Chapter 6
Results and Discussions

Abstract The present investigation attempted to represent the severity off water scarcity with the help of an indicator. As existing indexes have drawbacks like they do not considers the temporal variability of the input parameters, not includes quality of water as a parameter and also the influence of all the parameters are taken as equal. To compensate the above drawbacks of the existing water availability indicators and to estimate the situation of water availability in an optimal manner a new indicator was developed. The input parameter of the index was selected based on literature review followed by expert and stakeholder survey. The temporal variability was also included by taking the amplitude values of variation curves with respect time of the selected parameters. The quality parameter was also introduced with the help of Water Quality Index (WQI). Lastly a new MCDM method was created to assign priority values to the input parameters based on their importance in influencing the level of water scarcity. The method is new as it combines the output from AHP and FLDM to determine the weights of importance for the parameters. Moreover a cognitive ability was introduced to the index by applying ANN for finally estimating the value of the indicator. According to the results, the Frequency of Troughs in Annual Hyetograph (P) and Percentage Impervious Area (A) was found to be respectively the highest and lowest important parameter among the eight input parameters considered in the study. If criteria by which the importance of the alternatives are compared it can be said that Literature Survey and Data Availability was found to be most and Sponsor's Preference the least important criteria among the five criteria considered in the study. The accuracy of the ANN model was found to be above 99.95 % and the number of hidden layer and type of activation function was decided to be respectively three nodes in one layer and logistic function. The sensitivity analysis of the model was also performed and found to be coherent with the weights of importance of the parameters as determined in the MCDM step. The scenario wise prediction of the index value was also carried out. Based on the results it can be said that in industrially sensitive A2 the location having high level of urban population will always face the higher level of water scarcity. But in case of B2 such clear conclusions can not be made.

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Keywords Water limitation · Water quality index · AHP · FLDM · AHP-FLDM hybrid · Combinatorial ANN

6.1 Results from MCDM Applications

In the MCDM step five types of criteria were selected and compared with the help of the score as found from Eqs. 5.7–5.11.

According to the score of each of the criteria, Literature Survey and Data Availability was found to be most and Sponsor's Preference was the least important criteria among the five criteria considered in the present study (Table 6.1). The weights of the alternatives were found by comparing each other with respect to each of the criteria.

The result of the comparison by AHP and FDM is depicted in Table 6.2. According to the table, Frequency of Troughs in Annual Hyetograph (P) and Percentage Impervious Area (A) was found to be the most and least important parameters respectively among the eight factors considered. In both AHP and FDM method the same parameters was found to be the most and least preferred alternative.

6.2 Results from ANN Applications

The ANN model was developed to predict the Water Limitation Index (V) from different scenarios of the selected factors. The model was trained with feed forward polynomial neural networks. A combinatorial search to find the optimal weight was also carried out simultaneously. Figure 6.1 shows the comparison between actual data, model predicted data during the training process and the predicted data from the model. According to this figure the model has more than 99.95 % of accuracy level. The residual errors as depicted in Fig. 6.2 also seconded the satisfactory learning of the problem by the model. Most of the residuals lie in between the 2 times the standard deviation of the dataset which also shows the reliability of the developed model. From the frequency distribution of errors it can be observed that

Table 6.1 Table showing the criteria considered to compare the factors

Criteria	Total number	Total number of sources	Score	Rank
Literature survey	50	170	0.294	1
Expert survey	20	170	0.118	4
Stakeholders Survey	40	170	0.235	3
Sponsors Preference	10	170	0.059	5
Data availability	50	170	0.294	1

Table 6.2 Table showing the final weights of importance of the eight factors considered in the present study as determined by AHP and FDM method

