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Monitoring water input quality: early screening and system support through the application of an adapted multiple criteria decision making method

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ABSTRACT

The WHO estimates that, on average, dehydration caused by water borne illnesses claims up to 1.5 million lives a year, with a disproportionate number of casualties located in developing nations. In order to mitigate risks to public health, previous studies have helped to gain extensive insights and create management techniques to ensure that water quality standards are maintained. The present study will investigate a relatively neglected field, which is the need for the prioritization of monitoring the quality of a water treatment plant's inflow, which may vary significantly in quantity and quality throughout the day. The technique proposed for this investigation is a novel application of the multiple criteria decision making (MCDM) method, adapted particularly for the purposes of decision making for optimal scenarios, called the multi variable temporal decision making method for the selection of optimal solutions (MVTDMSOS). By cascading self-selecting neural network algorithms, which are implicit in such systems, this method is designed to eliminate human bias and aims to identify the priority parameters based on optimal, rather than normal, scenarios. The introduction of polynomial neural networks ensures adaptability and alacrity of the modeling framework. Test results encourage further application of the proposed technique.

Keywords: Analytical hierarchy process; Water treatment plant; Group method of data handling

1. Introduction

The role of water treatment plants (WTP) in ensuring good public health is well documented across the literature. For instance, Đukić et.al. [1] studied the means to implement the removal of heavy metals from aqueous solutions through the use of treated clay filters. A later study by Djukic et.al. [2] investigated the commercial viability of WTP systems through cost-benefit analyses carried out on infrastructure case studies. Rauch and Harremoes [3] also identified optimal design and real-time management of urban water treatment plants in order to ensure consistent safety standards in domestic and commercial water supplies. Similarly, Tchobanoglous and Burton [4] compiled a comprehensive wastewater engineering manual that addressed the most suitable ways to approach effluent disposal, wastewater reclamation, as well as advanced water treatment mechanisms. These studies have proven to be highly influential on the methods adopted to ensure the quality standards of supplied water are maintained around the world.

In practice, the issue of water treatment contains many challenges, including sudden changes in the quality of intake water, mal-performance of treatment instruments, degradation of system performance, lack of skilled manpower, etc., all of which reduce the overall performance efficiency of the plant. Of these challenges, the sudden change in quality of intake water especially impacts the quality of treated water that is distributed among consumers, meaning that real-time monitoring of the quality of intake water is necessary. At present, there are very few WTPs with installed real-time monitoring of intake water [5,6]. Most WTPs monitor multiple parameters, detecting daily changes, but monitor only the intake point so if, as often occurs, they detect the change too late, it gives scant opportunity for implementing compensatory measures. Also, due to the single-point multiple-parameter monitoring, the scope for implementing adaptive measures

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is limited. It can also be the case that systems are prone to human preference and so can easily be manipulated, leading to sub-optimal results. Some of the most common methods used to detect change in the quality of intake water are: sample collection from strategic points in and around the WTPs; sensor-based monitoring schemes [7,8]; adaptation of bio-indicator based quality [9]; trend analysis [10]; cluster analysis [11]; and chemo-metric analysis of the quality parameters taken from data collected at the intake point of the treatment plant [12].

The sample-based and sensor-based schemes are unfavorable due to the time (especially for the sample-based schemes) and cost involved in these types of monitoring systems. In the case of bio-indicator based systems, changes in the species and populations of bio-organisms often make it location-dependent. Cluster or trend analyses or index-based systems depend on the type and amount of data collected, accuracy of the modeling technology, as well as the number and type of input parameters selected to develop the model. Results may vary with location and time at which data was collected. These issues are why the present study proposes a method which will be free of human bias, adaptive to situations, consider only the significant parameters, and give results on the data collected from multiple points situated in strategic locations. Although the procedure uses sensors for real-time data collection, only the significant parameter along with time of data collection is preselected cognitively, so the requirement for sensor placement and operation is limited and does not involve large economic constraints. The advantage of multipoint data collection is that the compensatory system in the WTP can be warned early, so that the mechanism has sufficient time to avoid or prevent the uncertainty.

1.1. Objective

The main objective of the present investigation is to develop a real-time monitoring system for the identification of changes in water quality parameters of the intake of water into WTPs. This, in effect, also includes the development of a media through which multiple factors affecting water intake quality can be measured and compared based on the importance of each factor. For this reason, an indicator is developed to monitor all the correlated factors, but the identification of changes will be devised as per their influence on the overall quality of the intake water. Monitoring and identification is made at seven points before the intake point.

The indicator will be mapped with the input parameters using cognitive methodology, then a system-independent algorithm will be developed and installed to monitor the parameters for the detection of changes at seven different points. The methodology of development of the indicator and its implementation in the WTP is described in the next section.

1.2. Methodology in brief

The present study adopted a three-step methodology to achieve the objective. In the first step, the most important parameters (MIP) with respect to the WTP were identified by conducting a literature review. After the MIP were identified, the relative importance of the parameters were estimated with the help of two different multi criteria decision making methods, called the analytical hierarchy process (AHP) and a new method developed for the purposes of this present study, termed the multi variable temporal decision making method for selection of optimal solutions (MVTDMSOS).

After the relative importance of the parameters was determined, the group method of data handling (GMDH) was used to map the indicator along with the input parameters. The indicator was developed as the direct and inverse weighted function of the beneficiary and non-beneficiary parameters with respect to the change in the quality of water in the intake. This step ensures the generation of a system-independent algorithm that allows the current method to be independent from the platform, and also prevents any biases affecting decision-making by hiding the importance of the parameters.

By considering the temporal variation of the identified parameters at the selected points before the intake, we also incorporated the temporal impact of the parameter. Although only the four MIPs are incorporated into the model to predict the quality of water intake, in practice, seven different points before it are also monitored.

2. Methods adopted

Three different methods were utilized to achieve the objective of the present study. Specifically, one neural-modeling method and two decision-making methods were adopted. Section 2.1 and 2.2 describe the MCDM methods and 2.3 describes the neural-modeling method.

