Climate Change and Urbanization Impact on Hydropower Plant by Neural Network-Based Decision-Making Methods: Identification of the Most Significant Parameter

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Abstract

The change in climate and rate of urbanization affects and unbalances the equilibrium between the demand and supply of energy resources. Hydropower plants are one of the most affected systems. But not all the operational parameters get influenced by this change. The significance varies between the parameters and indicators. Until now, there are no studies which try to identify the most significant parameters which get mostly affected by the climatic as well as urbanization uncertainties. As a result, the present investigation aims to detect the main indicator which can represent the operational status of hydropower plants under climatic and urbanization impacts. The objective multi criteria decision-making methods followed the implementation of polynomial neural networks to estimate the significance of the indicators. Although the list of indicator is not exhaustive, the said features are mostly consulted before concluding on the operational status of the power plant. According to the results, the most significant parameter was efficiency of generator. In this aspect, it is to be noted that harmonic mean hierarchy process (HMHP) and measuring attractiveness by a categorical-based evaluation technique (MACBETH) methods were used as multi criteria decision-making methods and polynomial neural networks were used to predict the function which will represent the present status of a power plant. In this study, we also used sensitivity analysis.

Keywords Climate · Urbanization · Machine · Efficiency · Optimization · MCDM · Impact · HPP

Introduction

In recent years, production from hydropower plants is compromised due to the effect of change in the climatic pattern. The hydrology of the river is affected which in turn has changed the performance efficiency of hydropower plants attached to that river.

Climate change or global warming is the expected outcome of increases in atmospheric concentrations of “greenhouse” gases resulting from human activities. Many greenhouse gases, including carbon dioxide (CO₂), occur naturally and keep the earth warm by trapping heat in the atmosphere. Changes in the quantity and timing of river runoff, together with increased reservoir evaporation, will have a number of effects on the production of hydro-electric power by climate change. These include impacts upon system operation [1, 2], financial effects [1], and impacts on other energy sectors [1, 3, 4].

In the present century, rapid urbanization was observed in most of the countries. Many villages are transformed into cities and many cities were converted to metro cities which produced surging demand for power to satisfy the basic as well as special needs of the urban population. As a result, along with the conventional power plants, water-based energy sources are also affected.

Urban water supplies are used in households, industry, and commercial areas, as well as for urban services such as city washing, combating fire, maintenance of recreational lakes

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and swimming pools, and irrigation of recreational areas. Urbanization impacts on hydropower plant are financial effects [5, 6], electricity supply [5], and environmental [7].

Another problem that affects the power production from HPP is the failure of machines employed to assist in power production. The turbines, generators, transformers, pipe lines, and switch gears each of the element which are utilized to help in the power production can fail due to various regions like electrical or mechanical stress, over load, and lifetime.

Machine is the most important for technological development of HPP. Technology-control system depends on machine of HPP. Machine failure impact on hydropower plant is financial effects [8].

The impact of climate change, urbanization, and machine failure has reduced the performance efficiency of HPPs in many places of the world.

The assessment and prediction of hydropower unit's performance degradation is an important part of the research for the sake of the unit's safe and stable operation. Accurate prediction of performance degradation is the basis for drawing up the unit's maintenance plan. High-accuracy prediction can ensure hydropower units to run in more reasonably safe and stable condition. The forecast precision has a direct impact on the hydropower plants' economic benefit; therefore, it is necessary to carry out the performance degradation assessment and prediction to do a lot of research works so as to better ensure the reliability of hydropower units' operation [9, 10].

In this aspect, a major solution can be to identify the most significant parameter or group of parameters which is most affected by the climate change, urbanization, and machine failure. Then, these few parameters can be monitored to control the impact on the HPP performance.

The solution can be practically adopted by the application of some intelligent soft-computation tools by which the most significant parameters can be identified in an unbiased and objective manner.