		Weights	0.294	0.118	0.235	0.059	0.294	Weights	Ranks
			Expert survey	Stakeholders survey	Literature review	Sponsors preference	Data availability	Final weight	
Rank of importance	Frequency of Troughs in Annual Hyetograph (P)	P	1	1	2	5	1	0.256	
	Frequency of Peak in Annual Hydrograph (Q)	Q	1	1	1	5	2	0.248	
	Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	Dd	4	4	5	2	7	0.097	
	Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	Da	4	4	6	2	6	0.098	
	Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	Di	4	4	3	2	3	0.132	
	Percentage Impervious Area (last 10 years) (A)	A	7	7	6	7	3	0.088	
	Annual Average Area of Canopy (Ac)	Ac	7	7	3	7	3	0.101	
	Frequency of Troughs in Annual Water Quality Index curve (WQI)	WQI	1	1	6	1	7	0.169	
AHP	Frequency of Troughs in Annual Hyetograph (P)	P	0.278	0.278	0.174	0.064	0.340	0.259	1
	Frequency of Peak in Annual Hydrograph (Q)	Q	0.278	0.278	0.349	0.064	0.170	0.250	2
	Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	Dd	0.069	0.069	0.070	0.160	0.049	0.069	6
	Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	Da	0.069	0.069	0.058	0.160	0.057	0.068	7
	Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	Di	0.069	0.069	0.116	0.160	0.113	0.099	4
	Percentage Impervious Area (last 10 years) (A)	A	0.040	0.040	0.058	0.046	0.113	0.066	8
	Annual Average Area of Canopy (Ac)	Ac	0.040	0.040	0.116	0.046	0.113	0.080	5
	Frequency of Troughs in Annual Water Quality Index curve (WQI)	WQI	0.278	0.278	0.058	0.320	0.049	0.161	3

(continued)

Table 6.2 (continued)

		Weights	0.294	0.118	0.235	0.059	0.294	Weights	Ranks
			Expert survey	Stakeholders survey	Literature review	Sponsors preference	Data availability	Final weight	
FLDM	Frequency of Troughs in Annual Hyetograph (P)	P	0.288	0.288	0.176	0.131	0.288	0.252	1
	Frequency of Peak in Annual Hydrograph (Q)	Q	0.288	0.288	0.216	0.131	0.235	0.246	2
	Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	Dd	0.157	0.157	0.098	0.235	0.078	0.125	6
	Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	Da	0.157	0.157	0.078	0.235	0.105	0.128	5
	Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	Di	0.157	0.157	0.137	0.235	0.183	0.165	4
	Percentage Impervious Area (last 10 years) (A)	A	0.078	0.078	0.078	0.078	0.183	0.109	8
	Annual Average Area of Canopy (Ac)	Ac	0.078	0.078	0.137	0.078	0.183	0.123	7
	Frequency of Troughs in Annual Water Quality Index curve (WQI)	WQI	0.288	0.288	0.078	0.288	0.078	0.177	3

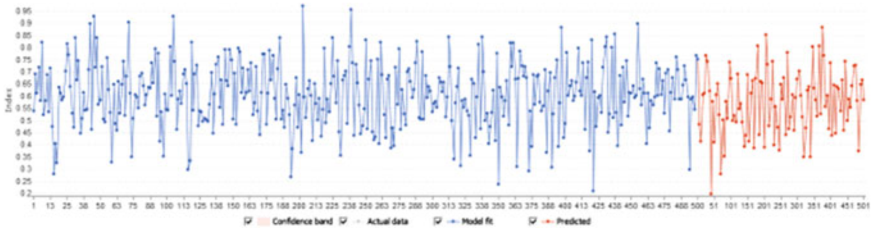

Fig. 6.1 Figure showing the comparison of actual data, model fit and predicted data of the model

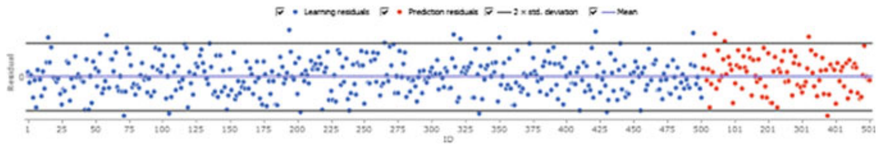

Fig. 6.2 Figure showing the residual errors of the model in the learning and prediction phase

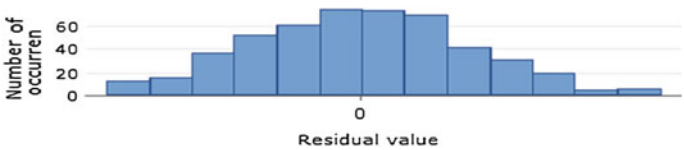

Fig. 6.3 Figure showing the frequency distribution of residual error

most of the deviations between the modelled and actual data are near to zero (Fig. 6.3).

