of iteration lies from 100 to 1000.

Table 8. Comparative study of convergence test for different GA -ANN model

	fitness value		
Iteration	Roulette wheel	Tournament	Rank
100	5.41E-05	4.34E-05	4.37E-05
200	4.36E-05	4.33E-05	4.36E-05
300	4.34E-05	4.46E-05	4.32E-05
400	4.32E-05	4.40E-05	4.32E-05
500	4.33E-05	4.34E-05	4.33E-05
1000	4.31E-05	4.44E-05	4.31E-05
5000	4.32E-05	4.42E-05	4.36E-05

6.5. Accuracy test

Next, the accuracy test has been conducted to observe liquid flow rate prediction capability under different experimental conditions i.e. sensor output voltage, pipe diameter, water conductivity & water viscosity. Two indexes respectively named as mean absolute error (MAE) & mean absolute percentage error (MAPE) and respectively defined as Eqs. (8) and (9) are adopted to indicate the error values between the experimental and the simulated current data.

$$IAE = |Fmeasured - Fcalculated| \tag{8}$$

$$\mathrm{MAP}E = \frac{1}{n} \sum_{i=1}^{n} \frac{IAE}{\mathrm{Fmeasured}} \tag{9}$$

Moreover, mean Absolute Error (TAE) can be defined as:

$$\mathrm{M}AE = \frac{\sum_{i=1}^{n} IAE_i}{n} \tag{10}$$

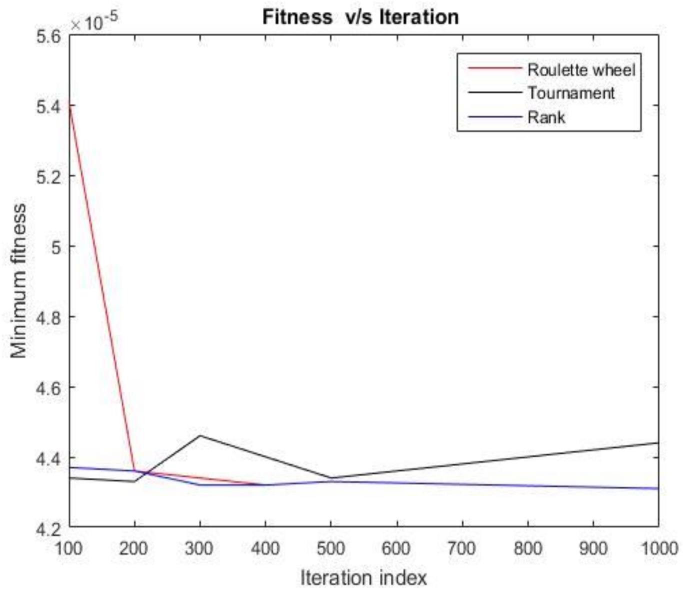

Figure 5. Minimum fitness for different GA+ANN based modelling of liquid flow process

where n is the number of measurements in the experimental dataset, $Fmeasured$ is the experimental value of liquid flow rate and $Fcalculated$ is the estimated value of liquid flow rate for a pipe diameter, liquid conductivity, viscosity and sensor output voltage. However, to calculate or estimate the values of liquid flow rate of liquid flow control process at different experimental conditions, the best output case of evolutionary algorithm has been considered where output i.e. RMSE is smallest among all different runs. The coefficient of the non linear models is obtained from GA ANN matlab code shown in table 9.

Table 9. Estimated optimal parameters by using GA- ANN based modelling of liquid flow control process

Method	w_{1},	w_2	w_3	w_4	β
Roulette wheel	0.0100	0.0100	0.0100	-0.0070	2.9607E-04
Tournament	0.0100	0.0100	4.990E-04	-0.0060	0.0053
Rank	0.0100	0.0100	0.0100	-0.0070	2.817E-04

Table 10. Comparative study based on Mean absolute error (MAE)

Case	Method	Mean Absolute Error
GA-ANN	Roulette Wheel	0.001365
	Tournament	0.001381
	Rank	0.001364

