Analytic Hierarchy Process (AHP) in selecting rainfall forecasting models

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ABSTRACT

The ranking of rainfall forecasting models is done in this study, using the capability of Analytic Hierarchy Process (AHP). The forecasting models are backprogation neural networks (BPNN) and regression models (RM) and were used previously in a study to forecast hourly rainfall for correction bias at gauging stations situated in the Shihmen reservoir, upstream the Tahan River (Northern Taiwan). AHP is based on pairwise comparison methodology and covers both training and validation of the above-mentioned two types of models. Training and validation were the higher level criteria of AHP. The statistical performance indicators (criteria) to evaluate the models in the AHP structure were Root Mean Squared Error (RMSE), Normalized Root Mean Squared Error (NRMSE) and Mean Absolute Error (MAE). These were the low level criteria of AHP. The overall preferences for rainfall/precipitation estimation were 68 % and 32 % for BPNN and RM models respectively. BPNN could be the first priority for the purpose of rainfall forecasting problem in the Shihmen reservoir.

Keywords: Analytic hierarchy, rainfall forecasting, qualitative, quantitative models.

1, INTRODUCTION

Rainfall data is the main generator for streamflow and its impacts on water systems cannot be neglected. Rainfall is one of the most important inputs for rainfall-runoff modeling. Forecasting models are normally used for relatively short and medium operation and planning of water projects. Examples of rainfall forecasting have been reported in the literature [1], [2], [3], [9], [10]. However, the use of AHP for rainfall forecasting or estimation hasn't been reported sufficiently, e.g. [11]. The current study focuses on this aspect of hydrological problem and helps the water manager, model developer to make a ranking/choice of the candidate models. Quite often forecasting methods are assessed based on their measurable performance statistical indicators or metrics [1]. As outlined, model comparison is usually done by assessing the magnitude of the different statistical metrics [3]. The modeler/end-user may face a dilemma for model comparison with a relatively higher number of performance criteria as well as a higher number of models. To this end, AHP is used as a multi-criteria decision making (MCDM) instrument to help consistently decision-makers to rank forecasting models. It is noted there are also other ranking tools for rainfall forecasting, such as scoring methods [9], [10]. However, they are not part of the scope of this study. For the current study, as mentioned previously, AHP is formulated and implemented, based on the literature [3], where rainfall forecasting is performed at a gauging station situated in the Shihmen reservoir, upstream the Tahan River (Northern Taiwan). Rainfall forecasting models, i.e. BPNN and RM were used primarily for bias correction in the precipitation products obtained from the radar-precipitation derived from the quantitative precipitation estimation and segregation using multiple sensors (QPESUMS) [3]. For more detail on QPESUMS, the reader is referred to [3]. The advantage of BPNN over RM is to capture non-linearity among the variables through hidden layers of the neural network architecture [7]. AHP focused mainly on prioritizing these models based on their forecasting capability. The main criteria used for AHP were Root Mean Squared Error (RMSE), Normalized Root Mean Squared Error (NRMSE) and Mean Absolute Error (MAE). It is not the intent of the current study to perform a rainfall forecasting exercise. In [3], no explicit ranking for performance analysis between BPNN and RM was conducted using existing multi-criteria decision making tools; rather the analysis was achieved just by observing the magnitudes of the performance criteria. The aim of the current paper is to rank/prioritise explicitly hydrological models; specifically rainfall forecasting models using AHP technique as a multi-criteria decision tool. "Model" and "technique", "forecasting" and "estimation" may be used interchangeably. The same applies to "rainfall" and precipitation.

2. AHP AND RAINFALL FORECASTING

AHP has been recognized to be very popular as a decision analysis tool since its introduction in the 1980's [5]. However care must be taken to validate AHP as a forecasting tool for risk analysis [8]. There is no doubt about the numerous applications of AHP to water related problems, e.g. [4]. However, its application to rainfall forecasting remains unexplored, except in a recent study where AHP has been applied to rainfall infilling problems in the ranking of watersheds. Hence the literature on AHP for rainfall forecasting, specifically in selecting neural network and regression techniques, remains almost inexistent. A complex problem can be structured into a hierarchy that is comprised of different levels:

-The higher level is mainly the goal of AHP.