2.1. Analytical hierarchy process (AHP)

Multiple criteria decision making (MCDM) is a decision-making analysis approach that evaluates competing choices within a scenario. It considers tradeoffs that may be inherent in a system such as quality and cost effectiveness, or efficiency and the time necessary to implement new methods, etc. One advantage of explicitly considering opportunity cost in decision-making scenarios, in particular WTPs, is that it often leads to more reasoned and better-informed decisions.

There are broadly two types of MCDM analyses methods; namely multiple criteria evaluation problems and multiple criteria design problems (this study utilizes the analytic hierarchy process, or AHP, which falls into the first category). The multiple criteria evaluation problems consider a finite set of alternatives and evaluate them based on their outcome within the scenario. Competing choices can then be classified or sorted and an optimal choice allocation can be defined. Alternatively, a system of preference classes can be described which ranks options based on outcome. Multiple criteria design problems, on the other hand, consider scenarios in which alternatives are not fully described. The alternatives can be infinite in number or may be of a large number if discrete numbers are outlined. Additionally, the choice set may not be fully known, leaving an element of uncertainty in the choice framework that the design process accounts for.

In practice, MCDM allows for both qualitative and quantitative parameters, and follows a pair-wise comparison of importance between the alternatives with respect to the criteria selected and the objective of the decision-making. Pair-wise comparison ensures the determination of the relative importance of alternatives, utilizing a scale to rate the pair-wise importance of the alternatives. It follows a unidirectional hierarchy, from the goal of the decision to the importance of the alternatives. This method is generally used when no specific utility function exists between the alternative and the criteria of decision-making.

The analytic hierarchy process is a specific type of MCDM proposed by Saaty in1990 [13]. It is a method used for evaluating complex decision-making processes. Debnath et al. [14] utilized this method for Grey Water Recycling, whereas Rasli et al, [15] and Rahmati et al. [16] have applied this method for selection of location for urban parks and for prioritization of watershed vulnerability, respectively. There are numerous applications for AHP in the problems of water resources and its management [17,18]. The satisfactory results depicted by the authors of these studies encourage the use of this method as a comparison with the new multi variable temporal decision making method for selection of optimal solution (MVTDMSOS).

The AHP is characterized by the categorization of attributes of the scenario into hierarchies, each of which can be scrutinized before the scenario as a whole is studied. These attributes can include any factor related to the scenario and are deliberately broad in nature. They may include qualitative as well as quantitative elements, may be either tangible or intangible, and may include both objectives and realities. The advantage of this approach is that the complexity of the scenario can be better evaluated if scope is present for the consideration of a broad range of attributes.

The hierarchy obtained is then subject to internal comparisons. The various elements are divided into pairs and compared with pairs of other elements at different points in the hierarchy. This evaluation can be either based on empirical evidence or on the decision maker's objectives, or both. This aspect of the AHP allows the use of decision maker's insight and rationale, which is often required in complex decision-making processes. Based on these comparisons, a numerical value is then attributed to each element of the hierarchy, which quantifies its significance relative to alternative pairs of criteria. This method does not offer a definitive solution to a complex problem; rather, it suggests which option from within a competing set is most likely to provide an optimal solution.

The AHP method was used to estimate the relative importance of the selected parameters with respect to the study objective; the manner in which it was applied is outlined in the following sections.

2.2. Multi variable temporal decision making method for selection of optimal solution (MVTDMSOS)

The MVTDMSOS is a form of MCDM that is being proposed in the present study to approximate the relative importance of parameters with respect to the criteria considered. It differs from the AHP method in that it will yield the priority value or weight of importance for each of the selected alternatives used for selection of the optimal (instead of the normal) solution. This implies that the estimated importance and selection of the option using this method will ensure system outputs are optimal.

Popular MCDM applications, such as AHP, approximate the relative weight of importance for a normal output from the decision-making process. The MVTDMSOS, however, attempts to ensure that the relative importance of the parameters will give an optimal output from the decision making process. The adaptation of this condition is aimed at helping the decision maker to adopt an output measure that will yield maximum benefit from the system.

Another difference between normal MCDM methods and this method is that it considers temporal variation of the parameters. Both the alternatives and its time-lagged states are included as alternatives. The summation of the product function of priority parameters and the priority values are considered as the objective function. The relationship between the parameter and the goal of decision-making with respect to the criteria considered are also included by positioning the proportional factors in the numerator and inversely proportional factors in the denominator. The proportionality of the factors change with the criteria and that is why separate objective functions have to be prepared for each of the criteria. This segmented nature of the optimization problem ensures the inclusion of the non-linearity that exists between the decision goal, criteria and the alternatives; as there will always be more than one objective function, the optimization procedure will always be multi-objective. The priority values of the parameters are considered as design variables, whereas the value of priority parameters is taken from the location for which the method is developed. As there will be different objective functions for each criterion, separate priority values for the parameters will be estimated for the different criteria. The priority value estimated for the criteria, which are directly proportional to the goal of the decision will be divided by the priority value determined for the non-beneficiary or inversely-proportional criteria. The final priority value of each of the parameters will be calculated from this ratio. The constraints of the design variable will lie between 0 (least significant) and 1 (most significant).

All the objective functions and the final ratio will be interlinked, and the values calculated at the same time. the polynomial neural network algorithm was implemented in an attempt to find the optimal value of the objective function.

2.3. Polynomial neural networks (PNN)

In recent years, simple neural network models have been replaced by more advanced and complex variants. Polynomial neural networks [19,20] are one such type of new and advanced modeling framework which follows the neural network architecture, but is self-sufficient in the selection of optimal topology and number of inputs required to accurately learn the modeling problem.