Table 11. Comparative study based on Mean absolute percentage error (MAPE)

Case	Method	Mean absolute percentage Error
GA-ANN	Roulette Wheel	0.649848
	Tournament	0.658574
	Rank	0.646371

The prediction error can be calculated using Root Mean Square Error (RMSE) which can be defined as follows

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{m}}\sum_{\mathrm{i}=1}^{\mathrm{m}}\left(\frac{\mathrm{X_{exp}}-\mathrm{X_{Cal}}}{\mathrm{X_{exp}}}\right)^2} * 100\% \tag{11}$$

$$\text{Accuracy} = (100\text{-RMSE})\ \% \tag{12}$$

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

Table 12. Comparative study based on root mean square error (RMSE) & accuracy

Case	Method	RMSE	Accuracy
GA-ANN	Roulette Wheel	0.001593312	98.42%
	Tournament	0.001617772	98.39%
	Rank	0.001593313	98.41%

Using these parameters, values of liquid flow rate of the liquid flow can be estimated for different cases or conditions. From table 10 & 11 describes a comparative study based on mean absolute error & mean absolute percentage error where it is clearly seen that Rank selected GA-ANN produce the best performering result. Table 12 shows Roulette wheel & Rank selected GA-ANN both have nearly same RMSE error & accuracy.

Figure 6 show the relative errors vs. different liquid flow rate measurement instances for GA-ANN based modelling respectively in three different selection of GA (Roulette wheel, Tournament & Rank). It can be clearly seen that the proposed Rank & Roulette wheel have the nearly same absolute error while Tournament selection having more error than above two. So we choose Rank selection GA-ANN is more suitable in terms of total absolute error in present process control system.

Figure 7 shows comparative study between experimental and calculated values of the outputs with respect to the number of instances, both the experimental & calculated flow rate is increased proportionally to the instances. Figure 8 represent the graph between deviation $(= \frac{X_{exp} - X_{Cal}}{X_{exp}})$ & experimental flowrate where the deviation is minimum between the flowrate of 250Lpm to 500 Lpm.

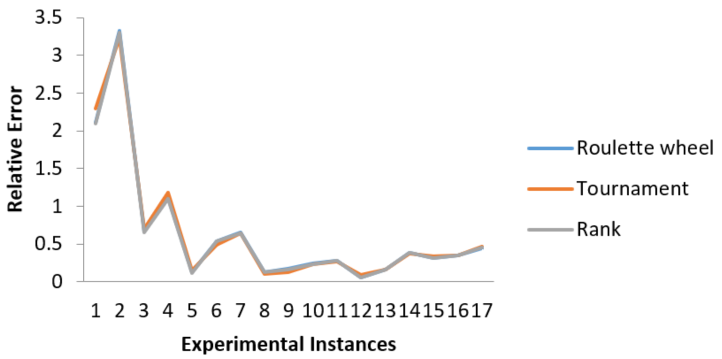

Figure 6. Relative errors for GA-ANN based modelling of liquid flow control process

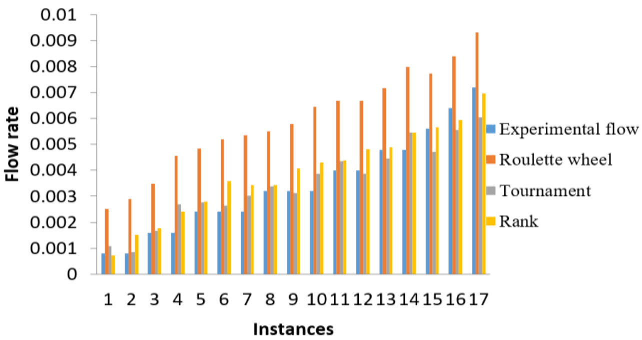

Figure 7. Comparisons of the characteristics of the experimental data and estimated liquid flow rate using GA-ANN based model