As a key discipline in the field of operational research, MCDM (multiple criteria decision-making) processes are those that attempt to create a standardized and rationalized framework of evaluation of complex scenarios in order to help decision-makers in making optimal decisions with respect to their objectives. Different MCDM methods yield different outcomes when applied to the same multi criteria problem. The selection of an appropriate MCDM method from a long list of MCDM methods is often not straight forward and may possibly control the final outcome of the decision-making process [11]. Pairwise comparison can be effective because it forces the decision-makers to give through consideration to all elements of decision problem [12]. The pairwise comparison seems to be insufficient and imprecise to capture the right judgments of decision-maker(s) with vagueness and uncertainty of data [13].

The problems encountered in the existing methods encourage the authors to propose a new method which is developed

based on the MCDM procedures but employs advantage of neural network architectures.

Objective of the Present Investigation

The objective of the present study was to identify the most significant parameter or parameters which are affected by the change in climate, rate of urbanization, and machine failures. The existing methods [14] require pairwise comparison of the parameters based on their influence on the decision-making objective. This method of comparison is not fixed and many researchers have applied various methodologies [15] to estimate the importance of one parameter over the other with respect to specific criteria or objective.

The present study will aim to propose a way through which rates the importance for a parameter with respect to the other parameter based on a criteria or objective. This method will not use any scale or any other method to rate the parameter importance separately; instead, this procedure will utilize an objective equation derived from the concept of neural network methodology and will estimate the weights of importance by maximizing the equation with the help of polynomial neural network method as programming technique for the optimization.

Once the maximization of the objective equation finds the optimal point, the magnitude of the weights, used as a design variable, will give the weights of importance of both criteria and alternative.

Based on these weights, the most significant parameter and rank of importance for each of the considered factors can be determined.

Another objective of the present investigation will be to estimate the performance efficiency of a HPP with the help of selected parameters under different climate change and urbanization scenarios. The scenarios for climate change were retrieved from Intergovernmental Panel on Climate Change and urbanization situation.

In this aspect, also, another polynomial neural network (PNN) model was developed to map the selected input parameters and the operational efficiency of the HPP. After the model is developed, the input parameters were adjusted based on the scenarios and change in efficiency was observed from the predicted plant efficiency.

Methods Adopted

In the present investigation, the PNN method was used to estimate the weights of importance for the selected parameters and also to map the relationship between the operational efficiency and selected parameters.

The artificial neural network or ANN was proposed by Bourquin and Agatonovic-Kustrin and Beresford [16, 17] in

1997. It is widely applied for predicting methane and percentage in biogas [18], urban air quality [19], and NO_x emission in a tangentially fired boiler [20]. The main advantage of the ANN is that it possesses the ability to learn quickly which is particularly appropriate for non-linear modeling. The large dimensionality and choice of training methodology are disadvantages of ANN. Since, in this present study, objective functions are non-linear, ANN is well suited for use in analysis. PNN is an advanced version of ANN which is different from the mechanism followed in the latter models. The main difference between the PNN and ANN lies in the way the topology of the network is identified and the manner in which the weightage of connections between the input and hidden, and hidden and output layers was estimated. Both these parameters are important in increasing the accuracy of the neural network models. The hierarchy in the MCDM method and the PNN method was the same which doubled the weight of the network model as two different procedures were executed through the same network. The application of simple ANN models will make the model heavier as it uses the separate iterations to find the optimal weightage of the connections and follows a trial and error method or complex search algorithms for identification of ideal number of hidden layers. But in case of PNN, the selection of hidden layers is confirmed automatically in the initial iterations reducing the requirement of repeated execution of the algorithm to identify the value of weightage which will yield minimum error in the predicted output.

Methodology Detail

In the present investigation, two objectives were achieved. At first, the most significant parameter was identified with the neural network-based MCDM method. In the second step, the same parameters were used to develop another PNN model to estimate operational efficiency of a HPP under different climatic and urbanization scenarios. The procedure details adopted for both the models are discussed in sections 3.1 and 3.2.