The group method of data handling (GMDH) [21] is a training algorithm which is applied to train PNN based models. It is a type of inductive analysis that uses datasets with multiple parameters to obtain an optimal allocation output, frequently used in data mining, prediction and optimization of problems, and in complex decision-making analyses. It is particularly effective at building complexity within decision-making models by using a base function, which aggregates multiple inputs into one output forming a partial model. These partial models can be aggregated until a model of optimal complexity can be generated, which in turn produces the optimal output. A key feature of this model is in the application of external criteria such as the minimization of least squares, in order to minimize variation within the decision output that could arise from subjective biases implicit in the scenario, or from natural variation.

The GMDH framework is versatile in the manner in which it can be applied in numerous partial models. One of the earliest was the multilayer inductive procedure, which proved to be very influential. Commonly known as polynomial neural networks, this method has been invaluable for the development of computational systems in the past. They display many similarities to biological neurons, where, when transmitter chemicals surpass a particular threshold, the neuron is activated and emits a signal through the axon. This signal might be sent to another synapse, which in turn may activate other neurons. This principle of chains of effects being initiated is abstracted and applied to artificial neural network (ANN) models.

ANN models can, in effect, approximate scenarios which may have a large number of inputs into a single output, which in turn can be used as an input into another model; in this way they replicate the multifaceted repercussions of decision characteristics that are present in multiple criteria decision-making processes. Thus, a given number of inputs can be applied multiple times in a given set of formulae, leading to output decisions which implicitly give greater significance to those criteria that are inputted the greatest number of times into the interim "hidden" algorithms.

However, the neural network algorithm has a drawback in that the number of hidden layers and inputs at which maximum accuracy can be achieved from the developed model has to be determined with the help of trial and error, or with the use of search algorithms. Such procedures are often time consuming and may not always ensure optimality, as results may change when a different method is adopted or may differ in the next trial.

For the purposes of this study, the GMDH is construed as an algorithm that follows the neural network topology. It self-selects the number of hidden layers and inputs with which the output can be considered most accurate. In this way, the time required for model development as well as the error that may arise from using search models can be mitigated, compared to the earlier methods. The model adopted here uses GMDH to map the selected parameters, with the indicator as an output, to generate a system that will predict the quality of water intake. This prediction will be free of bias, as the importance of each of the parameters will be hidden in the algorithm. The model will also be platform-independent and can be used in any similar system.

Along with GMDH, the present investigation also utilized quick combinatorial or combinatorial optimization [22] training algorithms to find the optimal value of the weights of the interconnections between the input, hidden and output layers for comparison with the result derived from the GMDH algorithm.

3. Methodology

As outlined in Section 1, the present study describes an approach to monitor the quality of water intake for surface WTPs. In order to facilitate this enquiry, an indicator was developed to represent the overall quality of the water with respect to the study objective. In this way a new multi criterion decision-making method was proposed. An existing MCDM was also used for the same purpose, with the input parameters and indicators being mapped with the help of a cognitive technology known as GMDH. This methodology is described in detail in Sections 3.1–3.5. Fig. 1 depicts a schematic diagram of the methodology adopted in the present study. Fig. 2 shows the hierarchy of goals, criteria and alternatives for the MCDM step. The algorithm of the MVTDMSOS method is shown in Fig. 3, while the development steps of the polynomial neural network model are depicted in Fig. 4.

3.1. Application of MCDM method to identify priority value

The MCDM method, as described in Section 2.1, is utilized in both objective and relative decision-making. It has the distinct advantage of providing unbiased priorities with respect to the decision objectives. The present study utilizes two MCDM methods: analytical hierarchy process (AHP) and a new decision making method, the multi variable temporal decision making method for selection of optimal solutions (MVTDMSOS), proposed for the first time in this study. The MCDM method involves three steps that are described in Sections 3.1.1–3.1.3.

3.1.1. Selection of criteria

The decision making analysis process is carried out here with respect to two different criteria: technical efficiency and economic liability. The former compares the alternatives with respect to their ability to impact the technical efficiency of the WTP and the latter represents the priorities in response to economic liabilities of the WTP that can be absorbed by alternatives.

3.1.2. Selection of alternatives

From the review of expert literature on the topic, it was found that changes in dissolved oxygen(DO), pH, turbidity and total dissolved solids(TDS) within a span of 24, 48 and 72 h have the maximum influence on performance efficiency of WTPs. That is why all twelve of these parameters were considered in the decision-making method, ranking them in terms of priority. Table 1 (in the appendix) summarizes and describes each of these parameters.

3.1.3. Application of aggregation methods

The alternatives were ranked as per their significance from a review of studies on the topic. Following this, the AHP method was applied. In effect, all the alternatives were compared both with each other and with respect to the criteria under consideration. Priority values were then

