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# Assessing optimal water quality monitoring network in road construction using integrated information-theoretic techniques

Mehrdad Ghorbani Mooselu[1]*, Helge Liltved[2], Mohammad Reza Nikoo[3], Atle Hindar[4], Sondre Meland[5]

## Abstract

The environmental impacts of road construction on the aquatic environment necessitate the monitoring of receiving water quality. The main contribution of the paper is developing a feasible methodology for spatial optimization of the water quality monitoring network (WQMN) in surface water during road construction using the field data. First, using the Canadian Council of Ministers of the Environment (CCME) method, the water quality index (WQI) was computed in each potential monitoring station during construction. Then, the integrated form of the information-theoretic techniques consists of the transinformation entropy (TE), and the value of information (VOI) were calculated for the potential stations. To achieve the optimal WQMNs, the Non-dominated Sorting Genetic Algorithm II and III (NSGA-II, and III) based multi-objective optimization models were developed considering three objective functions, including i) minimizing the number of stations, ii) maximizing the VOI in the selected network, and iii) minimizing redundant information for the selected nodes. Finally, three multi-criteria decision-making models, including Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE), and Analytical Hierarchy Process (AHP) were utilized for choosing the best alternative among Pareto optimal solutions considering various weighing scenarios assigned to criteria. The applicability of the presented methodology was

[1] Ph.D. Research Fellow, Department of Engineering Sciences, University of Agder, Norway, mehrdad.g.mooselu@uia.no. (Corresponding Author).
[2] Professor, Department of Engineering Sciences, University of Agder, Norway.
[3] Associate Professor, Department of Civil and Environmental Engineering, Shiraz University, Shiraz, Iran.
[4] Norwegian Institute for Water Research (NIVA), Gaustadalléen 21, 0349 Oslo, Norway.
[5] Norwegian Institute for Water Research (NIVA), Gaustadalléen 21, 0349 Oslo, Norway; Norwegian University of Life Sciences (NMBU), Faculty of Environmental Sciences and Natural Resource Management, PO 5003, 1432 Ås, Norway.

assessed in a 22 km long road construction site in southern Norway. The results deliver significant knowledge for decision-makers on establishing a robust WQMN in surface water during road construction projects.

**Keywords:** Water quality monitoring network, CCME-WQI, Value of information, Transinformation entropy, NSGA-II and NSGA-III, Multi-criteria decision-making models.

## *1. Introduction*

Road construction makes physical, chemical, and biological impacts on receiving aquatic environments. The spatiotemporal impacts of road construction may cause acute alterations (Vikan and Meland, 2013). Hence, it is vital to assess the receiving water quality during road construction. Water quality monitoring networks (WQMN) are designed for quantitative data on the spatiotemporal variation of water quality. The provided information is applied by decision-makers for reliable assessment of water quality and supporting adopted policies for protecting the water resources (Alfonso and Price, 2012; Behmel et al., 2016). The importance of surface water in delivering water demands with adequate quality and the significant economic burden of the monitoring systems necessitates an optimum design of WQMN. Optimization of WQMN balances the fiscal burden of monitoring networks while a sufficient source of qualitative information is provided (Alizadeh et al., 2018; Alilou et al., 2019). This optimization will allow decision-makers to check deviations from set water quality standards in national and international water regulations (Pourshahabi et al., 2018a; Maymandi et al., 2018). The design of a robust WQMN is still a debatable topic, in which the selection of optimal locations for stations is crucial (Alilou et al., 2019).

Several studies focused on the difficulties in determining the sampling objectives, water quality parameters to be monitored, location of stations (Alilou et al., 2018, and 2019), and variations in sampling frequency (Karamouz et al., 2009; Zeng et al., 2016; Khorshidi et al., 2018). The optimization process is a key step towards a comprehensive monitoring program in which every element of the existing WQMN is evaluated, and the monitoring objectives are met (Behmel et al., 2016; Pourshahabi et al., 2018b). Utilizing an optimized monitoring system has been extensively considered in water resources management owing to their better performance compared to opinion- and rule-based methods (Khorshidi et al., 2018). A review of previous studies indicates the lack of knowledge on the optimization of the WQMN in surface water during road construction. Hence, in this paper, two information-theoretic techniques, including Value of Information (VOI) and Transinformation Entropy (TE), were integrally (Pourshahabi et al., 2018a; Khorshidi et al., 2020) used for the optimal design of WQMN in a road construction project.

