An Intuitive View to Compare Intelligent Systems

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***Abstract* – In this study, one of the most complicated problems in Water Resources Engineering, i.e., Rainfall-Runoff modeling is introduced and nine soft computing-based modeling approaches are considered to describe the rainfall-runoff process in a particular case study. For each of these nine approaches, many modeling choices are evaluated and the best modeling choice is selected by an intuitive two-stage competition among all modeling choices for a particular modeling approach. This competition is then applied among the best modeling choice of applied approaches and the best one is highlighted. The results shows that the modeling efficiency increases by moving toward neural modeling; particularly, the fuzzy clustering-based neural network is the most efficient and accurate paradigm among performed systems for modeling rainfall-runoff process in the considered case study. In addition, for interpreting the results, a new concept, i.e., intelligence space, and its consequent definitions are introduced that can be used as a general framework for comparing intelligent systems.**

I. INTRODUCTION

In many modeling problems, numbers of modeling alternatives exist that can be considered as a suitable system for modeling a particular problem. This condition is more highlighted, when we are in the context of computational intelligent systems. In many situations, we are faced with many, for example, feedforward neural network structures that model a process with a low error index; however, we should take a particular system as the final model. In addition, there may exist more than one successful approach. Generally, in every modeling problems many conceptual, system-theoretical and soft computing-based models can be considered as a powerful system for modeling the process. Traditionally, this problem is solved by considering a case study and an error index for models under consideration and evaluating this error measure among them in validation phase. However, is it logical to stick on the behavior of the system in validation phase, only based on one error index?

Considering the ever-increasing computational abilities and introduction of new methods of deduction and multi-criteria decision making, it is now justified to use different criteria for evaluating models and considering every phase of modeling procedure for behavior analysis of different systems. With a well-established method, it is possible to get an insight to the performance and the ability of different modeling approaches in a particular problem.

It is proved that Rainfall-Runoff process is one of the most complex phenomena for modelling in Water Resources Engineering [1]. The problem is inherently non-linear and dynamic; therefore, simple modelling approaches collapse in tracking the process especially in continuous modelling problems. In this study, nine approaches are applied for one of the most famous data set of the current rainfall-runoff modelling literature, i.e., Leaf River basin, near Collins, USA and the behaviour of these models are evaluated in different time intervals. For model development in all of approaches, many modelling choices are tested and then, based on performance evaluation of these choices in different modelling intervals, the best choice is highlighted. This is done by an intuitive two-stage competition among these choices in a way that a choice that gathers the most scores is selected. These scores are allocated based on different error indices in all of modelling intervals. Then, based on this procedure, some new concepts such as intelligence space, intelligence vector, and intelligence index are introduced for comparing these nine modelling approaches, which can be used as a general framework for determining computational intelligence quotation (CIQ).

II. RAINFALL-RUNOFF PROCESS

Rainfall-runoff process is accepted as one of the most complex and nonlinear real-world phenomena in the field of water engineering. The process consists of the movement of rainfall through different media and its transformation to the runoff in channels either natural or man-made. Many mathematical approaches can be found in the literature, which are proposed for the purpose that an accurate estimation of runoff can be made by knowing the quantity and quality of rainfall for an assumed area [11].

Rainfall-runoff modeling is assumed to find a description for transformation of the total rainfall volume to the corresponding reduced runoff volume in an area [1]. The total volume of the rainfall during one rainy event W_{rf} is determined based on the data collected on the watershed area A, by the following equation: $W_{rf} = A * H$, where H represents the average height of rainfall. The other convenient way to estimate the total rainfall volume is given as follows: $W_{rf} = A\int_{T_0}^{T_r} i * dt$, where i is the rainfall intensity in meter per second, T_0 and T_r are starting and ending time of rainfall event. The runoff volume W_q, is estimated on the basis of hydrograph data in the following way:

$W_Q = A\int_{T_0}^{T_r} Q * dt = A\int_{T_0}^{T_r} i_e * dt$, where Q represents hydrograph runoff ordinate on the outlet of the watershed, i_e is net or effective intensity of the rainfall. The runoff volume or effective rain is defined by the following equation: $H_e = W_Q / A$. The difference is defined by the following way: $W_{rf} - W_Q$ is the retained water volume (water volume deficit) that varies with time, i.e., similar rainfall volumes may result in significantly different runoff volumes on the same watershed profile, proving the non-stationary of the rainfall-runoff processes. The strongly emphasized non-linearity of the rainfall-runoff process is the other manifestation of the complexity of the internal watershed structure. This internal structure is a consequence of the composition of a large number of relatively permanent and changeable essential features.. There is no universal model designed for the rainfall-runoff process, since the model developed for the certain watershed may appear to be quite unusable for the other area [1].