-The middle level (criteria) helps the decision maker or modeler to rank the alternatives (e.g. forecasting models) within the goal limits.

-The lower level is comprised of the rainfall forecasting models or alternatives among which the modeler or water manager makes a choice to reach the goal.

A likert scale 1 to 9 is normally used in the AHP methodology. Hence 1 shows equal importance between elements; 3: moderate importance; 5: strong importance; 9: extreme importance. Intermediate values 2, 4, 6 and 8 are also used during AHP process. From the scale/level of importance, weights of alternatives can be computed in order to rank the alternatives. Hence AHP combines both qualitative and quantitative approach. For more detail on AHP, the reader is referred to [5].

Pairwise comparisons are summarized in a judgment matrix or pairwise comparison matrix (PCM). Consistency/validity of pairwise comparisons is always checked during AHP implementation [5]. Consistency check is carried out by calculating the consistency ratio (CR). This ratio is given by Eq. (1) and should be always less than 10 % for the pairwise comparisons to be consistent.

$$CR = \frac{CI}{RI} \tag{1}$$

Where
CI is the consistency index given by Eq. (2).
RI is the random index and its values are given for different dimensions (n) of the judgment matrix

$$CI = \frac{\lambda_{MAX} - n}{n-1} \tag{2}$$

Where:
λ_{MAX} is the maximum Eigen value of the matrix.

3. DATA AVAILABILITY

Data is mainly the results of comparative performance of backpropagation neural network (BPNN) and the regression model (RM) for hourly rainfall forecasting and was extracted from the literature [3]. This data was the rainfall product QPESUMS after bias correction by using BPNN and RM as depicted in Table 1. AHP formulation and implementation were based on data in Table 1. The performance indicators are summarized in Table 1 for training and validation, performed for 1-350 hour and 504-641 hour respectively. The performance criteria are expressed in mm/h of rainfall.

Table 1. Comparative performance of BPNN and RM for rainfall forecasting, as extracted from [3]

Performance indicators	BPNN		RM	
	Training	Validation	Training	Validation
RMSE (mm/h)	3.3	2.4	3.4	2.6
NRMSE (mm/h)	0.4	0.39	0.42	0.43
MAE (mm/h)	2.0	1.6	2	1.6

4. AHP FORMULATION AND IMPLEMENTATION

From Table 1, based on a 3-level hierarchy, AHP was formulated as follows:
Level 1: The goal is defined for selecting short-term forecasting models; i.e. BPNN and RM.
Level 2: Training and validation stages are the higher level criteria for performance analysis of the above-mentioned techniques.
Level 3: The performance indicators RMSE, NRMSE and MAE are the lower level criteria and play a significant role for ranking of forecasting models. These models are the alternatives. The RMSE values may not capture well high flows, whereas the MAE values are not weighted for high flows [3].
Level 4: The two rainfall forecasting models; i.e. BPNN and RM are the alternatives.

The higher level criteria and lower level criteria are the main criteria and sub-criteria. Figure 1 shows the hierarchy of AHP for ranking rainfall forecasting models.

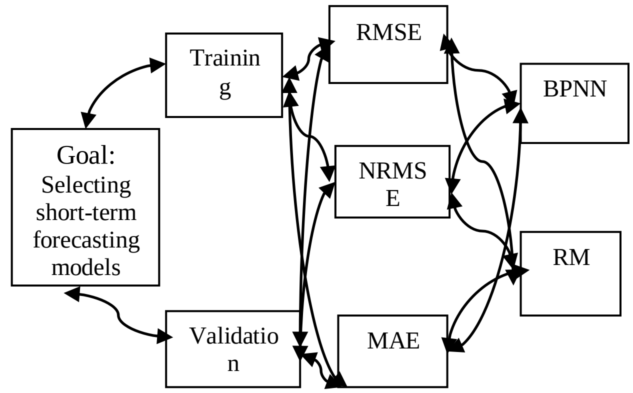

Figure 1. Hierarchy representation for ranking rainfall forecasting models

In the following section, AHP is implemented.