Development of Neural Network-Based Multi Criteria Decision-Making Method

In any compensatory MCDM method which follows a hierarchical structure, the importance of a set of alternative is determined with respect to a set of criteria based on the decision-making objective. A pairwise comparison is made to estimate the importance of one parameter over the other on the basis of the selected criteria and with respect to the objective. The importance of the parameter is represented as per a scale of ratings or based on a score or rank assigned based on the score. The rating of both the parameter and the factor with which it is

compared is used in ratio AHP (analytical hierarchy process) [21] or as a difference of ratings MACBETH (measuring attractiveness by a categorical-based evaluation technique) [22] to estimate the importance of the parameter with respect to the other parameters. A matrix is prepared with the ratings and aggregate of rows (AHP) or columns DEMATEL (decision-making trial and evaluation laboratory) [23] gives the relative importance of the parameter representing the row or column. The problem with this procedure is it involves multiple steps (like retrieval of rating, comparison of ratings and aggregation to find the overall rating of the parameter). In some methods like EVAMIX (evaluation of mixed data) [24], segregation of beneficiary and non-beneficiary parameters with respect to the objective are also required to be conducted before the pairwise comparison.

In the present investigation, the requirement to follow multiple steps to find the weights of importance is avoided by adopting a single equation to estimate the decision function and maximizing the function to identify the weights of importance of the parameter at the optimal scenario.

The objective function was developed following the concept of artificial neural network (ANN). In ANN modeling, the output is predicted with the help of the inputs, weights of the connection between input and hidden and hidden and output layer, and some activation function. The basic steps followed to predict the output are given in Eqs. 1.2 and 1.1.

If x and y are the input and output after the hidden layer and i and j represent the number of nodes and layers and z be the output which is being predicted and j and k be the number of nodes and layers in the hidden function, then at j th and k th layer of hidden and output layer, the respective function is predicted by:

$$Y_j = m\{(\sum w_{ij}x_{ij}) + b_{ij}\} \quad (1.1)$$

$$Z_k = n\left\{\left(\sum g_{jk}y_{jk}\right) + k_{jk}\right\} \quad (1.2)$$

where, b and k are the biases and w and g are the weights of the connection and m and n are the activation function at the hidden and output layer. b_{ij} represents bias between the i th and j th layers of hidden and k_{jk} represents bias between the j th and k th layer of hidden.

In case of compensatory MCDM following a hierarchical structure, an analogy can be made between the Eq. 1.1 and estimation of parameters with respect to the criteria and Eq. 1.2 with the final importance of the parameter based on the importance determined in the criteria layer.

If C and O represent the aggregated importance of the parameter with respect to the criteria and decision objective respectively and i , j , and k are the number of parameters and criteria respectively, then Eqs. 2.1 and 2.2 will estimate the aggregation of importance for each parameter with respect to the criteria and summation of importance of each criterion.

$$C_j = (u_j \sum p_i f_{ij}) \quad (2.1)$$

$$O_k = (v_j \sum g_j C_{jk}) \quad (2.2)$$

where f , p , and g are the value of the parameters, weight of importance of the parameters, and the criteria respectively. C_{ij} represents the aggregated importance of the parameter with respect to the j th to k th criteria. u and v are integer constants which are directly proportional to the electability of the criteria. Both p and g are random numbers and vary within 0 to 1.

The values of Eq. 2.1 are super imposed on the Eq. 2.2 to make a single equation for optimization. Accordingly, the PNN method was used to iterate the function for 10,000 times with a set of preconfigured dataset consisting of 3500 data nodes. The division of training and testing phase of data was fixed at 60 and 40. The Group Method of Data Handling was used as training algorithm, for the model. The root mean square error (RMSE) between the actual and output data was used as fitness function to monitor learning accuracy.

After the model was developed, it was used for iteration of the objective function until and unless the convergence is achieved. At the point of convergence, the value of the design variable, i.e., p and g was used as the weight of importance for the corresponding parameter and criteria.

A positive integer constant was utilized in place of the magnitude of the parameters.

Development of PNN Model for Mapping the Selected Parameter and the Operating Efficiency of Hydropower Plant

After the most significant parameters were selected with the help of the weights determined in section 3.1, the next and final step was to establish a relationship between the selected parameters and the operating efficiency of the plant.