Modern literature of rainfall-runoff modeling contains two main approaches: the conceptual (physical modeling) and system theoretic modelling [11]. The conceptual rainfall-runoff models attempts to provide reliable approximation of physical mechanisms, determining the hydrologic cycle. The conceptual models are convenient for understanding of the hydrologic process, but they are not efficient in stream flow forecasting (prediction at specified watershed location). In such situations, the system theoretic approach is a more convenient tool. The system theoretic approach is generally based on the differential equation models designed for direct mapping between the inputs and outputs. The ARMAX (auto-regressive moving average with exogenous inputs) linear models for time series analysis, developed by Box and Jenkins, have been frequently used [5]. These models are easy to develop and practical for use, but they are not appropriate tools for modelling of nonlinear dynamic processes such as the rainfall-runoff, and may show unsatisfactory performance [1]. Furthermore, many studies reported that calibrations of models have many computational difficulties [14] and the natural orientation of the process imposes a great deal of uncertainty in to the modeling procedure. In addition, many models are based on some assumptions, which do not hold in the real process [16]. Thus, the modeling of the rainfall-runoff process is still a challenging problem.

Since the early of 1990s applications of soft computing paradigms have been reported in the context of rainfall-runoff modelling [2], [3], [4], [5], [7], [8], [10]. These researches show that soft computing-based approaches can be considered as a powerful alternative and/or complement for describing rainfall-runoff process.

III. MATHEMATICAL FRAMEWORK, CASE STUDY AND APPLIED MODELS

The first step in all modeling problems is obtaining an *Information set* about system behavior and parameters. The information may be numerical, linguistic, physical or experimental laws, and generally, the combination of these sources. However, in many modeling problems, the dimension of information set tends to be very large. So the modeller is forced to extract the most efficient information parameters and identify the *Data set*. Mathematically, it can be shown as:

$$I_{t\times n} \xrightarrow{f_1} D_{t\times n_e} \quad n_e << n \tag{1}$$

In above equation I is information set, D is data set, f_1 is extracting operator and n_e is the number of parameters considered in data set. It must be noted that D contains both input and output data:

$$D_{t\times ne} = D_{t\times n_i} \oplus D_{t\times n_o} \tag{2}$$

In which, n_i and n_o are number of input and output parameters respectively. It is obvious that $n_i + n_o = n_e$. If n_o is not equal to one it means that we have multi-output system. This system can be easily converted to n_o single output systems.

After data identification phase, the modeling phase should be started. The first step is selecting an approach or mathematical engine which relates input to output. Mathematically it can be shown as:

$$D_i \overset{f_2}{\Rightarrow} D_o \tag{3}$$

In which f_2 is the mathematical paradigm, which relates input to output. It can be a Neural Network, Fuzzy system or any other modeling approach. After proper approach selection, the structure of the system, which relates input values to output ones, should be identified. . As an illustration, if feedforward neural network is selected for modeling, the number of hidden layers, the number of neurons in each hidden layer, the activation functions and etc. should be identified by the modeler before training. Mathematically it can be shown as:

$$D_i \overset{f_3}{\Rightarrow} D_o \; such\ that \;\; f_3 \in F(f_2) \tag{4}$$

In above equation, f_3 is the proper structure, and $F(f_2)$ indicates to family of possible structures in modeling framework f_2 . When proper structure is identified, the model parameter should be identified. Model parameters are determined in order to minimize an error or a set of error measures. In other words, the proper structure f_3 is calibrated to produce a mapping between inputs and output values:

$$D_i \xrightarrow{f_4} D_0 \;\; such\ that \;\; f_4 \in F(f_3) \tag{5}$$

In above equation f_4 is the final model which produces an optimal mapping between inputs and output and $F(f_3)$ indicates to family of possible calibrated models for particular structure f_3 . After calibration of the model, the behavior of the model should be evaluated by an unseen data set and a vector of error measures. It can be shown as:

$$D_i' \xrightarrow{f_4, E} D_0' \tag{6}$$

In which, E is the error measure for calibrated structure f_4 in confronting with unseen data D'. Now, the model can be established by:

$$M = \{D_{t \times n_e}, f_4, E\} \quad (7)$$

That means a model as an integration of data, calibrated structure, and an error vector.

Leaf River basin rainfall-runoff data set, the case study of this research, is one of the frequently used case studies in current rainfall-runoff investigations [3], [4], [5], [10]. The basin is located north of Collins, Mississippi, with an area of approximately 1950 km^2. A reliable data set is available that represents a variety of hydrologic conditions and phenomena. The data set consists of forty (1948-1987) years of mean daily streamflow (m^3/s), daily potential evapotranspiration (mm/day), and incremental six hours areal rainfall (mm per 6 hours. The modelling objective is simulating on step ahead of stream flow quantity based on past stream flows, evapotranspiration and rainfall measures. For continuos simulations of Leaf River rainfall-runoff process, nine approaches are examined that described briefly as below:

1) Mamdani fuzzy system: As proved, fuzzy systems are universal approximator [15] and can be used for forecasting the next state of a system based on previous states and inputs. We consider that:

$$Q(t) = f(Q(t-1),\ldots,Q(t-3), R(t-1),\ldots R(t-3) \quad (8)$$

It means that the current streamflow Q in time interval t is a function of streamflow and rainfall R in intervals *t-1*, *t-2*, and *t-3*. Based on Mamdani view point this relation can be converted to a linguistic rule base system, in which both antecedents and consequence variables are fuzzy sets [15].

2) TSK fuzzy system: The only difference between TSK fuzzy systems and Mamdani fuzzy system is in their consequence parts [15]. For considered case study, the input/output relation was assumed as Equation (8).

3) Mamdani hierarchical fuzzy system: One of the main problems in fuzzy systems is the *curse of dimensionality*. This problem can be decreased by considering a hierarchical topology for fuzzy models [6]. For considered case study it was assumed that all rainfall inputs was lumped in an fuzzy index, i.e., *Rainfall index*. The same procedure was applied for streamflow components and fuzzy variable *Runoff index* was produced for streamflow data. This hierarchical fuzzy system can be shown as below:

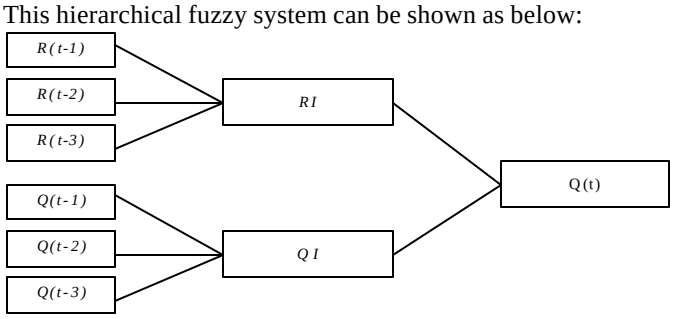

Fig. 1 Structure of hierarchical fuzzy system for considered case study

4) TSK hierarchical fuzzy system: The developed TSK hierarchical fuzzy system for considered case study is the same as above figure. However, the fuzzy rule consequences for each layer were assumed as linear relations.

5) Feedforward neural network modeling: Since 1990s, many studies shows that neural networks can be very efficient in the context of rainfall-runoff modeling [3], [8]. Again Equation 8, was assumed for input/output relation in the considered case study.

6) Cascade forward neural network modeling: Cascade forward neural networks can be considered as the generalization of feed forward ones. In this configuration, all neurons in previous layers can be connected to the current layer [7]. Equation (8) is the input/output function.

7) ANFIS neuro-fuzzy system: In ANFIS configuration, a TSK fuzzy system is described as a feedforward neural network. So learning algorithms can be imposed to the fuzzy system [6]. The data set of case study was assumed as previous approaches.