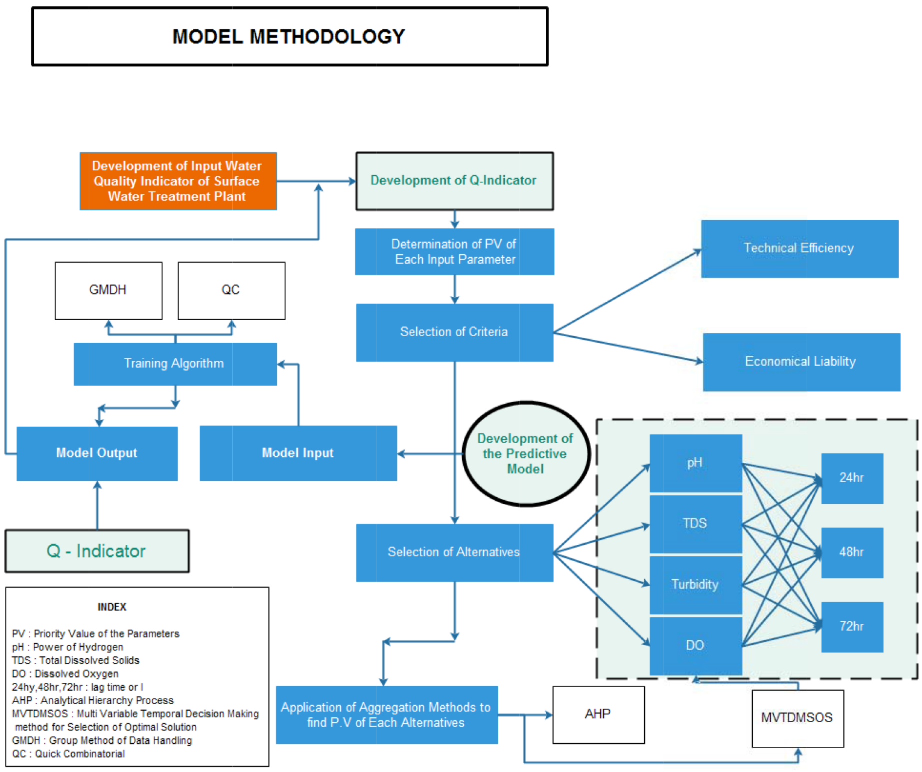

Fig. 1. Schematic diagram of the methodology adopted in the present study.

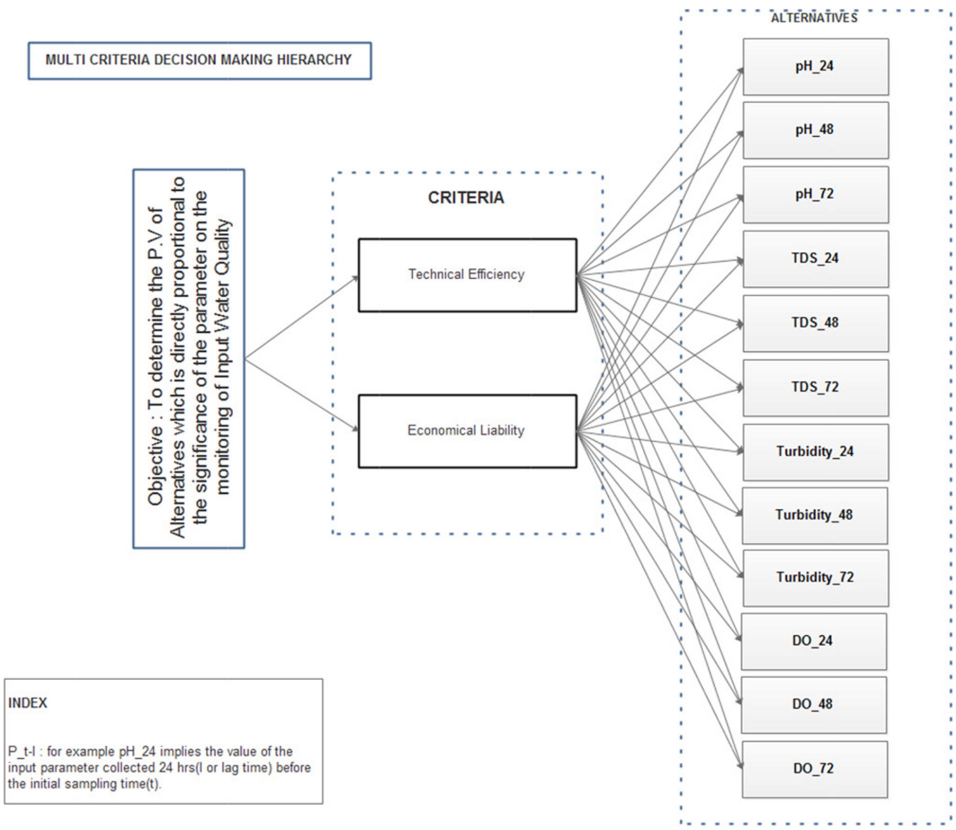

Fig. 2. Hierarchy diagram of the decision making problem.

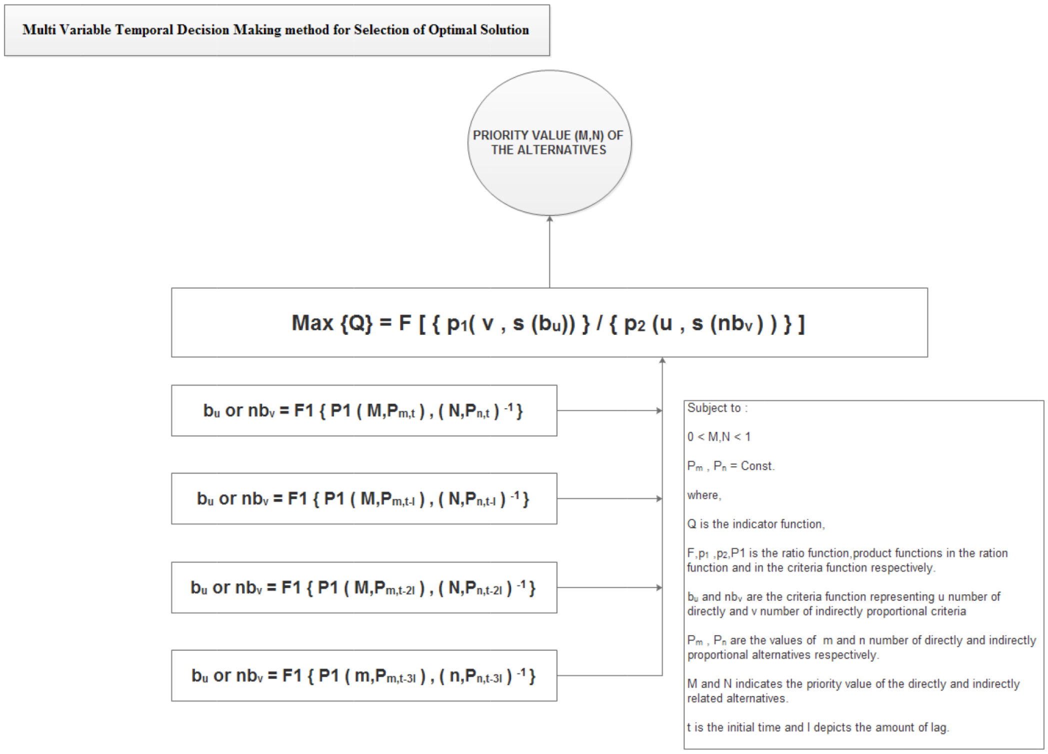

Fig. 3. Schematic diagram of the methodology for the MVTD approach.