Here, also the training data was collected from the generation of situations that may exist between the selected input and output parameters. The total number of training data was 3500 among which 60% was used for training and remaining 40% was utilized for testing the model performance based on the known value of the output. The GMDH was used as training algorithm and RMSE was utilized as fitness function.

Development of the Uncertain Scenario

The scenario for climatic uncertainty was collected from IPCC SRES A2 and B2. The magnitudes of the input parameters for the climate change and land use scenarios are given in Table 1.

Table 1 The description about the factors

Serial number	Criteria	Why use?
1	Climatic impact [1, 2]	If climate change is increased, then efficiency of HPP is decreased because impacts of climate change affect operation, financial effects, and impacts on other energy sectors.
2	Urbanization impact [5, 7]	Science urbanization impacts on hydropower plant (HPP) are financial effects, electricity supply, and environmental, so urbanization impact is inversely proportional to efficiency of HPP.
3	Impact of machine failure [8]	As machine failure impact on hydropower plant is on financial effects, so this criteria is non-beneficial with efficiency of HPP.
	Parameters	Why use?
1	Efficiency of penstock [25, 26]	For run-of-the-river hydroprojects, a portion of a river's water is diverted to a channel, pipeline, or pressurized pipeline (penstock) that delivers it to a waterwheel or turbine. The moving water rotates the wheel or turbine, which spins a shaft. The motion of the shaft can be used for mechanical processes, such as pumping water, or it can be used to power an alternator or generator to generate electricity.
2	Efficiency of turbine [25, 27]	The turbine turns the generator rotor which then converts this mechanical energy into electrical energy and the system is called hydroelectric power station.
3	Efficiency of generator [26, 27]	As well known, hydroturbines convert water pressure into mechanical shaft power which can be used to drive an electricity generator.
4	Efficiency of transformer [28]	All the electricity made at a power plant comes first through transformers which raise the voltage, so it can travel long distances through power lines. (Voltage is the pressure that forces an electric current through a wire.) At local substations, transformers reduce the voltage, so electricity can be divided up and directed throughout an area. Transformers on poles (or buried underground, in some neighborhoods) further reduce the electric power to the right voltage for appliances and use in the home.

Fig. 1 Location of Gumti HPP

Study Area

Gumti is one of the larger rivers in Tripura, India, which flows westward and discharges into Bangladesh. Due to the construction of a dam for the hydropower plant, a large reservoir was created, known as the Gumti reservoir. This reservoir is at the upper catchment of the Gumti River. The storage capacity of the reservoir is 23,570 ha meter. The submerged area at F.R.L of 92.05 m and M.W.L. of 95.25 m was found to be 46.34 and 74.86 km² respectively. With the help of this reservoir, the Gumti hydropower plant generates power to mitigate the crisis of power in Tripura. The design capacity of this hydropower plant was 15 MW. It has three units. The first and second units were commissioned in 1976 and the last in 1984. However, out of a 15-MW capacity, at present, only 8-

to 9-MW power is produced from Gumti HPP during the rainy season. During the dry season, production reduces to 0.5 MW. The numbers of turbine of this HPP are three and all these turbines are Francis [29]. Figure 1 shows the location of Gumti HPP.

The Gumti River is the largest river of this state, flowing from the eastern side of the state towards the western side of Tripura. The river Gumti originates from the hill range; Longtarai passes through four subdivisions of the state, viz., Tirthmukh, Amarapur, Udaypur, and Sonamura. This river enters into the territory of Bangladesh in the subdivision Sonamura. For the purpose of pisciculture, various dams have been constructed on this river. Several reservoir connections with this river have been made where a good quantity of fishes of different species is cultivated [30].