The model equation for the developed neural network framework is given in Eq. 6.1.

$$\begin{aligned} V = {} & 2.04026e{-}14 + P\times 0.2557 + Q\times 0.248136 + Dd\times 0.0966396 + Da\times 0.0980004 \\ & + Di\times 0.131631 + A\times 0.0876199 + Ac\times 0.10138 + WQI\times 0.169 \end{aligned} \tag{6.1}$$

The performance metrics of the model is shown in Table 6.3. The Model Fit column of the table shows the performance of the model during the training process.

The Predictions column depicts the performance of the framework in the prediction stage, i.e., the input data for which model has predicted the output was not included in the data with which the model was trained.

From the table it can be clearly observed that mean absolute error was about 0.52 % more in Prediction stage with respect to the Training phase which is natural because at the time of prediction the model has to predict the output for unknown

Table 6.3 Table showing the performance metrics of the model

Performance metrics	Model fit	Predictions
Maximum negative error	-1.22×10^{-14}	-1.21×10^{-14}
Max positive error	1.44×10^{-14}	1.32×10^{-14}
Mean absolute error	4.19×10^{-15}	4.41×10^{-15}
Root mean square error	5.21×10^{-15}	5.33×10^{-15}
Standard deviation of residuals	5.21×10^{-15}	5.29×10^{-15}
Correlation coefficients	1	1

situations of the inputs. The Root Mean Square Error is also higher by 2.3 % in Prediction stage compared to training phase. But the correlation coefficient was found to be same for both the phases.

According to the performance metrics shown in Table 6.3 the model can be concluded as satisfactorily trained and ready for predictions of the unknown scenarios.

6.3 Results from the Sensitivity Analysis

A sensitivity analysis was also performed to test the sensitivity of the model to test whether the influence of parameters depicted by weights of importance was successfully corroborated into the model predictions. According to Fig. 6.4 the

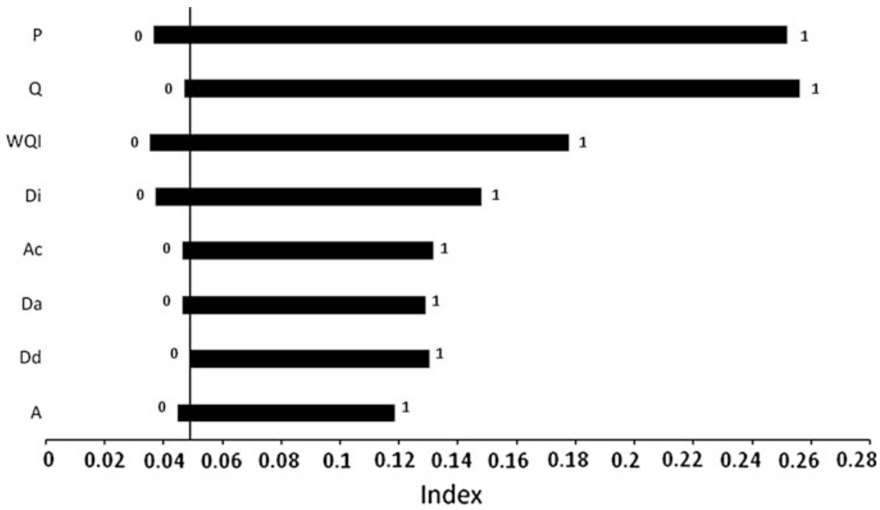

Fig. 6.4 Figure showing the sensitivity of each of the parameters towards the index

Table 6.4 Table showing the swing of the factors in the model

Input variable	Percent swing (%)
P	31.2
Q	29.4
WQI	13.6
Di	8.3
Ac	4.9
Da	4.6
Dd	4.5
A	3.7

tornado diagram of sensitivity analysis depicts that the sensitivity of the most and least important parameter of the model is same as the highest and lowest important parameter as found by the MCDM technique and represented by the weights of importance.