Information obtained from stations in receiving streams may provide diverse signals with different values to the decision-maker. Therefore, an information theory-based method (the concept of VOI) was applied to design an optimized WQMN with the highest value for qualitative information from the stations (maximum VOI), which could provide a reasonable view of the whole system. On the other hand, monitoring networks with the same number of stations (but separate locations) and comparable VOI, may bring in a different level of information redundancy. Thus, the TE method was employed for minimizing the mutual (redundant) information in the selected monitoring network. As an example, the spatial distance of monitoring stations can affect the TE level in any pair of potential stations. Therefore, minimizing the TE value would, in this case, result in a monitoring network with a more spatial distribution of monitoring sites and, subsequently, a better understanding of water quality variations (Khorshidi et al., 2018). Very few works have been published using the combination of VOI and TE. In these, optimum sensor placement (Khorshidi et al., 2018) and optimum WQMN in reservoirs (Pourshahabi et al., 2018; Maymandi et al., 2018) were explored. However, the lack of an integrated method, capable of taking the advantages of both methods in surface water quality is quite apparent. Also, one of the most significant challenges related to the application of information theory in surface water quality monitoring is related to the type of applied data for computing prior and posterior probabilities. Therefore, in this study, using the sampling data from the field, a hybrid form of information-theoretic techniques was proposed for the optimum design of a WQMN in surface water, and a road construction project.

The Non-dominated Sorting Genetic Algorithm II and III (NSGA-II and NSGA-III) were then developed according to three objectives, including 1) minimizing the number of monitoring stations; 2) minimizing redundant information among monitoring stations; and 3) maximizing VOI in the selected WQMN. Finally, three different multi-criteria decision-making (MCDM) models, including Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE), and Analytical Hierarchy Process (AHP) were used to achieve the best alternative on the Pareto-optimal solutions. The paper contributes to filling the knowledge gap in the following cases, which have not been adequately attended in previous assessments:

1) Computing the prior and posterior probabilities in the information theory based on water quality data from the field sampling and experimental analyses
2) Application of the Canadian Council of Ministers of the Environment (CCME) Water Quality Index (WQI) in surface water for optimization of WQMN during the road construction project
3) Utilizing NSGA-III for optimization of the WQMN in surface water and road project
4) Proposing a feasible framework consists of a water quality index, an integrated form of information theory techniques, efficient optimization, and decision-making models for monitoring network in surface water.

The feasibility of the proposed framework was assessed over a 22 km length of a new highway in southern Norway.

## *2. Material and Methods*

For optimization of the WQMN, a six-step approach (outlined in Fig. 1) is developed by coding in Matlab *ver. R2016b*.