Table 2 Performance metrics of the developed models

Model number	Serial number	Model name	RMSE	<i>R</i>	COVAR	PI	EPI
1	1	P21_TR	0.000658	0.992171	0.000027	1447.628	1296.947
	2	P22_TE	0.000805	0.983678	0.000017	1196.492	
2	3	P11_TR_A	0.000592	0.997559	0.000071	1504.489	1308.800
	4	P12_TE_A	0.000774	0.995813	0.000072	1178.340	

Fig. 2 Weights of criteria

Results

Selected Criteria and Parameters

In this present study, criteria and parameters were selected based on the survey of the literatures. Nearly 100 literatures were analyzed to find out the significant factors controlling expenditure in HPP. When all these data of each criterion and parameters are normalized, then all these data of factors are unitless. Here, all these data are normalized by average of each data. Table 1 shows the description about the factors.

Development of the PNN Model for Optimization of the Objective Equation

The PNN model was developed in two configurations. In one form, the output function was transformed by the arc tangent function and for the other, it was not transformed. The RMSE, correlation coefficient (R), and covariance between the actual and predicted data from the two different configurations and for training and testing phase were estimated. The more the R value, the more reliable the development model will be, whereas the lesser the RMSE and COVAR, the better the model performance will be. As the metrics were related in two different ways with the performance of the model, an equivalent function was developed by dividing the R value

by the summation of RMSE and COVAR for both training and testing phases. After the Performance Index (PI) for both phase was calculated, 60% of the testing PI and 40% of the training PI was aggregated to find the Equivalent Performance Index (EPI) which represents the overall model reliability.

The metrics RMSE depicts the difference between the actual and model-predicted data. Correlation between the actual and predicted data will estimate the relationship between both kinds of data. The value of R shall be nearer to unity which will indicate satisfactory level of learning by the model about the present problem. In case of variance between two variables, the metrics like covariance is determined. The lesser the variance between the actual and predicted output data, the better the reliability of the model is. Table 2 shows the performance metrics of the developed models.

According to the results, the model which predicts the arc tangent transformation of the objective equations (Eqs. 2.1 and 2.2) is found to be a better model compared to the other model where the non-converted objective function was used as output. The selection is eminent if the value of EPI is compared. The EPI of model no. 1 is 1.09 times larger than that of model no. 2. The RMSE of model 1 is 0.89 times lesser compared to that of model 2, whereas the correlation of model 1 is 1.005 times more than that of the model 2. Only in case of covariance, the metric is 2.612 times greater than that of model 2 which can be attributed to the way training data was generated.

Fig. 3 Weights of parameter

Table 3 Performance metrics of the model developed for the prediction of operating efficiency of the power plant

Model no.	SLNO	Model name	RMSE	<i>R</i>	COVAR	PI	EPI
3	1	P31_TR	0.000006	0.999998	0.018679	53.516	53.469
	2	P32_TE	0.000009	0.999998	0.018705	53.437	
4	3	P41_TR_A	0.000045	0.999999	0.013999	71.204	70.608
	4	P42_TE_A	0.000051	0.999999	0.014192	70.210	

Most Significant Parameter

The results from the optimization steps depict that the most significant parameter with respect to the study objective is efficiency of generators (see Fig. 2) followed by turbine and transformer. In case of criteria, impact from urbanization (see Fig. 3) was found to be most important compared to the other two criteria selected for the present study. For validation of optimization results, we used one existing MCDM method namely HMHP proposed by P. Majumder, A.K. Saha, and M. Majumder [31] and MACBETH proposed by Bana e Costa and Vansnick [32]. The results found from HMHP and MACBETH also matches with the results found from optimization.

Development of the Predictive Model for Estimation of Operating Efficiency

The performance metrics of the PNN model developed for estimation of operating efficiency from the selected input parameters is given in Table 3. In this case, a four input and one output model was developed with the help of GMDH training algorithm. The output was transformed by arc tangent function and compared with the model developed without the transformation of the output.

The operating efficiency of the selected hydropower plant was calculated with the help of Eq. 3.