The Swing Percentage also seconded this conclusion. The results from the sensitivity analysis confirmed that the model was successful in mapping the importance of the parameters in the output (Table 6.4).

6.4 Scenario Analysis

The model was applied for the situation in Farakka Barrage in the Ganga River, Mahi on River Mahi and Peranai in River Vaigai. Table 6.5 shows the model output. From the results it can be clearly concluded that Peranai and Farakka are most and least vulnerable regions to the problems of water shortage. The severity of water scarcity is most in Peranai followed by Mahi and Farakka. The real situation of these places seems to match with the manner in which the index has represented the water shortage situation.

The climatic impact was also analyzed with the help of the index for these same three locations (Table 6.6).

In the normal scenario that is the present situation Vaigai has the highest level of water scarcity followed by Mahi and Farakka. The shortage of water availability is highest in Vaigai. More than the other two locations considered in the study. Mahi has the highest availability of water followed by Farakka.

In case of A2 scenario Mahi has the higher level of water scarcity than the other two locations for all the three time slabs although the intensity reduces in the 2071–2100 time slab. For B2 scenario Mahi has the highest level of water shortage in the last time slab but Farakka and Vaigai has the higher level of scarcity in the middle and first time slab respectively.

Table 6.5 Table showing the situation of the parameters in the three selected locations under normal and changed climate scenario (ranked in descending manner i.e. higher value receives higher rank)

Parameters	Value of the parameters			Normalized value			Scenario
	Farakka	Mahi	Vaigai	Farakka	Mahi	Vaigai	
Frequency of Troughs in Annual Hyetograph (P)	4	3	3	0.400	0.300	0.300	Normal scenario
Frequency of Peak in Annual Hydrograph (Q)	1	1	3	0.200	0.200	0.600	
Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	2	3	2	0.286	0.429	0.286	
Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	3	3	3	0.333	0.333	0.333	
Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	2	6	2	0.200	0.600	0.200	
Percentage Impervious Area (last 10 years) (A)	35	55	25	0.304	0.478	0.217	
Annual Average Area of Canopy (Ac)	65	45	75	0.351	0.243	0.405	
Frequency of Troughs in Annual Water Quality Index curve (WQI)	4	8	6	0.222	0.444	0.333	
Frequency of Troughs in Annual Hyetograph (P)	6	4	4	0.429	0.286	0.286	A2: 2010–2030
Frequency of Peak in Annual Hydrograph (Q)	3	4	4	0.273	0.364	0.364	
Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	4	6	3	0.308	0.462	0.231	
Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	4	5	5	0.286	0.357	0.357	
Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	6	9	4	0.316	0.474	0.211	
Percentage Impervious Area (last 10 years) (A)	55	75	35	0.333	0.455	0.212	
Annual Average Area of Canopy (Ac)	45	25	65	0.333	0.185	0.481	
Frequency of Troughs in Annual Water Quality Index curve (WQI)	2	7	5	0.143	0.500	0.357	
Frequency of Troughs in Annual Hyetograph (P)	7	5	5	0.412	0.294	0.294	A2: 2031–2070
Frequency of Peak in Annual Hydrograph (Q)	4	5	5	0.286	0.357	0.357	
Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	5	7	4	0.313	0.438	0.250	
Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	5	7	6	0.278	0.389	0.333	
Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	7	11	5	0.304	0.478	0.217	
Percentage Impervious Area (last 10 years) (A)	65	85	45	0.333	0.436	0.231	
Annual Average Area of Canopy (Ac)	35	15	55	0.333	0.143	0.524	
Frequency of Troughs in Annual Water Quality Index curve (WQI)	4	8	6	0.222	0.444	0.333	

(continued)

Table 6.5 (continued)