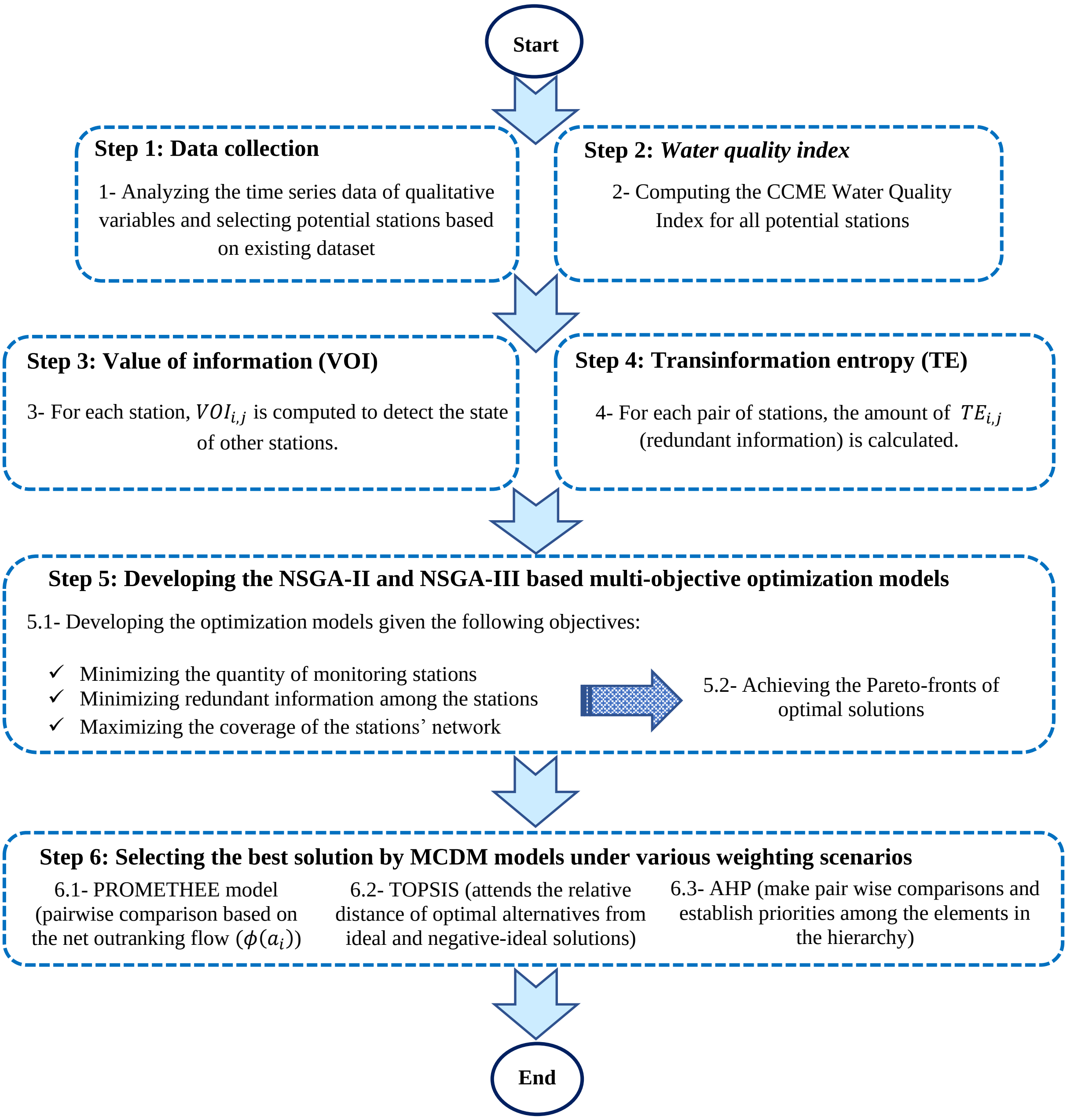



**Fig.1** The proposed methodology for optimization of the WQMN in surface water

The first step is to select potential stations based on existing datasets. Notably, the dataset consists of a) pre-construction monitoring and b) monitoring during the construction phase. However, the methodology is developed based on the latter part, including 42 measurements for each station. For all stations, the water quality index (step 2), the value of information (step 3), and the transinformation entropy (step 4) are calculated. Thereafter, the NSGA-II and III based optimization models were developed (step 5), and finally, the best solution was chosen using the MCDM models (step 6). In the next sub-sections, the applied methods are explained in more detail.

### *2.1 Data collection*

The study area was the construction site of the new 22 km long highway (E18) from Arendal to Tvedestrand in the southern part of Norway (Fig. 2 includes a map of the area). The construction area consisted of seven catchments (the first digit in the number of stations shows the number of discharge area, see Fig. 2). There are different main streams and side streams that are connected. The construction activities (e.g., excavation, drilling, and blasting, transport, tunnel, and bridge construction) and the resulted runoff is the main source of pollution in surface water during road construction. Several monitoring stations were irregularly established on receiving main streams and side streams to assess spatiotemporal variation of surface water quality due to construction activities (Fig. 2). The location of stations is not dependent on the hydrological aspects in the catchment. Hence, the water flow in these streams and the amount of road construction runoff are not the subjects of the proposed methodology and consequently are not simulated. Samples for analysis were collected regularly throughout the pre-construction (2015-2016) and construction phase (2017-2019). The parameters included general water quality parameters (pH, alkalinity, conductivity, Fe, Mn, Na, Cl, Ca, Mg, K, Al and $SO_4^{2-}$), trace elements (As, Ba, Cd, Co, Cr, Cu, Ni, Mo, Pb, Hg, and Zn), nutrients ($NH_4$-N, $NO_3$-N, total-N, total-P), organic matter parameters (color, chemical oxygen demand, total organic carbon), particulate matter parameters (suspended solids and turbidity) and organic micropollutants (polycyclic aromatic hydrocarbons; the $PAH_{16}EPA$-group).