If OE is the operating efficiency of the HPP,

$$\text{then OE} = P_{\text{act}}/P_{\text{pot}} \quad (3)$$

where

$$P_{\text{pot}} = m \times g \times H_{\text{net}} \times \eta_{\text{rated}} \quad (3.1)$$

$$P_{\text{act}} = m \times g \times H_{\text{net}} \times \eta_{\text{actual}} \quad (3.2)$$

The m , g , and H_{net} are the mass, acceleration due to gravity, and net head respectively. P_{pot} and P_{act} are the potential and actual powers generated in the HPP. η_{rated} and η_{actual} are respectively the rated and working efficiency of the power components.

The difference between potential and actual efficiency arises due to the degradation in rated efficiency of the power component. Although the net head changes with flow in the river, at fixed head, the efficiency of the power components mainly influences the OE.

That is why, for the present case, a fixed head hydropower plant was selected. Rated efficiency of all the power component is taken as 0.95 and the variance of efficiency of the components was randomly selected to generate the training data for the model.

The efficiency of the penstocks was not included in the calculation of the actual plant efficiency. But, the parameter was included as input to the model because of its influence on the input energy fed to the turbine.

Table 3 depicts the EPI value of the two models developed for prediction of the interrelationship between the input efficiencies and output operating efficiency of the power plant. As per the EPI value, model no. 2 was selected. The relative difference of EPI between the two models is 32.05%. Although the RMSE value of model 3 is lower than 0.142 and 0.178 times compared to that of model no. 4, the correlation and covariance of model 4 is 1.000001 times and 1.334 and 1.318 times during training and testing phases respectively compared to that of model 3.

Fig. 4 Present scenario

Fig. 5 Scenario analysis with respect to climate change

Result from the Uncertainty Analysis

The efficiency of penstock, turbine, generator, and transformer in the study area is presently at 85, 85, 90, and 95% respectively (see Fig. 4). As an impact of climate change, it is predicted that during A2 and B2 scenarios, the rainfall will increase. The intensity of increase will be more in A2 compared to B2 scenario. The impact of the increased rainfall will be increase in operating time of the power component. On the other hand, as assumed in A2 scenario that uncontrolled industrialization will take place during this scenario, the demand for energy will also be escalating. In the B2 scenario, it is assumed that controlled industrialization will take place maintaining all the regulations for saving environment and releasing minimum carbon. As a consequence, demand will be lesser compared to that in A2 scenario. In A2 scenario, the erosion will be more compared to that in B2 scenario. That is why the impact on conveyance efficiency of penstocks will be higher compared to the efficiency of the power component, but the intensity will be more in A2 than that of B2 scenario.

In total, ten representative scenarios, five each for A2 and B2, from 2020 to 2070, were configured based on the assumptions of IPCC. Each situation is a representative of a decade.

Similarly, the representative data for the different scenarios of urbanization is also determined. According to the Polestar model, there are four types of storyline that can be adopted by the future world. Among the four story lines, market forces and policy reforms seem to be conventional and also similar to IPCC A2 and B2 scenarios [33]. Accordingly, the scenarios were created including the impact of growth in population and assuming an increase in large farmlands. It is to be noted that although net urbanization is predicted to decrease, the growth of population will sustain up to 2050 and then some stagnation is predicted [34, 35]. That is why demand for food will increase and so will be the requirement for energy.

Although it is also predicted that an increased use of bioenergy [36] will take place, it will also increase the land use conversion and decrease the availability of land. The impact of biofuels is not included in development of the scenarios for the present investigation.

In the case of urbanization scenarios, also ten representative data were estimated for the five decades each for the MF and PR story lines.

According to the results, shown in Figs. 5 and 6, intensity of impact on operational efficiency due to change in climate is more compared to the change in urbanization. The maximum

Fig. 6 Scenario analysis with respect to urbanization

Fig. 7 Sensitivity analysis of alternatives

change of 25.032% was observed in 2061–2070 decade for A2 scenario whereas in the similar scenario of land use change in the same decade, the decrease in OE was found to be 4.626% only. This can be explained from the fact that the study area is selected from a comparatively scarcely populated location where rate of urbanization is more compared to that in similar peri-urban cities. Also, the increase in rainfall as predicted in IPCC A2 scenario for the Tripura region increases by 30% (approx). That is why requirement of operation has also increased and as a result efficiency of power, components were decreased compared to those in the land use scenario. If all the change observed in climate change and urbanization scenarios was compared the intensity of change for A2, B2 is more compared to MF, PR. The average of changes observed in climate change scenarios is 15.452% compared to that of 1.401% in urbanization scenarios. The difference is more than 11 times to the average change observed in the urbanization scenarios.