Pairwise comparisons of performance criteria

The judgement (comparison) matrix was constructed based on the pairwise comparisons carried out on performance criteria: RMSE, NRMSE and MAE. A moderate level of importance was assigned to RMSE over MAE [6], as RMSE seems to be predominately used in the literature. The author of the current study subjectively considered the normalized root mean squared error NRMSE moderately important over the usual RMSE. Such a subjective consideration was validated by conducting a consistency check of pairwise comparisons. Table 2 summarizes the pairwise comparisons among performance criteria.

Table 2. Pairwise comparison of performance criteria (RMSE, NRMSE, MAE)

	RMSE	NRMSE	MAE
RMSE	1	0.5	3
NRMSE	2	1	4
MAE	0.33	0.25	1
	3.33	1.75	8

Pairwise comparisons between training and validation stages for rainfall forecasting

Training and validation are important stages for model performance assessment, which correspond to two sets of data respectively. Normally the original data series is split into data sets to carry out training and validation stages. It is expected that models perform well during both training and validation. Hence, an equal intensity of importance was allocated to the two stages as shown in Table 3.

Table 3. Pairwise comparisons between validation and training

	Training	Validation
Training	1	1
Validation	1	1
	2	2

Pairwise comparisons between forecasting models

Pairwise comparisons among forecasting models; BPNN and MR were conducted using the 3 performance criteria. Table 1 suggests that BPNN can be considered slightly important over RM when considering criterion RMSE during training stage of forecasting models. The author used the level of importance between 1 and 3, as depicted in Table 4a. Conversely a value of 1/2 or 0.5 has been used when comparing RM with respect to RMSE during training. Table 4a shows the summarised pairwise comparisons between rainfall forecasting models during training with respect to RMSE. In a similar way, the rest of pairwise comparisons were conducted with respect to NRMSE and MAE for training stage. Pairwise comparisons among statistical indicators have been carried out in the past [6]. Hence Tables 4b, 4c were obtained respectively. Likewise pairwise comparisons of models were carried with respect to RMSE, NRMSE and MAE for validation stage. The results for validation stage were then summarised in Tables 4d, 4e and 4f.

Table 4a. Pairwise comparisons between rainfall forecasting models with respect to RMSE during training

	BPNN	RM
BPNN	1	2
RM	0.5	1
	1.5	3

Table 4b. Pairwise comparisons between rainfall forecasting models with respect to NRMSE during training

	BPNN	RM
BPNN	1	2
RM	0.5	1
	1.5	3

Table 4c. Pairwise comparisons between rainfall forecasting models with respect to MAE during training

	BPNN	RM
BPNN	1	2
RM	0.5	1
	1.5	3

Table 4d. Pairwise comparisons between rainfall forecasting models with respect to RMSE during validation

	BPNN	RM
BPNN	1	2
RM	0.5	1
	1.5	3

Table 4e. Pairwise comparisons between rainfall forecasting models with respect to NRMSE during validation

	BPNN	RM
BPNN	1	3
RM	0.33	1
	1.33	4

Table 4f. Pairwise comparisons between rainfall forecasting models with respect to MAE during validation

	BPNN	RM
BPNN	1	1
RM	1	1
	2	2

5. ANALYSIS OF RESULTS AND DISCUSSION

The weights of performance criteria have been derived from Table 2 through AHP methodology and presented in the last column of Table 5. It is can be seen that that NRMSE carries the highest weight (56 %). The RMSE comes is the second highest with 32 % in weight and MAE in last position with 12 % in weight. These results could imply that the water manager/decision maker or modeler could have a higher preference intensity for NRMSE than for the other two criteria for both training and validation. It is important to mention that subjective considerations by the author may influence these results. However, the level of subjectivity in the judgment is acceptable since the computed consistency ratio (CR) is 0. 8 %.