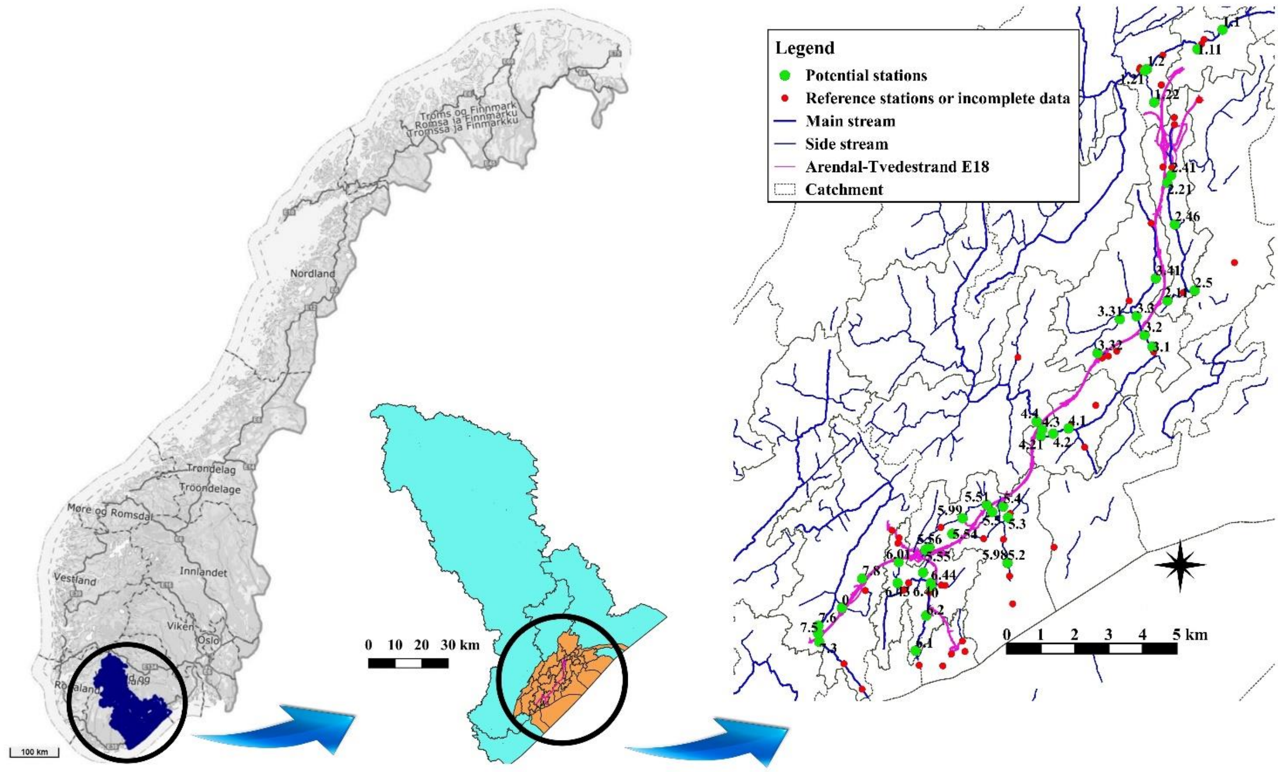



**Fig.2** The E18 highway (Arendal-Tvedestrand) and the established monitoring stations

Of the time series from all established stations, the stations with relatively complete time series over the total sampling period were selected, which are shown by green circles in Fig. 2 (hereafter called potential monitoring stations). Reference stations, which were not affected by road construction activities, were not included as potential monitoring stations. The red circles in Fig. 2 show both reference stations and the stations with relatively incomplete time series.