8) Fuzzy clustering-based neural network modeling [9]: in this approach, the idea of fuzzy clustering is combined with feedforward neural networks for achieving a two-layer system, in which the first layer classifies the rainfall-runoff patterns and the second maps the input values to output. In brief, *n* fuzzy clusters was assumed for rainfall-runoff data and for each fuzzy pattern a feedforward neural networks was trained for mapping from input to output values. The training data for each pattern was selected based on the *degree of belongness* of data to a particular cluster. Finally the results of all clusters are integrated as a weighted average of all *n* neural networks [9]. Figure 2. shows this hybridization between fuzzy clustering and feedforward neural network modeling. Input/output relation is assumed as before.

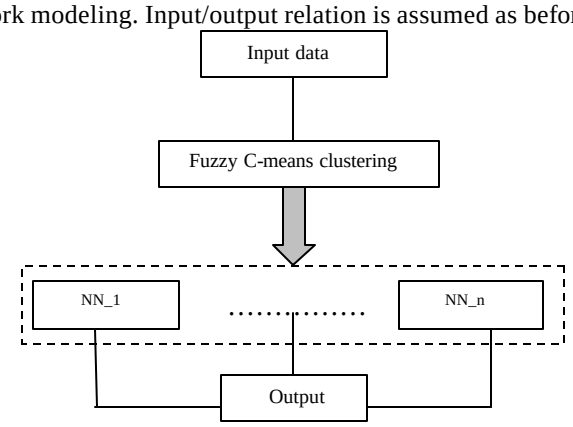

Fig. 2 The idea of fuzzy clustering-based neural network modeling

9) Evolutionary neural networks modelling: In this approach, genetic algorithms are used for structure and/or parameter identification of feedforward neural networks. For this purpose, first the best neural structure for describing the rainfall-runoff process in considered case study is found by a simple genetic algorithm [12] and then based on separate data set the identified structure is trained by hybridization between a real code genetic algorithm and back-propagation [12]. In this approach the best input variables among all potential variables of information set are selected based on correlation analysis. The detailed explanation of this approach has been reported in [10]

As previously described case study information set consists of forty years (1948-1987) of 6-hour areal rainfall, daily potential evapotranspiration and daily runoff quantities in Leaf River basin.

For modelling development in the form described in equations (1) through (8), the information set was divided to four 10-years data as below:

A) Information between 1948-1957: This information set was used for input selection, initial parameter identification, structure identification and/or calibration of modelling choices.

B) Information between 1958-1967: This information set was used for calibration and/or sensitivity analysis of modelling choices.

C) Information between 1968-1977: This interval was used for validation of modelling choices. The behaviour of model in this interval can be interpreted as the *short term extrapolation capability* of modelling choices.

D) Information between 1978-1987: This interval was again used for validation of modelling choices. However, the behaviour of model in this interval should be interpreted as the *long term extrapolation capability* of modelling choices.

IV. MODELING PROCEDURE AND COMPETITION AMONG ALTERNATIVES

For all of nine considered approaches, many modelling choices are tested. The purpose is finding the best modelling choice of a particular approach. For doing that following steps are done:

1) For each approach, modelling parameters are select from more important and sensitive parameters to less important ones. For instance in neural network modelling approach, fist the best training method is selected. Then the optimal hidden neurons are identified and finally the best training supervisor is chosen.

2) For each modelling choice, six error measures are calculated in all of four modelling intervals. These error measures are:

$$EP = Q_p - \hat{Q}_p \tag{9}$$

That is the error in simulating the peak of the hydrograph. Q_p is the observed peak and $\hat{Q}_p$ is simulated one.

$$EV = \frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)}{\sum_{i=1}^{n} Q_i} \tag{10}$$

That is representing the ability of modelling choice in satisfying mass conservation. This error measure is zero when the total runoff volume is the same in observed hydrograph and simulated one.

$$MAE = \frac{\sum_{i=1}^{n}\left|Q_i - \hat{Q}_i\right|}{n} \tag{11}$$

That is the mean absolute of errors and is a measure of first order error.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{n}} \tag{12}$$

That is root mean square of errors and represents the average error of a modelling choice.

$$Cor. = \frac{\sum_{i=1}^{n}(\hat{Q}_i - \overline{\hat{Q}})^2}{\sum_{i=1}^{n}(Q_i - \overline{Q})(\hat{Q}_i - \overline{\hat{Q}})} \tag{13}$$

That is correlation coefficient and represents the linear correlation between observed and simulated runoff quantities.

$$N-S\ Co. = 1 - \frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{n}(Q_i - \overline{Q})^2} \tag{14}$$

That is Nash-Sutcliffe coefficient and is the sum of squares of differences between the estimated and observed discharges.