Parameters	Value of the parameters			Normalized value			Scenario
	Farakka	Mahi	Vaigai	Farakka	Mahi	Vaigai	
Frequency of Troughs in Annual Hyetograph (P)	8	6	6	0.400	0.300	0.300	A2: 2071–2100
Frequency of Peak in Annual Hydrograph (Q)	5	6	6	0.294	0.353	0.353	
Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	6	7	5	0.333	0.389	0.278	
Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	6	7	7	0.300	0.350	0.350	
Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	9	11	7	0.333	0.407	0.259	
Percentage Impervious Area (last 10 years) (A)	75	84	55	0.350	0.393	0.257	
Annual Average Area of Canopy (Ac)	25	16	45	0.291	0.186	0.523	
Frequency of Troughs in Annual Water Quality Index curve (WQI)	5	9	3	0.294	0.529	0.176	
Frequency of Troughs in Annual Hyetograph (P)	3	2	2	0.429	0.286	0.286	B2: 2010–2030
Frequency of Peak in Annual Hydrograph (Q)	2	2	3	0.286	0.286	0.429	
Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	4	6	5	0.267	0.400	0.333	
Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	3	6	6	0.200	0.400	0.400	
Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	2	2	2	0.333	0.333	0.333	
Percentage Impervious Area (last 10 years) (A)	35	55	25	0.304	0.478	0.217	
Annual Average Area of Canopy (Ac)	65	45	75	0.351	0.243	0.405	
Frequency of Troughs in Annual Water Quality Index curve (WQI)	2	2	2	0.333	0.333	0.333	
Frequency of Troughs in Annual Hyetograph (P)	2	2	3	0.286	0.286	0.429	B2: 2030–2070
Frequency of Peak in Annual Hydrograph (Q)	3	2	2	0.429	0.286	0.286	
Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	5	5	4	0.357	0.357	0.286	
Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	5	3	4	0.417	0.250	0.333	
Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	3	2	1	0.500	0.333	0.167	
Percentage Impervious Area (last 10 years) (A)	30	50	40	0.250	0.417	0.333	
Annual Average Area of Canopy (Ac)	70	50	60	0.389	0.278	0.333	
Frequency of Troughs in Annual Water Quality Index curve (WQI)	3	4	2	0.333	0.444	0.222	

(continued)

Table 6.5 (continued)

Parameters	Value of the parameters			Normalized value			Scenario
	Farakka	Mahi	Vaigai	Farakka	Mahi	Vaigai	
Frequency of Troughs in Annual Hyetograph (P)	2	2	2	0.333	0.333	0.333	B2: 2071–2100
Frequency of Peak in Annual Hydrograph (Q)	2	2	2	0.333	0.333	0.333	
Frequency of Peaks in Annual Water Demand curve for Domestic Consumers (Dd)	5	6	5	0.313	0.375	0.313	
Frequency of Peaks in Annual Water Demand curve for Agriculture Consumers (Da)	5	5	7	0.294	0.294	0.412	
Frequency of Peaks in Annual Water Demand curve for Industrial Consumers (Di)	4	4	3	0.364	0.364	0.273	
Percentage Impervious Area (last 10 years) (A)	25	40	35	0.250	0.400	0.350	
Annual Average Area of Canopy (Ac)	75	60	65	0.375	0.300	0.325	
Frequency of Troughs in Annual Water Quality Index curve (WQI)	3	3	2	0.375	0.375	0.250	

Table 6.6 Table showing the predicted index value for the selected locations under normal and changed climate scenarios

Case study	P	Q	Dd	Da	Di	A	Ac	Model1.Index	Rank w.r.t water shortage
Farakka (Ganga River)	0.4	0.2	0.286	0.333	0.2	0.304	0.351	0.343	3
Mahi (Mahi River)	0.3	0.2	0.428571	0.333333	0.6	0.478261	0.243243	0.409	2
Peranai (Vaigai River)	0.3	0.6	0.285714	0.333333	0.2	0.217391	0.405405	0.435	1