*2.2 Water quality index (WQI)*

Monitoring programs provide detailed qualitative data, including many water quality variables, and it is challenging to evaluate the experienced water quality for sensitive aquatic organisms (Nikoo et al., 2011). The Canadian Council of Ministers of the Environment (CCME) Water Quality Index (WQI), see Khan et al., (2005) and Nikoo et al., (2011), is a useful management tool for producing a meaningful interpretation of qualitative data, i.e. for evaluation of water quality (Terrado et al., 2010; Nikoo et al., 2011; Munna et al., 2013), classification of water quality (Boyacioglu 2009; Nikoo and Mahjouri, 2013), and water management (Khan et al., 2005). Since optimization of WQMN given a specific water quality variable may not be necessarily reliable in terms of other qualitative variables, the CCME-WQI was utilized to get a more comprehensive view of the water quality in receiving streams.

The CCME index operates according to different end-use objectives and is thereby flexible in selecting suitable parameters (Nikoo et al., 2011). The index allows site-specific reference objectives and standards to be integrated into the rankings process (Khan et al., 2005). Therefore, this index can be developed based on different national water quality criteria and limits (Nikoo et al., 2011). The CCME-WQI incorporates three variance values (scope, frequency, and amplitude) to achieve the overall water quality state in the form of a unitless number between 0 and 100. There are five categories based on the values of CCME-WQI, including poor (≤44), marginal (45-64), fair (65-79), good (80-94), and excellent (95-100). The application of the CCME-WQI necessitates water quality guidelines or water quality objectives (Mahagamage and Manage, 2014). Hence, in this study, the water quality regulations set by the discharge permit for the construction phase of E18 Arendal-Tvedestrand, released by the Environment Department of Agder County, Norway, was applied for every single station (see Table A1). In this permit, regarding the location of stations, each one has specific limits for water quality parameters. More information related to CCME-WQI is presented in Appendix 1.

The CCME-WQI was applied to determine the water quality at the potential monitoring stations based on five categories (excellent, good, fair, marginal, poor), as prior and posterior probabilities and define the "Value Matrix" that shows the cost (value or damage) of decision-makers' act given the various states in each station.

*2.3 Value of information (VOI)*

The VOI technique was developed by Grayson (1960) to evaluate the importance of obtained new information in the decision-making process. Over the past few decades, the VOI technique has been widely used for time-series analysis in water-related topics, including optimal monitoring network in reservoirs (Maymandi et al., 2018), design of groundwater quality monitoring networks (Hosseini and Kerachian, 2017), designing contamination warning system (Roberts et al., 2009; Khorshidi et al., 2018), and impact assessment and flood monitoring (Verkade and Werner, 2011; Alfonso and Price, 2012; and Alfonso et al., 2016).

Each monitoring station might have different states (e.g., excellent, good, fair, marginal, and poor) and can contribute with relevant water quality information (message) to other stations. Each message (of water quality from each station) affects the decision about the state of the system, and if it is true or false, the message can be of value or damage, respectively. Therefore, by measuring at a potential monitoring station, prior probabilities could be corrected (using Baye's theorem). The VOI theory evaluates the importance of new information and updates the earlier probability, $p(s)$, about the state of a system (Alfonso and Price, 2012; Pourshahabi et al., 2018a). In Bayes' theorem, the posterior (updated) probability considering the new information is represented as Eq. 1 (Khorshidi et al., 2018):

$$\mathrm{P(s|m)} = \frac{\mathrm{P(m|s).P(s)}}{\mathrm{P(m)}} \quad (1)$$

where,

| | |
|---|---|
| $\mathrm{p(s)}$ | Earlier probability for being in state "s", |
| $\mathrm{p(m)}$ | Probability for receiving message "m", (given new data), |
| $\mathrm{p(m|s)}$ | Conditional probability of receiving the message "m" when the system is in state "s", |
| $\mathrm{p(s|m)}$ | The posterior (updated) probability for state of system following the delivery of message "m" (given new data). |

When new information appears, if the message "m" from station "$i$" is sent for the decision-maker to sense the state "s" in station "$j$", the VOI of the station "$i$" for this process is calculated by Eq. 2 (Alfonso and Price, 2012):

$$VOI_{(i,j)} = \sum_{m} p(m) \left[ \max_{a} (\sum_{s} C(a,s) p(s\,|m)) - \max_{a} (\sum_{s} C(a,s) p(s)) \right] \quad (2)$$

Where, $C(a,s)$ shows the value (cost) of the action"$a$" chosen among available alternatives to coupe up with the state "s" in the monitoring station "j". The action "$a$" is valued by its distance to the state "s". The closer it is to "s", the more valuable the action "$a$" is (Pourshahabi et al., 2018a). The $C(a,s)$ is defined through the "Value Matrix", in which arrays are the differences between the mid values of five categories in CCME-WQI (see section 2.2), and show the cost (value or damage) of each action regarding the various states in potential stations. The arrays of "Value Matrix" have an active role in computing the $VOI_{i,j}$. Hence, the matrix should be determined based on a valid standard, which in this study is CCMW-WQI. The applied "Value Matrix" is presented in Table 1.