3) An intuitive two-stage competition is performed among all modeling choices in order to identify the best modeling choice. In the first stage, all mentioned error measures are calculated in four information intervals. Therefore, totally, 24 measures were determined. Then, the modeling choices obtaining the best measures are identified and a score is allocated to them. In the second stage, the mean and variance of each error measures in four modeling intervals are determined and the modeling choice that gathers the most measures is identified. Overally, 36 scores can be allocated. Now, the modeling choice that gathers the most scores is selected as the best modeling choice. It can be interpreted that the first step is a measure of accuracy and the second is an index for robustness, since in first step an individual error measures are important, however in the second the overall behavior of error measures in four modeling intervals is the goal. Table (1), shows this competition among 3 modeling choices. it can be found that the modeling choice 3 gathers 20 scores and performs better than other modeling choices.

The introduced competition was applied for all modeling approaches. A brief report about selecting the best choice of each approach is described as below:

TABLE I

AN EXAMPLE FOR INTRODUCES TWO STAGE COMPETITION (A) STAGE 1 (B) STAGE 2

EP	EV (%)	MAE	RMSE	Cor	N-S Co	
261.57	5E-05	7.2734	18.92	0.967	0.93356	1
252.54	0.0029	7.4845	18.917	0.967	0.93358	2
245.28	0.0031	9.5549	20.971	0.958	0.91838	3
3	1	1	2	1	2	
EP	**EV (%)**	**MAE**	**RMSE**	**Cor**	**N-S Co**	
293.23	0.0158	8.9478	20.177	0.951	0.90365	1
1299.1	0.4999	25.006	66.671	0.046	-0.052	2
165.14	0.0041	6.0028	15.528	0.973	0.94294	3
3	3	3	3	3	3	
EP	**EV (%)**	**MAE**	**RMSE**	**Cor**	**N-S Co**	
680.97	0.0243	10.413	31.913	0.848	0.6696	1
710.09	0.5475	26.739	58.347	0.074	-0.1044	2
683.5	0.041	9.1666	77.934	0.579	-0.9704	3
1	1	3	2	3	1	
EP	**EV (%)**	**MAE**	**RMSE**	**Cor**	**N-S Co**	
248.66	0.0156	11.094	25.083	0.941	0.88323	1
857.34	0.5757	29.912	76.108	0.048	-0.0751	2
204.96	0.0018	7.9607	20.04	0.964	0.92546	3
3	3	3	3	3	3	

(A)

EP (CMS)	EV (%)	MAE (CMS)	RMSE (CMS)	Cor	N-S Co	
43023.8	1E-04	2.87287	34.7360082	0	0.014	1
186183	0.073	101.4893	631.648247	0.2	0.256	2
58280.7	4E-04	2.550572	878.488216	0	0.902	3
1	1	3	1	2	3	
EP (CMS)	**EV (%)**	**MAE (CMS)**	**RMSE (CMS)**	**Cor**	**N-S Co**	
371.108	0.014	9.43205	24.02325	0.9	0.848	1
779.768	0.406	22.28538	55.01075	0.3	0.176	2
324.72	0.013	8.17125	33.61825	0.9	0.454	3
3	3	3	1	1	1	

(B)

1) Mamdani fuzzy system: For obtaining fuzzy rules in all modeling choices the counting algorithm was performed. Two or three fuzzy memberships were selected for input variables in their universe of discourse. The fuzzy membership functions were selected among seven different forms for fuzzy members. Also, MAX/MIN and PRODUCT/SUM operators are evaluated. Totally 28 Mamdani fuzzy choices are developed and a Mamdani fuzzy system with 3 pi-membership functions with PRODUCT/SUM operators performs the best.