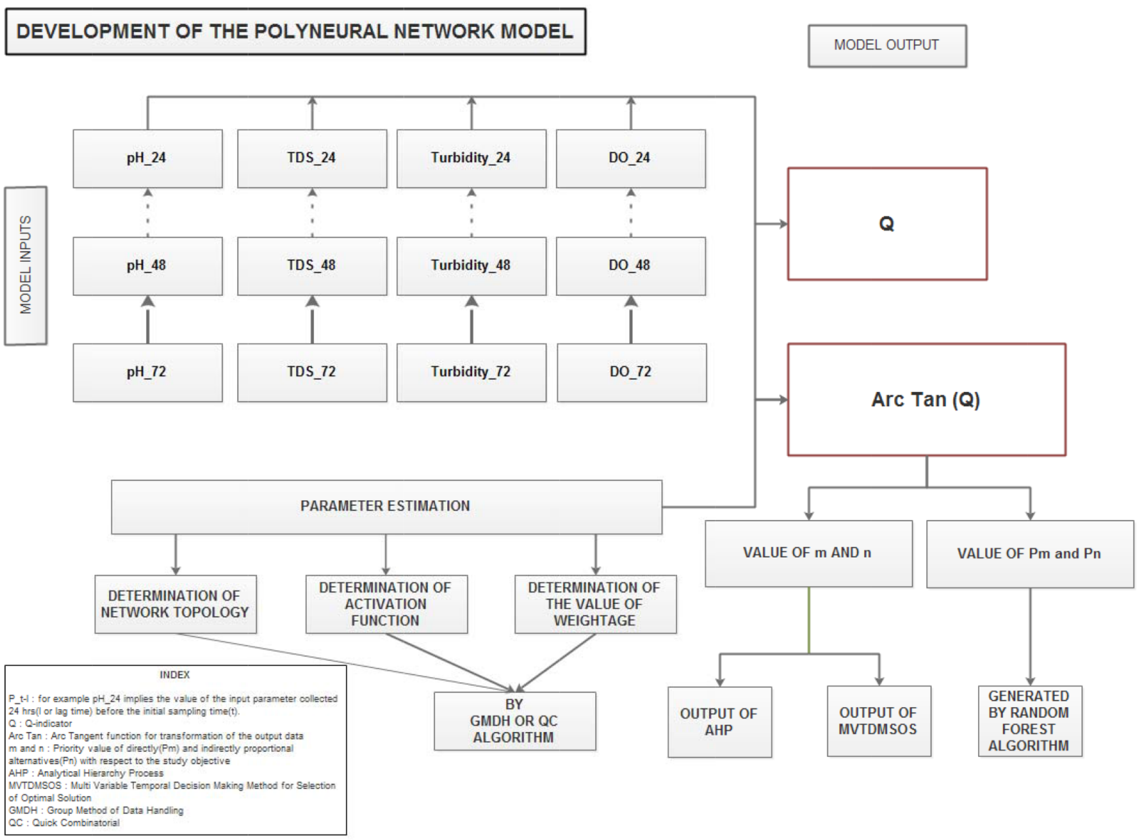

Fig. 4. Schematic diagram of the methodology adopted in the development of polynomial neural network model.

Table 1
Criteria and alternatives considered in the AHP MCDM method

Name of the criteria	Description
Technical efficiency	The technical or functional efficiency or the property of the parameter which increases the quality of the water.
Economic liability	The economic liability will depend on the hazardous impact that can be implemented by the parameter. The economical liability is directly proportional to the hazard potential of the parameter.
Name of the alternatives	Description
Change in the dissolved oxygen concentration within 1 d	The change in the concentration of the parameter within 24 h of first sample collection. The concentration of DO is directly proportional to the usability of the intake water but inversely proportional to the requirement for treatment.
Change in the dissolved oxygen concentration within 2 d	The change in the concentration of the parameter within 48 h of first sample collection. The concentration of DO is directly proportional to the usability of the intake water but inversely proportional to the requirement for treatment.
Change in the dissolved oxygen concentration within 3 d	The change in the concentration of the parameter within 72 h of first sample collection. The concentration of DO is directly proportional to the usability of the intake water but inversely proportional to the requirement for treatment.
Change in the pH Concentration within 1 d	The change in the concentration of the parameter within 24 h of first sample collection. The concentration of pH is directly proportional to the usability of the intake water but inversely proportional with the requirement of treatment within the range of 6.5 to 7.5, but the relationship changes with lesser value of 6.5 and larger value of 7.5.
Change in the pH Concentration within 2 d	The change in the concentration of the parameter within 48 h of first sample collection. The concentration of pH is directly proportional to the usability of the intake water but inversely proportional with the requirement of treatment within the range of 6.5 to 7.5, but the relationship changes with lesser value of 6.5 and larger value of 7.5.
Change in the pH Concentration within 3 d	The change in the concentration of the parameter within 72 h of first sample collection. The concentration of pH is directly proportional to the usability of the intake water but inversely proportional with the requirement of treatment within the range of 6.5 to 7.5, but the relationship changes with lesser value of 6.5 and larger value of 7.5.
Change in the turbidity concentration within 1 d	The change in the concentration of the parameter within 24 h of first sample collection. The concentration of Turbidity is inversely proportional to the usability of the intake water but directly proportional with the requirement for treatment.
Change in the turbidity concentration within 2 d	The change in the concentration of the parameter within 48 h of first sample collection. The concentration of Turbidity is inversely proportional to the usability of the intake water but directly proportional with the requirement for treatment.
Change in the turbidity concentration within 3 d	The change in the concentration of the parameter within 72 h of first sample collection. The concentration of Turbidity is inversely proportional to the usability of the intake water but directly proportional with the requirement for treatment.
Change in the total dissolved solid (TDS) concentration within 1 d	The change in the concentration of the parameter within 24 h of first sample collection. The concentration of TDS is inversely proportional to the usability of the intake water but directly proportional with the requirement for treatment.
Change in the TDS concentration within 2 d	The change in the concentration of the parameter within 48 h of first sample collection. The concentration of TDS is inversely proportional to the usability of the intake water but directly proportional with the requirement for treatment.
Change in the TDS concentration within 3 d	The change in the concentration of the parameter within 72 h of first sample collection. The concentration of TDS is inversely proportional to the usability of the intake water but directly proportional with the requirement for treatment.