**Table 1** The "Value matrix" for calculation of the $VOI_{i,j}$

| | $C(a, s)$, (the cost (damage) of action $a$, when the station has the state of "s") | | | | |
|---|---|---|---|---|---|
| | **Poor** | **Marginal** | **Fair** | **Good** | **Excellent** |
| **Poor** | 1 | -32.5 | -50 | -65 | -75 |
| **Marginal** | -32.5 | 1 | -17.5 | -32.5 | -42.5 |
| **Fair** | -50 | -17.5 | 1 | -15 | -25 |
| **Good** | -65 | -32.5 | -15 | 1 | -10.5 |
| **Excellent** | -75 | -42.5 | -25 | -10.5 | 1 |

*Raws*: Decision-maker's actions and *Columns*: stations' states

Because all arrays in Table 1 show damage, they are negative values. The rows represent the activities ($a$) of decision-maker according to their belief about the water quality at the monitoring station, and columns indicate the various states of the monitoring station ($s$), that may occur. For example, if the water quality at the station $i$ is in "Good" condition (WQI value 80-94, and the mid-value of this category is 87) and the decision-maker declares it to be "Poor" (WQI value 0-44 and the mid-value of this category is 22), this wrong decision will lead to (87-22=65) 65 units of damage (cost) in the scale of CCME-WQI. Considerably, the arrays on the matrix diameter, are set to one instead of zero, to keep the probabilities multiplied by the matrix diameters and play their role in VOI calculation.

*2.4 Transinformation entropy (TE)*

The core idea behind the theory of entropy is the evaluation of the information content for a series of data (Shannon 1948). In this method, TE quantifies the mutual (redundant) information between two variables (or dataset) (Pourshahabi et al., 2018b). The entropy method can also predict the probabilities of possible water quality levels at upstream stations based on observed variation in quality levels of a downstream location (Karamouz et al., 2009). Different functional forms of this method have also been effectively utilized for qualitative analyses, management, and network design in groundwater (Mogheir et al., 2009; Masoumi and

Kerachian, 2010; Owlia et al., 2011; Mondal and Singh, 2012; Alizadeh and Mahjouri, 2017; Keum et al., 2017; Hosseini and Kerachian, 2017), reservoirs (Lee et al., 2014; Nikoo et al., 2016; Maymandi et al., 2018), rivers (Jha and Singh, 2008; Karamouz et al., 2009; Mahjouri and Kerachian, 2011; Memarzadeh et al., 2013; Pourshahabi et al., 2018a, b), and rainfall and streamflow monitoring networks (Krstanovic 1992a, b; Stosic et al., 2017).

A new monitoring station provides more qualitative information and consequently reduces the uncertainty in the water quality evaluation. The additional value of each new station may vary, however. TE can show the redundant information in a WQMN, which is mainly because of spatiotemporal correlation among the qualitative variables. Therefore, TE is efficiently applicable to the optimization of WQMN design (Karamouz et al., 2009). In the proposed framework, the concept of TE is employed to achieve the amount of mutual information between stations and help to identify essential and unnecessary stations. In most of the WQMNs, many qualitative variables are measured, which their time series have non-normal (asymmetrical) probability distribution function and necessitates applying the discrete form of entropy theory for evaluating the efficiency of the monitoring system. (Memarzadeh et al., 2013; Alizadeh et al., 2018). There are different basic ways to measure information according to entropy, including marginal, joint, conditional, and transinformation entropies. (Karamouz et al., 2009). Given a discrete random variable $x$, the marginal entropy is defined by $H(x)$ as Eq. 3:

$$H(x) = \sum_{i=1}^{N} p(x_i)\, log\, p(x_i) \tag{3}$$

Where $N$ characterizes the number of events such as $x_i$ with the probability of $p(x_i)$ $(i = 1, \dots, N)$. The joint (total) entropy for two independent random variables (e.g., $x$ and $y$) is the probability of accruing both of them simultaneously and expressed as the sum of their marginal entropies.