Table 5. Criteria weights for performance criteria

	RMSE	NRMSE	MAE	Weights
RMSE	0.300	0.286	0.375	0.320
NRMSE	0.601	0.571	0.500	0.557
MAE	0.099	0.143	0.125	0.122
	1.000	1.000	1.000	1

The weights of training and validation stages presented in Table 6 were derived from Table 3 and showed that they have equally preference of 50 % respectively. This situation is justified from the consideration that the weights were considered to have the same level of importance. The modeler, in all instances, will assign equal weights when carrying out both stages.

Table 6. Forecasting stage weights

	Training	Validation	**Average**
Training	0.5	0.5	**0.5**
Validation	0.5	0.5	**0.5**
	1	1	**1**

Table 7a. Weights of forecasting models with respect to RSME, during training stage

	BPNN	RM	Average
BPNN	0.667	0.667	0.667
RM	0.333	0.333	0.333
	1.000	1.000	1.000

As depicted in Table 7a, the two rainfall forecasting models have 67 % and 33 % in weights of preferences, when pairwise comparisons are conducted with respect to RMSE. This suggests that the decision-maker or the modeler will assign more preference to BPNN as opposed to RM, when criterion RMSE is considered on its own. Similar results were obtained in Tables 7b and 7c.

Table 7b. Weights of forecasting models with respect to NRSME, during training stage

	BPNN	RM	Average
BPNN	0.667	0.667	0.667
RM	0.333	0.333	0.333
	1.000	1.000	1.000

Table 7c. Weights of forecasting models with respect to MAE, during training stage

	BPNN	RM	Average
BPNN	0.667	0.667	0.667
RM	0.333	0.333	0.333
	1.000	1.000	1.000

The results for validation stage are not presented here in a table format. However, the results obtained for pairwise comparisons among forecasting models (BPNN and RM) during validation stage, with respect to RMSE were 67 % and 33 % in weights. The results for pairwise comparisons among forecasting models respect to NRMSE were 75 % and 25 % for BPNN and RM. Finally, the weights for BPNN and RM were 50 % and 50 % with respect to MAE.

When all performance criteria are considered simultaneously, the overall weights in the ranking of rainfall forecasting models were 68 % and 32 % for BPNN and RM respectively. The summary of overall ranking is depicted in Table 8. For rainfall forecasting capability, it could be said that the decision maker, modeler or end user will have more priority on BPNN as opposed to RM. These results enhance the relatively higher forecasting capability of BPNN for rainfall radar obtained from QEPSUMS [1]. Beyond the literature [3], AHP demonstrates transparently the selection of the rainfall forecasting models as well as their respective weights in the prioritization process.
The validity of the above exercise is only applicable to the case of the Shihmen reservoir, upstream the Tahan River (Northern Taiwan). The 3 criteria and the data set stages used here apply. Hence the case of these specific performance criteria applies as well. Other forecasting models could have impacted on the overall ranking for rainfall forecasting.

Table 8. Overall weights of forecasting models

		BPNN		RM	
		Training(0.5)	Validation(0.5)	Training (0.5)	Validation(0.5)
0.32	RMSE	0.21344	0.21344	0.10656	0.10656
0.557	NRMSE	0.371519	0.418307	0.185481	0.138693
0.122	MAE	0.081374	0.061	0.040626	0.061
		0.666333	0.692747	0.332667	0.306253
		0.67954		**0.31946**	

6. CONCLUSION AND SUGGESTION

The application of AHP has been extended to rainfall forecasting problems, in ranking hydrological models; i.e. BPNN and RM. The AHP methodology was restricted to a case of training and validation of these models. The overall preferences on rainfall forecasting models were 68 % and 32 % respectively for the Shihmen reservoir, upstream the Tahan River (Northern Taiwan). These results were consistent through AHP technique, hence acceptable to guide the water manager/decision-maker or modeler in ranking rainfall forecasting models. This study is a case of transparent methodology in the choice of models for rainfall forecasting. It is suggested that more cases should be carried out where AHP is applied to more forecasting models other than BPNN and RM as well as more performance criteria. Data from catchments other than Shihmen reservoir catchment should be tested.

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