Another point of contention is that although in climate change scenarios, only decrease in OE was observed with respect to the baseline, but for urbanization scenarios, change is positive in all the PR scenarios. This observation can be explained by the fact that in PR scenario, sustainability of the environment as well as mankind is given the top most priority and hence the demand for energy was regulated. The main focus was on environment and socio-economic developments. In case of B2, social and environmental sustainability was the top priority but as the world was segregated and also rainfall is predicted for an increase as per the PRECIS climate model for the study area, demand can be controlled but not limited.

Sensitivity Analysis

In different case studies, the validation of the model was conducted by sensitivity analysis and the application of the model. From Fig. 7, it can be seen that the most important parameter found by the PNN MCDM of efficiency of generator is the most sensitive input parameter for performance of the HPP, with a swing2 value of 41.5%. The least most sensitive parameter is efficiency of penstock with swing2 values of 2.4%. Swing2 value is the deviation in input parameter.

Conclusion

The present investigation attempts to identify the key parameters which are affected by the impact of climate change and urbanization and due to these uncertainties machine failures. In this aspect, a new method for decision-making was developed based on the concept of the neural network architecture. The new method was successful to identify the priority parameter as a result of the optimization procedure on the developed objective equation based on the neural network concept. We compare the result of existing MCDM techniques. In the next step, another model was prepared to estimate operational efficiency of the HPPs under changed climate as well as urbanization scenarios. At the end, sensitivity analysis was applied for identifying sensitive parameter. The models were developed with the help of PNN method. A four input and one output model was developed and used for prediction of the OE under ten different climatic and urbanization scenarios. The scenarios were developed based on the IPCC SREC A2 and B2 scenario and Polestar models GSG-based story lines, MF, and PR respectively for the climate change and urbanization scenarios. According to the results, the most significant parameter which can be affected by the climatic and urbanization scenarios is identified as the efficiency of generators. As per the results of the scenario analysis, the impact of climate change on the OE was found to be more severe compared to that of the urbanization scenarios. The results from the investigation suggested that it is better to prepare for mitigation of the climate change rather than the change in rate of urbanization which is also predicted to be lower in the latter half of the first five decade of the twenty first century. The efficiency of generator is required to be monitored with utmost priority followed by the efficiency of the turbines. Two existing MCDM techniques also support the result of PNN. As per various literatures, this two-power component is the most important element to maintain the OE of any power plant. The PNN model developed for the decision-making step was found to have an accuracy of 99.941 and 99.923% respectively in the training and testing phase of the selected configuration of the model (model no. 2). The correctness of the models developed for the prediction purpose was found to be 99.995 and 99.994% respectively for the training and testing phase of the selected model (model no. 4). The result from

the scenario analysis suggested that if A2 scenario becomes true in 2061–2070, there will be a maximum decrease in the OE and if land use scenario: PR story line is found to be adopted in the future world of 2020–2030; the change in OE will be largest (an increase of 6.056%) compared to that in any other scenario developed for the impact of urbanization followed by land use change scenario of the 2031–2040 decade which will be equal to an increase of 5.247% compared to the baseline. Although results may change if the PNN models were trained with a different data set, the new MCDM is an approach which was successful in making a decision just like the hierarchical compensatory MCDMs but in one step or by a single equation. According to the result of sensitivity analysis, efficiency of HPPs is the most sensitive parameter. Another drawback may be the exclusion of the efficiency of drives, but the adopted procedure of selection has selected only the most cited and recommended parameters. Another limitation of the study is the exclusion of the population change even as an exogenous variable. But, the present investigation has concentrated on the urban population only as the effect of the climate or urbanization change will mostly create hazard on the urban compared to the rural population.

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