calculated with the help of the product of the weight matrix; this shows the importance of a given factor in achieving the criteria, which can then be compared to the weight matrix of the alternatives with respect to the same criteria. The result of this is that the product gives the overall priority value of each of the alternatives.

Through the use of the MVTDMSOS model, an objective equation was developed. In this way, the objective function becomes directly proportional to the product sum of the priority values and the magnitude of the considered alternatives. This is beneficiary to the study's objectives and as such, is inversely proportional to the non-beneficiary parameters.

The priority values of all the parameters were taken as design variables, having a constraint of 0 to 1. The neural network is used as the programming technique in order to maximize the objective equation. The values of the design variables at the optimal point give the priority values of the parameters in the MVTDMSOS.

In the case of MVTDMSOS, the objective equation was formulated with the help of the 24, 48 and 72 h variations of the parameters.

3.2. Development of the Q-indicator

The Q-indicator was developed as the ratio of all the beneficiary and non-beneficiary parameters with respect to study's objective. The product of the priority value and the magnitude of the beneficiary and non-beneficiary alternatives was integrated separately and the ratio of the results yielded the Q-indicator, which is directly proportional to the quality of the intake water. Thus, the higher the Q-indicator, the lower the vulnerability or requirement to adjust the functionality of the WTP.

3.3. Development of polynomial neural network based models to map the input alternative to the output Q-indicator

In total, 24 different models were developed to estimate the Q-indicator from the input parameters. Table 2 shows the characteristics of the 24 different models. In summary, it can be concluded that number of inputs varied from 4 to 12. The type of data transformation was also changed between the Arc Tangent function and no transformation. The MCDM method was also varied between MVTDMSOS and AHP, and the training algorithm varied between the GMDH and the Quick Combinatorial (QC) process. In total three models were prepared for each with 4, 8 and 12 inputs, respectively. Therefore, a total of twelve models were developed with the priority value derived from MVTDMSOS and AHP methods, and the same number of models developed again with the GMDH and QC training algorithms.

The predictions from the models were compared with each other based on performance metrics like mean absolute error (MAE) [23], root mean square error (RMSE) [24] and the correlation coefficient (*r*) [25]. These three metrics were calculated with the help of the predicted data from the models, along with the actual data set which was fed into the model for training. A model prediction with high correlation and low MAE and RMSE shows that the predicted data is in concordance with the actual data. The metrics were calculated for the data used for training as well as testing, whereas the measurement from the testing phase was given higher priority compared to the metrics derived from the training phase. In general, sixty percent of the data was used for training and forty percent for testing.

The data for training and testing was generated with the help of the Random Forest Algorithm, where 10000 points of data was generated from which 4 set of data was used for training and testing purposes. Each set contained 250 points of data. The data were generated by considering the nor-

Table 2
Performance metrics of the selected models

Number of input	Number of output	Data transformation	WVDM	Training algo
4	1	None	MVTDMSOS	GMDH
4	1	Arc Tan of O/P	MVTDMSOS	GMDH
4	1	Arc Tan of O/P	MVTDMSOS	QC
4	1	None	MVTDMSOS	QC
8	1	None	MVTDMSOS	GMDH
8	1	Arc Tan of O/P	MVTDMSOS	GMDH
8	1	Arc Tan of O/P	MVTDMSOS	QC
8	1	None	MVTDMSOS	QC
12	1	None	MVTDMSOS	GMDH
12	1	Arc Tan of O/P	MVTDMSOS	GMDH
12	1	Arc Tan of O/P	MVTDMSOS	QC
12	1	None	MVTDMSOS	QC
4	1	None	AHP	GMDH
4	1	Arc Tan of O/P	AHP	GMDH
4	1	Arc Tan of O/P	AHP	QC
4	1	None	AHP	QC
8	1	None	AHP	GMDH
8	1	Arc Tan of O/P	AHP	GMDH
8	1	None	AHP	QC
8	1	w	AHP	QC
12	1	None	AHP	GMDH
12	1	Arc Tan of O/P	AHP	GMDH
12	1	None	AHP	QC
12	1	Arc Tan of O/P	AHP	QC

mal distribution pattern for each of the parameters, and the output was calculated with the help of the function used to calculate the Q-indicator.

3.4. Sensitivity analysis

The sensitivity of the input parameters was estimated with the help of the 'One Factor at a Time' (OFAT) method [26], where one factor is changed to see the impact on the output of the model. The significance of each of the parameters and robustness of the selected model can be identified with the help of this analysis.

3.5. Case study

A case study utilized for the application of these models was selected from an area in the northeastern part of India. A surface water treatment plant there, which supplies treated water to semi-urban consumers, was identified and the indicator was used to monitor the quality of the water intake at eight different points, including the intake point.

The results from this study were expected to give the overall quality of the water or vulnerability of the water in the treatment plant from seven different points located before the intake point.

4. Results and discussion

Tables 3a and b show the results from using the MVTDMSOS and AHP methods, respectively. The priority values of the parameters, as determined by the two demonstrated methods that are in the tables, are included in the appendix. Table 4 shows the RMSE, MAE and *r* achieved from the comparison of the actual and predicted values from the prepared models in training as well as in the testing phase. The results from the sensitivity analysis were revealed in Table 5, while the value of the indicator with respect to the concentration of DO, pH, TDS and turbidity are identified and listed in Table 6.