Scenario: A2; Time slab 2010–2030

Case study	P	Q	Dd	Da	Di	A	Ac	WQI	Model1. Index	Rank w.r.t water shortage
Farakka (Ganga River)	0.428571	0.272727	0.307692	0.285714	0.315789	0.333333	0.333333	0.142857	0.363705	3
Mahi (Mahi River)	0.285714	0.363636	0.461538	0.357143	0.473684	0.454545	0.185185	0.5	0.448344	1
Peranai (Vaigai River)	0.285714	0.363636	0.230769	0.357143	0.210526	0.212121	0.481481	0.357143	0.376058	2

Scenario: A2; Time slab: 2031–2070

Case study	P	Q	Dd	Da	Di	A	Ac	WQI	Model1. Index	Rank w.r.t water shortage
Farakka (Ganga River)	0.411765	0.285714	0.3125	0.277778	0.304348	0.333333	0.333333	0.222222	0.374224	3
Mahi (Mahi River)	0.294118	0.357143	0.4375	0.388889	0.478261	0.435897	0.142857	0.444444	0.434958	1
Peranai (Vaigai River)	0.294118	0.357143	0.25	0.333333	0.217391	0.230769	0.52381	0.333333	0.378925	2

Scenario: A2; Time slab: 2071–2100

Case study	P	Q	Dd	Da	Di	A	Ac	WQI	Model1.Index	Rank w.r.t water shortage
Farakka (Ganga River)	0.4	0.294118	0.333333	0.3	0.333333	0.350467	0.290698	0.294118	0.390636	2
Mahi (Mahi River)	0.3	0.352941	0.388889	0.35	0.407407	0.392523	0.186047	0.529412	0.432522	1
Peranai (Vaigai River)	0.3	0.352941	0.277778	0.35	0.259259	0.257009	0.523256	0.176471	0.364949	3

Scenario: B2; Time slab: 2010–2030

Case study	P	Q	Dd	Da	Di	A	Ac	WQI	Model1. Index	Rank w.r.t water shortage
Farakka (Ganga River)	0.428571	0.285714	0.266667	0.2	0.333333	0.304348	0.351351	0.333333	0.38835	3
Mahi (Mahi River)	0.285714	0.285714	0.4	0.4	0.333333	0.478261	0.243243	0.333333	0.388585	2
Peranai (Vaigai River)	0.285714	0.428571	0.333333	0.4	0.333333	0.217391	0.405405	0.333333	0.411173	1

(continued)

Table 6.6 (continued)

Scenario: B2; Time slab: 2030–2070										
Case study	P	Q	Dd	Da	Di	A	Ac	WQI	Model1. Index	Rank w.r.t water shortage
Scenario: B2; Time slab: 2030–2070										
Case study	P	Q	Dd	Da	Di	A	Ac	WQI	Model1. Index	Rank w.r.t water shortage
Farakka (Ganga River)	0.285714	0.428571	0.357143	0.416667	0.5	0.25	0.388889	0.333333	0.438228	1
Mahi (Mahi River)	0.285714	0.285714	0.357143	0.25	0.333333	0.416667	0.277778	0.444444	0.386625	2
Peranai (Vaigai River)	0.428571	0.285714	0.285714	0.333333	0.166667	0.333333	0.333333	0.222222	0.363254	3
Scenario: B2; Time slab: 2071–2100										
Case study	P	Q	Dd	Da	Di	A	Ac	WQI	Model1. Index	Rank w.r.t water shortage
Farakka (Ganga River)	0.333333	0.333333	0.3125	0.294118	0.363636	0.25	0.375	0.375	0.398132	2
Mahi (Mahi River)	0.333333	0.333333	0.375	0.294118	0.363636	0.4	0.3	0.375	0.409712	1
Peranai (Vaigai River)	0.333333	0.333333	0.3125	0.411765	0.272727	0.35	0.325	0.25	0.380263	3

In case of A2 the last time slab was found to be worse for all the three locations whereas in case of B2 the middle time slab shows the higher level of scarcity than the other two time slabs.

Mahi has the higher level of urbanization followed by Vaigai and Farakka. Vaigai is also geo-physically prone to water scarcity. Its catchment has low water retention capacity. That is why in the normal situation also, Vaigai has the highest level of scarcity compared to other two locations. As an impact of Climate change situation of Mahi worsens in A2 but change in scarcity level is highest for Farakka from first to middle time slab in B2 scenario of climate change. Again in A2 scenario Mahi was clearly found to be most vulnerable but in case of B2 all three locations become most vulnerable in the three different time slabs.