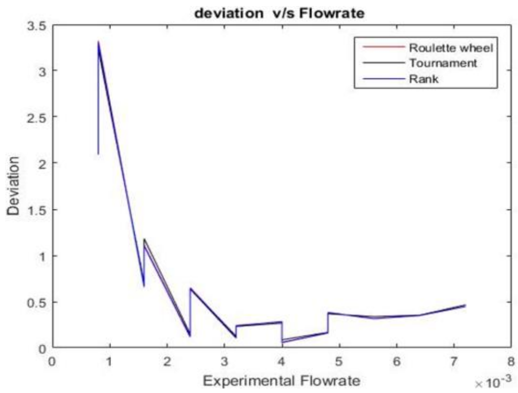

Figure 8. Deviation vs. Experimental flowrate

7. Conclusions

Modelling & optimization of liquid flow control in a process industry is an interesting task for the researchers. Generally, most of the process control industry liquid flow rate is depends upon the voltage output of sensor (Anemometer type flow sensor), diameter of the pipe, liquid (water) viscosity and conductivity of the experimental liquid. In present work Initially, 134number of measurements (i.e. liquid flow rate) have been observed from laboratory at different experimental conditions (i.e. for different values of pipe diameter and sensor voltage, flow rate, liquid conductivity, viscosity). Among this data sets 117 number of datasets used for train purpose by using GA – ANN & rest 17 number of datasets is used for testing purpose.In this study, our aim is to model the liquid flow control process so that we can find a relationship between liquid flow rate, pipe diameter, sensor output voltage, water viscosity & conductivity by keeping the water density at constant (as because due to the variation of water density the change in sensor output voltage & flow rate is very tiny). For this modelling purpose initially we have used ANN as non-linear models to establish the relationship between the variables of liquid flow control process then we find out the optimal values of the coefficient of the models using some suitable selection of GA –ANN hybrid optimization so that estimated liquid flow rate fit, best with the experimental results. For this purpose, we have proposed three different pattern selection (Roulette wheel, Tournament & Rank) Genetic Algorithm version and observed their efficiency for the modelling of liquid flow control process

Numerical simulations are performed and the statistical analysis of the results is also given. All the results indicate that the performances of the proposed Rank selected hybrid Genetic Algorithm neural network outperformed the others for the most of the cases of modelling for liquid flow control but the major disadvantages of Rank selected GA-ANN is it has comparatively high convergence rate.

More detailed and accurate modelling of the liquid flow control process including liquid density as an input variable is the future aspect of this work. Moreover except the hybrid GA –ANN evolutionary algorithm how the efficiency, accuracy, convergence speed, stability and success rate of the present process control is improved by the metaheuristics optimization technique is also future aspect.

References

Amin N. A. S. (2006). Hybrid artificial neural network−genetic algorithm technique for modelling & optimization of plasma reactor. *Industrial & Engineering Chemistry Research*, Vol. 45, No. 20, pp. 6655-6664. http://dx.doi.org/10.1021/ie060562c

Bera S. C., Chakraborty B., Kole D. N. (2007). Study of a modified anemometer type flow meter. *Sensors & Transducers Journal*, Vol. 83, No. 9, September, pp. 1521-1526.

Bera S. C., Roy J. K. (2001). An approach to the design and fabrication of a micro processor based flow meter using resistance and semiconductor probe. *IETE Technical Review*, Vol. 18, No. 5, pp. 355-360. http://dx.doi.org/10.1080/02564602.2001.11416983

Chaki S., Ghosal S. (2015). A GA–ANN hybrid model for prediction & optimization for CO_2 Laser MIG Hybrid welding process. *International Journal of Automotive and Mechanical Engineering*, Vol. 11, pp. 2458-2470. http://dx.doi.org/10.15282/ijame.11.2015.26.0207

Chau K. W. (2007). Reliability and performance-based design by artificial neural network. *Advances in Engineering Software,* Vol. 38, No. 3, pp. 145-149. http://dx.doi.org/10.1016/j.advengsoft.2006.09.008

Chen G., Zhu M., Yu H., Li Y. (2007). Application of neural network in image definition recognization. *IEEE International Conference on Signal Processing & Communications*, pp. 1207-1210. http://dx.doi.org/10.1109/ICSPC.2007.4728542