4.1. Most important parameter

As per the results of the MVTDMSOS and AHP analyses (Tables 3.1a and b), pH was found to have the highest contribution towards controlling the overall quality of the water intake, for 24 h, or for both 24 h and 48 h, changes in the concentration of the parameters. If 24, 48 and 72 h changes are considered together, and then the most important parameter is identified to be the change in DO within 72 h. Conversely, in the AHP results, it was found that the change in the concentration of turbidity and DO within 24 h were the two most important factors which, respectively, increase and decrease the vulnerability of the intake of water.

4.2. Selection of the best model

Among the 24 models developed in the study for the estimation of the indicator (as shown in Table 4) models

Table 3b
AHP results

Criteria	Tech	Eco		
Weight of criteria	0.600000	0.400000	P.V	RANK
cDO	0.322240	0.080562	0.225573	2
cpH	0.080562	0.107416	0.091303	4
cTurbidity	0.161123	0.322247	0.225573	1
cTDS	0.107416	0.161123	0.128899	3
c2DO	0.064449	0.040281	0.054782	5
c2pH	0.040281	0.046035	0.042583	8
c2Turbidity	0.046035	0.064449	0.053401	7
c2TDS	0.053708	0.053708	0.053708	6
c3DO	0.035805	0.026854	0.032225	9
c3pH	0.026854	0.029295	0.02783	12
c3Turbidity	0.029295	0.035805	0.031899	11
c3TDS	0.032225	0.032225	0.032225	9

Table 3a
Result from the MVTDMSOS results

Input parameter	Priority value	Rank of the parameter	Input parameter	Priority value	Rank of the parameter	Input parameter	Priority value	Rank of the parameter
cDO	0.466786	2	cDO	0.609791	5	cDO	0.727	3
cpH	0.919769	1	c2DO	0.757507	2	c2DO	0.457	5
cTurbidity	0.061954	4	cpH	0.865247	1	c3DO	0.993	1
cTDS	0.117456	3	c2pH	0.622108	3	cpH	0.379	7
			cTurbidity	0.621488	4	c2pH	0.926	2
			c2Turbidity	0.079348	8	c3pH	0.431	6
			cTDS	0.485498	7	cTurbidity	0.706	4
			c2TDS	0.607813	6	c2Turbidity	0.245	8
						c3Turbidity	0.031	10
						cTDS	0.013	12
						c2TDS	0.019	11
						c3TDS	0.235	9

Table 4
Performance metrics of the developed models for the present objective

Name of the model	Number of input	Number of output	Data transformation	Decision making method	Training algo	Training MAE (%)	Training RMSE (%)	Training r (%)	Testing MAE (%)	Testing RMSE (%)	Testing r (%)	Rank
4NOGM1	4	1	None	MVTDMSOS	GMDH	3.04	5.98	99.96	3.65	11.44	99.95	15
4AOGM2	**4**	**1**	**Arc Tan of O/P**	**MVTDMSOS**	**GMDH**	**0.16**	**0.23**	**99.98**	**0.33**	**1.2**	**99.96**	**1**
4AOQM3	4	1	Arc Tan of O/P	MVTDMSOS	QC	5.66	19.56	80.32	8.79	34.67	76.36	19
4NOQM4	4	1	None	MVTDMSOS	QC	64.17	175.61	77.09	86.58	238.09	67.38	24
8NOGM5	8	1	None	MVTDMSOS	GMDH	2.9	4.86	99.92	2.84	3.77	99.75	11
8AOGM6	8	1	Arc Tan of O/P	MVTDMSOS	GMDH	0.51	0.98	99.95	0.49	0.74	99.94	4
8AOQM7	8	1	Arc Tan of O/P	MVTDMSOS	QC	4.15	9.23	97.12	3.49	5.23	97.02	14
8NOQM8	8	1	None	MVTDMSOS	QC	23.98	43.47	77.11	21.46	32.46	87.69	22
12NOGM9	12	1	None	MVTDMSOS	GMDH	3.75	5.08	99.57	4.23	6.62	99.34	13
12AOGM10	12	1	Arc Tan of O/P	MVTDMSOS	GMDH	0.68	1	99.67	0.79	1.16	99.5	5
12AOQM11	12	1	Arc Tan of O/P	MVTDMSOS	QC	1.93	3.5	96.76	1.86	3.67	97	8
12NOQM12	12	1	None	MVTDMSOS	QC	22	33.78	84.49	21	31.08	87.35	21
4NAGM13	4	1	None	AHP	GMDH	4.61	20.55	99.96	3.44	6.8	99.93	16
4AAGM14	4	1	Arc Tan of O/P	AHP	GMDH	1.19	4.39	99.97	1.36	4.92	99.95	10
4AAQM15	4	1	Arc Tan of O/P	AHP	QC	6.04	19.73	99.01	6.34	16.26	99.06	17
4NAQM16	4	1	None	AHP	QC	55.51	145.61	85.44	55.05	148.06	94.72	23
8NAQM17	8	1	None	AHP	GMDH	1.93	3.01	99.92	1.89	2.98	99.86	6
8AAGM18	**8**	**1**	**Arc Tan of O/P**	**AHP**	**GMDH**	**0.28**	**0.4**	**99.95**	**0.32**	**0.48**	**99.92**	**2**
8NAQM19	8	1	None	AHP	QC	17.71	28.48	88.67	18.07	34.78	92.6	20
8AAQM20	8	1	Arc Tan of O/P	AHP	QC	2.93	5.84	93.67	2.67	6.18	94.36	12
12NAGM21	12	1	None	AHP	GMDH	1.97	2.88	99.83	2.31	3.18	99.77	7
12AAGM22	**12**	**1**	**Arc Tan of O/P**	**AHP**	**GMDH**	**0.32**	**0.43**	**99.9**	**0.41**	**0.65**	**99.82**	**3**
12NAQM23	12	1	None	AHP	QC	9.88	15.75	93.85	10.01	14.36	95.73	18
12AAQM24	12	1	Arc Tan of O/P	AHP	QC	2.1	3.54	95.35	2.19	3.28	95.42	9

which have 4 input parameters trained with GMDH and which use the results from MVTDMSOS (Model No. 4, AOGM2) were found to be more reliable predictive frameworks compared to the other 23 models (if the output data is transformed by the Arc Tangent function.)