The reason can be attributed to the strict environmental regulations that will be imposed on the locations and also to detrimental increase of population which becomes highest in the middle time slab but in the last slab change in density reduces compared to other two time slabs. Whereas in A2 scenario a steady increase in population density was predicted.

The Figs. 6.5 and 6.6 shows the comparison of the value of index in the selected region under three time slabs of A2 and B2 scenario.

The index developed with the help of MCDM techniques and ANN model seems to be performing satisfactorily. The introduction of this index will help the engineers and city planners to identify vulnerable regions with respect to water availability. Thus allocation of funds for mitigation will also become easier and logical.

Fig. 6.5 Figure showing the index value for the three time slabs of A2 Scenario (*1* Farakka, *2* Mahi, *3* Peranai)

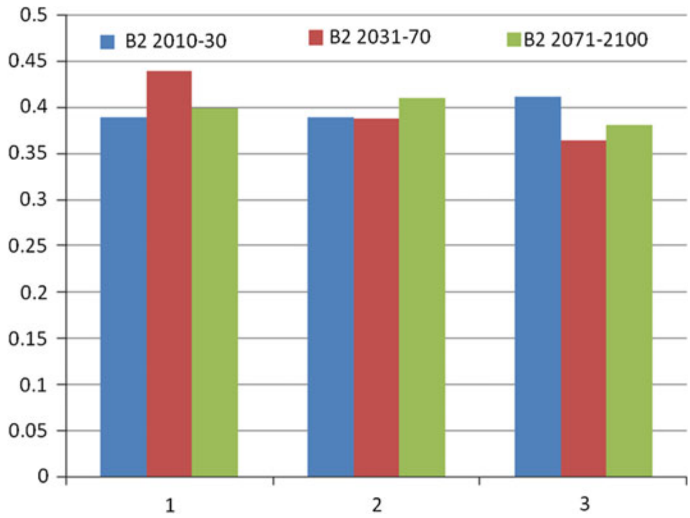

Fig. 6.6 Figure showing the index value for the three time slabs of B2 scenario (*1* Farakka, *2* Mahi, *3* Peranai)

6.5 Discussions

The index developed with the help of MCDM techniques and ANN model seems to be performing satisfactorily. The introduction of this index will help the engineers and city planners to identify vulnerable regions with respect to water availability. Thus allocation of funds for mitigation will also become easier and logical.

The proposed index takes the output from both human and documentary sources. That is why, both subjective and objective decision making can be incorporated in the index. As the index is cascaded with the ANN model, the necessity for repeat application of the MCDMs whenever a new location is included in the decision making becomes void. Thus it saves time as well as maintains uniformity in the decision making. The inclusion of normalized value of the input ensures that no error due to scale difference of the factors can be included. The factors were collected after a thorough search within the available and related literatures. This withholds the objectivity of the selection of factors without any human interference. But as the anthropogenic holisticity can not be denied, the feedback about the factors from the experts and stakeholders are also included.

The major disadvantage of the index is it requires the data for eight parameters which is often a tedious and difficult work to accomplish. But as the index accepts normalized value only the ranked values of the factors can be used. Another issue of concern is the value for the two similar locations becomes nearly equal having differences like 0.001–0.002. In this regard the hairline difference between the two index value will makes it difficult for the decision maker to interpret. But if the percentage of the index value is incorporated the difference is somehow becoming prominent.

The index provided the opportunity to identify the vulnerable regions logically and in an objective manner. With the help of the index, fund allocation for taking mitigative actions so that the deterioration of the situation can be prevented.

The fund allocation will be realistic and less controversial due to its need based nature. The hostility which are commonly observed in case allocation of development funds can also be nullified. The index can also be used to develop a country wise or watershed wise maps depicting the variation of water shortage within the selected range. The map can be prepared for present or normal as well as uncertain scenarios due to climatic and urbanization changes.