2) TSK fuzzy systems: The modeling choices for TSK fuzzy approach are selected the same as Mamdani approach with PRODUCT/SUM operators. The only difference is in the fuzzy consequences that were obtained by Least Square Estimator. Again, the system with 3 pi-membership functions with PRODUCT/SUM operators performs as the best.

3) Mamdani hierarchical fuzzy system: In Mamdani hierarchical fuzzy approach, the fuzzy rules in the first layer were found based on the hydrologic knowledge of rainfall and runoff patterns in considered case study. The rules in second layer were obtained by counting algorithm. Other variables are the same as Mamdani fuzzy approach. The results shows that a Mamdani hierarchical fuzzy system with 3 pi-membership functions with PRODUCT/SUM operators is the best modeling choice for simulating rainfall-runoff process in considered case study.

4) TSK hierarchical fuzzy system: The modeling choices for TSK hierarchical fuzzy approach are the same as Mamdani hierarchical approach with PRODUCT/SUM operators. The only difference is in the fuzzy consequences that were obtained by Least Square Estimator. Again, the system with 3 pi-membership functions with PRODUCT/SUM operators performs as the best.

5) Feedforward neural network modeling: All choices had one hidden layer with 2 to 16 neurons. Also, 11 different algorithms are tested for calibrating the choices. For evaluating the influence of the supervisor of training, four different objective functions are checked. Overally, A modeling choice with 6 hidden neurons that uses Lovendberg-Marquat algorithm with sum squares of errors for calibration and 82 epoch of training, is the best choice.

6) Cascade forward neural network modeling: Developing choices are the same as feedforward approach. The choice with 4 hidden neurons that uses Lovendberg-Marquat algorithm with mean absolute of errors for calibration and 24 epoch of training performs the best.

7) ANFIS neuro-fuzzy system: For developing ANFIS choices, subtractive clustering was used for rule generation. 2 to 7 fuzzy memberships with four different shapes were assumed for variables in antecedent part. The results show that an ANFIS system with seven Gussian-two sided membership functions performs the best.

8) Fuzzy clustering-based neural network modeling: The fuzzy entropy of information set is assumed one. Modeling choices may have 2 to 40 clusters. The neural structure for each cluster is constant and has four neurons in its hidden layer. Training data for clusters neural networks are found in three different degree of belongness, i.e., 0.1, 0.5, and 0.9 levels of possibility. The results show that the system with 40 clusters and threshold level 0.9 for selecting training data is the best fuzzy clustering-based neural network model.

9) Evolutionary neural networks modeling: A detailed description of modeling procedure for this approach has been reported in [10] During the competition, the 12-input parameters system, with considering elitism for genetic algorithms that finally converge to a four layer feedforward neural network with 6 and 8 neurons in hidden layers performs as the best evolutionary neural networks model for considering case study.

V. COMPARISON AMONG APPROACHES AND THE CONCEPT OF INTELLIGENCE SPACE

The proposed competition was performed among the best choices of all applied modelling approaches. Beside the aforementioned paradigms, a famous conceptual rainfall-runoff model, i.e., HEC-HMS model of US Army Corps of Engineers was also used for describing the process in the applied case study. Generally, soft computing-based approaches perform better in describing the rainfall-runoff process. The only superiority of HEC model is its least error in peak. It means that HEC-HMS maybe better simulate the flood peak which is an initial parameter in all engineering designs. However, it has a lower performance in continuous description of the process and forecasting the next stage runoff. Specifically, the fuzzy clustering-based neural networks modelling approach gives the most accurate system for describing rainfall-runoff process in Leaf River watershed.