The RMSE and MAE achieved by the selected model in the testing phase was found to be 0.33% and 1.20%, respectively, whereas the correlation coefficient was found to be equal to 99.96%. The metrics, similar to MAE, display a larger mean absolute error of 3.03%, or 0.6 times the RMSE of the selected model. In addition, the correlation at the testing period was found to be 0.04% less than that of the second best model, in the case of the model output for the data with which the model was not trained.

4.3. Sensitivity analysis

The results of the sensitivity analysis of the two beneficial parameters were 0.265 and 0.294, whereas for the non-beneficiary factors, the importance of the parameters was found to be 0.206 and 0.235, respectively. All the sensitivity indicators corresponded to the priorities of the parameters.

4.4. Case study

The water quality was identified at the seven different points; along with the intake point. It was found that water quality of the intake point was worse than the other seven points. The best quality of water was found to be at point P6, and once this part of water reached the intake point, the dosing pattern needs to be adjusted.

The changes in the beneficiary quality parameters were at a maximum (and variation in the non-beneficiary quality parameters at a minimum) in P6, as compared to other points. However, at the intake point, the change in beneficiary and non-beneficiary parameters was minimum and maximum, respectively, and that is why the requirement for change in functionality of the treatment plant was highest for water at the intake point and lowest at P6 compared to the other five points. This indicates that, with the help of the Q-indicator, users can make informed decisions on any changes in the operating policy of the WTP.

Table 5
Sensitivity analysis of the selected model (Model: 4AOGM2)

Name of parameters	Sensitivity
cDO	0.264706
cpH	0.294118
cTurbidity	−0.205882
cTDS	−0.235294

4.5. Scientific benefit

The Q-indicator enables any engineer at the surface water treatment plant to monitor the quality of the water intake. They may also adjust various points of functionality in the WTP to maintain the reliability of the treated water produced from the plant.

The Q-indicator is in practice both objective and cognitive, with no probability of bias from external influences. It considers the impact of the quality parameters on technical efficiency and the potential of increasing hazards to affect the plant's instruments. That is why the value of the indicator becomes proportional to the increase in the plant's efficiency. The indicator can also be used in various ways to identify and mitigate any reduction in the plant's efficiency. As it is portable, it can be encoded in digital instruments or fed into the distributed control or Supervisory Control and Automated Device Accessories based systems so that the entire process of quality deterioration and compensatory measures to mitigate the situation can be automated. These processes of limiting human interference can have positive repercussions on efficiency because biases and other cognitive errors are excluded.

4.6. Limitation

The dependence of the indicator upon the parameters, criteria and methods to find the relative weights can change the value of the indicator for the water samples collected from two different locations. That is why the selection of alternatives, criteria and methods of determination for the priority values can be streamlined with the help of a policy.

The indicator was only applied in the present study area; however, estimation of the indicator for other loca-

Table 6
Values of the indicator for the intake point and seven points before the intake

Point	cDO	cpH	cTurbidity	cTDS	Q-indicator value
Intake	0.231994	0.212158	0.951498	0.529875	0.105495
P1	0.810959	0.014459	0.500007	0.836428	0.111873
P2	0.250382	0.534467	0.181505	0.376415	0.13226
P3	0.814876	0.880367	0.389815	0.06644	0.138281
P4	0.847045	0.63894	0.410725	0.789808	0.129955
P5	0.23386	0.540415	0.31231	0.625608	0.126828
P6	0.439774	0.669392	0.21737	0.029508	0.138309
P7	0.699758	0.200556	0.905062	0.700315	0.117001

tions could enrich the quality of the indicator and further enable the tool to be used to reduce the impact of disasters.

5. Conclusion

The present investigation proposed a new methodology to identify the changes in quality of water to be treated in a water treatment plant. An indicator was developed with the most important parameters being used as input variables. These parameters were identified with the help of MCDM technology. A self-adaptation characteristic was included in the index by the application of polynomial neural networks.

A case study of a WTP in a semi-urban city was also presented and used as raw data in the indicator models. From these results, it is evident that the index can be used to monitor the changing quality of intake water. Such indicators can be useful for the introduction of automation and real-time monitoring technology in water treatment plants, which can be both financially and technically beneficial.

From the results of the study, it was found that changes in concentration of DO within 24 and 72 h, as well as changes in turbidity within 24 h and changes in pH within 24 h, contribute the most to changing the overall quality of the intake water, which can have economic and technical benefits. The self-adaptive capability of the index was introduced by implementing polynomial neural networks, through which 24 different models were developed. The model output determined by MVTDMSOS with four inputs was found to have better performance metrics compared to the other models. The best model was used to estimate the Q-value of the water at seven different points, as well as the intake point of the selected WTP.

The results indicate that at the time the quality of water was monitored, the intake point had the most detrimental and point no.6 the highest water quality among all the points considered in the evaluation. These shows a requirement for adjustment in the treatment mechanism for intake when the water of P6 reaches the point of intake of the WTP. If no adjustment were adopted, then over-use of chemicals and other unnecessary expenditures might be incurred which can have repercussions for the profitability of the plant. Although the present methodology depends largely on the type of MCDM methods adopted to identify important parameters (and also to select parameters), the indicator can still be useful for maintaining optimal performance in any WTP, regardless of the manner of analysis used. Indeed, there is scope for mitigating this limitation through the adoption of a uniform methodology applied by the regulation authority of WTPs.

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