Cook D. F., Ragsdale C., Major R. (2000). Combining a neural network with a genetic algorithm for process parameter optimization. *Engineering Applications of Artificial Intelligence*, Vol. 13, No. 4, pp. 391-396. http://dx.doi.org/10.1016/S0952-1976(00)00021-X

De Jong K. A., Spears W. M., Gordon D. F. (1993). Using genetic algorithms for concept learning. *Machine Learning*, Vol. 13, pp. 161-188. http://dx.doi.org/10.1007/BF00993042

Goldberg E. E. (1989). *Genetic algorithm in searching, optimization, and machine learning*. Reading MA: Addison-Wesley.

Griva I., Nash S., Sofer A. (2009). *Linear and nonlinear optimization*, Springer Science.

Grzesiak L., Meganck V., Sobolewski J., Ufnalski B. (2007). Genetic algorithm for parameters optimization of ANN based speed controller. *The International Conference on "Computer as a Tool"*, pp. 1700-1705. http://dx.doi.org/10.1109/EURCON.2007.4400689

Kulaksiz A. A., Akkaya R. (2012). Training data optimization for ANNs using genetic algorithm to enhance MPPT efficiency of a stand-alone PV system. *Turkish Journal of Electrical Engineering & Computer Sciences*, Vol. 20, No. 2, pp. 241-254. http://dx.doi.org/10.3906/elk-1101-1051

Leung C., Member C. (1994). A hybrid global learning algorithm based on global search and least squares techniques for back propagation neural network Networks. *International Conference on Neural Networks*, pp. 1890-1895. http://dx.doi.org/10.1109/ICNN.1997.614187

Moazenzadeh R., Mohammadi B., Shamshirband S., Chau K. (2018). Coupling a firefly algorithm with support vector regression to predict evaporation in Northern Iran. *Engineering Applications of Computational Fluid Mechanics*, Vol. 12, No. 1, pp. 584-597. http://dx.doi.org/10.1080/19942060.2018.1482476

Moh'd S., Ahmed A. S. (2006). Optimization of hot wire thermal flow sensor based on neural net model. *Applied Thermal Engineering*, Vol. 26, No. 8-9, pp. 948-955. http://dx.doi.org/10.1016/j.applthermaleng.2005.08.004

Nakawiro W., Erlich I. (2009). A combined GA-ANN strategy for solving optimal power flow with voltage security constraint. *Power and Energy Engineering Conference*, pp. 1-4. http://dx.doi.org/10.1109/APPEEC.2009.4918036

Sardiñas R. O., Rivas Santana M., Brindis E. A. (2006). Genetic algorithm-based multi-objective optimization of cutting parameters in turning processes. *Engineering Applications of Artificial Intelligence*, Vol. 19, No. 2, pp. 127. http://dx.doi.org/10.1016/j.engappai.2005.06.007

Satish C. B., Samik M. (2012). Study of a simple linearization technique of a P-N junction type anemometer flow sensor. *IEEE Transaction Instrumentation and Measurement*, Vol. 61, No. 9, pp. 545-552.

Taormina R., Chau K., Sivakumar B. (2015). Neural network river forecasting through baseflow separation and binary-coded swarm optimization. *Journal of Hydrology*, Vol. 529, No. 3, pp. 1788-1797. http://dx.doi.org/10.1016/j.jhydrol.2015.08.008

Venkata S. K., Roy B. K. (2012). An intelligent flow measurement technique using ultrasonic flow meter with optimized neural network. *International Journal of Control and Automation*, Vol. 5, No. 4, pp. 185-196. http://dx.doi.org/10.2316/P.2012.769-033

Wu C. L., Chau K. W. (2011). Rainfall-Runoff modeling using artificial neural network coupled with singular spectrum analysis. *Journal of Hydrology*, Vol. 399, No. 3-4, pp. http://dx.doi.org/10.1016/j.jhydrol.2011.01.017