It may be interesting to link the results to the concept of computational intelligence and compare these approaches based on this definition. Based on Bezdek viewpoint, computational intelligence systems have three main features, i.e., *learning capability*, *accuracy* and *robustness*. If three different numerical measures are defined for these features, then a 3-dimentional space can be distinguished, in which each dimension represents one of the above 3 characters. For scaling this space, first a measure should be selected. This measure can be one of the applied error indices. Then, for a particular system, three different values should be identified in order to locate it in this space. Regarding to introduced modelling procedure, and separating the data set to four modelling intervals, it is simple to allocate a measure that describes the location of a particular system on each dimension. The learning capability measure can be defined by the error index value in calibration period, i.e, duration between 1948-1957. For accuracy, the error values in four modelling intervals can be averaged in order to produce an overall estimation for accuracy. For robustness, the behaviour of model in verification phase should be focused. As described before, 2 different modelling intervals were used for evaluating the behaviour of each system in

confronting with unseen data. Therefore, the mean value of error indices for 1968-1977 and 1978-1987 can represent a measure of robustness. By this approach, for each system an *intelligence vector* define the system in the *intelligence space*. The *intelligence index* for a particular system can be defined as:

$$\Sigma = \sqrt{\Gamma_{LEARNING}^{2} + \Gamma_{ACCURACY}^{2} + \Gamma_{ROBUSTNESS}^{2}} \qquad (15)$$

In which Σ is the intelligence index and Γ is the measure for each dimension of intelligence space. If the locations of different systems are fixed in the intelligence space, then an intelligence path can be distinguished for a particular problem that shows the way to the best system approach. For applied case study, the intelligence path is shown in Figure 3. The Nash-Sutcliffe error index is used for measuring the values of each dimension of intelligence space. Figure 4. shows the objections of this path on learning-accuracy surface. The least intelligence system among applied models, as can be expected, is HEC-HMS that is not an intelligence-based approach. Other stations on this path are Mamdani fuzzy approach, TSK fuzzy approach, Mamdani hierarchical fuzzy system, TSK hierarchical fuzzy approach, ANFIS neuro-fuzzy model, evolutionary neural network modeling, cascade forward neural network approach, feedforward neural network approach, and fuzzy clustering-based neural modeling, respectively.

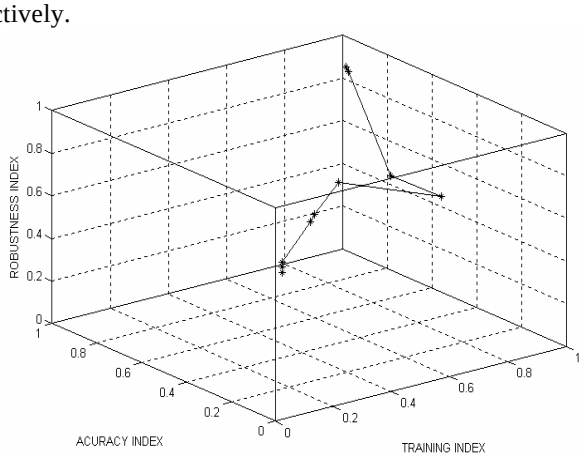

Fig. 3 Intelligence path of applied approaches for introduced case study

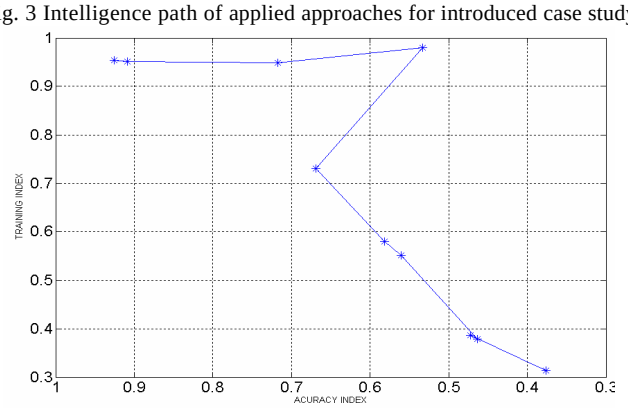

Fig. 4 The objection of Intelligence path of applied approaches on learning-accuracy surface

V. CONCLUSION

In this study, one of the most complicated natural modelling problems, i.e., rainfall-runoff process was focused and different modelling approaches were used for simulating the process in Leaf River basin. For selecting the best modelling choice, a 2-stage competition is designed. In the considered case study, the results show that the modelling efficiency increases by moving toward neural modelling; particularly, the fuzzy clustering-based neural network is the most efficient and accurate paradigm among performed systems for modelling rainfall-runoff process.

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