$$H(x,y) = H(x) + H(y) \tag{4}$$

Conditional entropy of $x$ given $y$ is the uncertainty remaining in $x$ when $y$ is known, and vice versa:

$$H(x|y) = H(x,y) - H(y) \tag{5}$$

Transinformation entropy calculates the mutual (redundant) information between each pair of stations (e.g., $x$ and $y$) and is calculated by the following equation (Pourshahabi et al., 2018a, b) (Khorshidi et al., 2020):

$$TE(x,y) = -\sum_{i=1}^{n}\sum_{j=1}^{n} p(x_i, y_j)\, ln\left[\frac{p(x_i, y_j)}{p(x_i)p(y_j)}\right] \tag{6}$$

where,

| | |
|---|---|
| $n$ | The number of stations |
| $p(x_i)$ | The occurrence probability of $x_i$, |
| $p(y_j)$ | The occurrence probability of $y_j$, |
| $p(x_i, y_j)$ | The joint probability for $x_i$ and $y_j$. |

In this study, the amount of transformed information was determined for each pair of potential monitoring stations.

### *2.5 Optimization models*

The NSGA-II (Deb et al., 2002) algorithm utilizes non-dominant sorting, and crowded comparison approaches in a single-objective form of the genetic algorithm to evaluate variety between non-dominated options. On the other hand, the Non-Dominating Sorting Genetic Algorithm III (NSGA-III) is a multi-objective algorithm with the basic structure similar to the NSGA-II, which maintains diversity based on reference points (Deb & Jain, 2014). NSGA-III does not require additional parameters compare to NSGA-II and eliminates the weaknesses of NSGA-II considering the lack of uniform diversity and absence of lateral diversity preserving operator among the current best non dominated solutions (Deb & Jain, 2014; Jain & Deb, 2014).

The NSGA-II and III based optimization models were developed according to the three following objectives: *i*) minimizing the number of potential monitoring stations ($U_1$), *ii*) maximizing the VOI in the selected network ($U_2$), and *iii*) minimizing redundant information among the selected stations ($U_3$). Hence, VOI and TE were determined for all pairs of potential stations in a WQMN and resulted in two square matrices, in which the arrays in $i^{th}$ row and $j^{th}$ column define $VOI_{i,j}$ and $TE_{i,j}$, respectively. Accordingly, the optimization models were formulated as in Eqs. (7-10) to achieve an optimal WQMN.

$$Minimize\ U_1 = \sum_{i=1}^{M_P} \rho_i \tag{7}$$

$$Maximize\ U_2 = \sum_{\forall j} \max_i(\rho_i \times VOI_{i,j}) \tag{8}$$

$$Minimize\ U_3 = \sum_{i=1}^{M_P} \sum_{\forall j \neq i} \left(\frac{TE_{(i,j)} - TE_{min(i)}}{TE_{max(i)} - TE_{min(i)}}\right) \tag{9}$$

$$\sum_{i=1}^{M_P} \rho_i = M_{opt} \tag{10}$$

where:

| | |
|---|---|
| $U_i$ | The values for the utility functions of the objectives, |
| $M_{opt}$ | The optimized number of monitoring stations, |
| $M_P$ | The number of potential monitoring stations, |
| $\rho_i$ | Binary variable (0 if potential station $i$ is not selected as a monitoring station, otherwise 1), |
| $VOI_{i,j}$ | Value of information in $i^{th}$ station for detecting the state of $j^{th}$ monitoring station, |
| $TE_{i,j}$ | The transinformation entropy between station $i$ and station $j$. |
| $TE_{\min(i,j)}$ | The minimum transinformation entropy between station $i$ and other stations |
| $TE_{\max(i,j)}$ | The maximum transinformation entropy between station $i$ and other stations |

The characteristics of the best structure for the NSGA-II and III algorithms, including population size and the number of generations, were achieved over a sensitivity analysis. The optimization models deliver the Pareto front (trade-off curve) between objectives (Alizaseh et al., 2017; Mooselu et al., 2020), which consists of the right answers for the optimization problem. So, the MCDMs (next paragraph) are required for the decision-maker to get the best solution.

*2.6 Multi-criteria decision-making models*

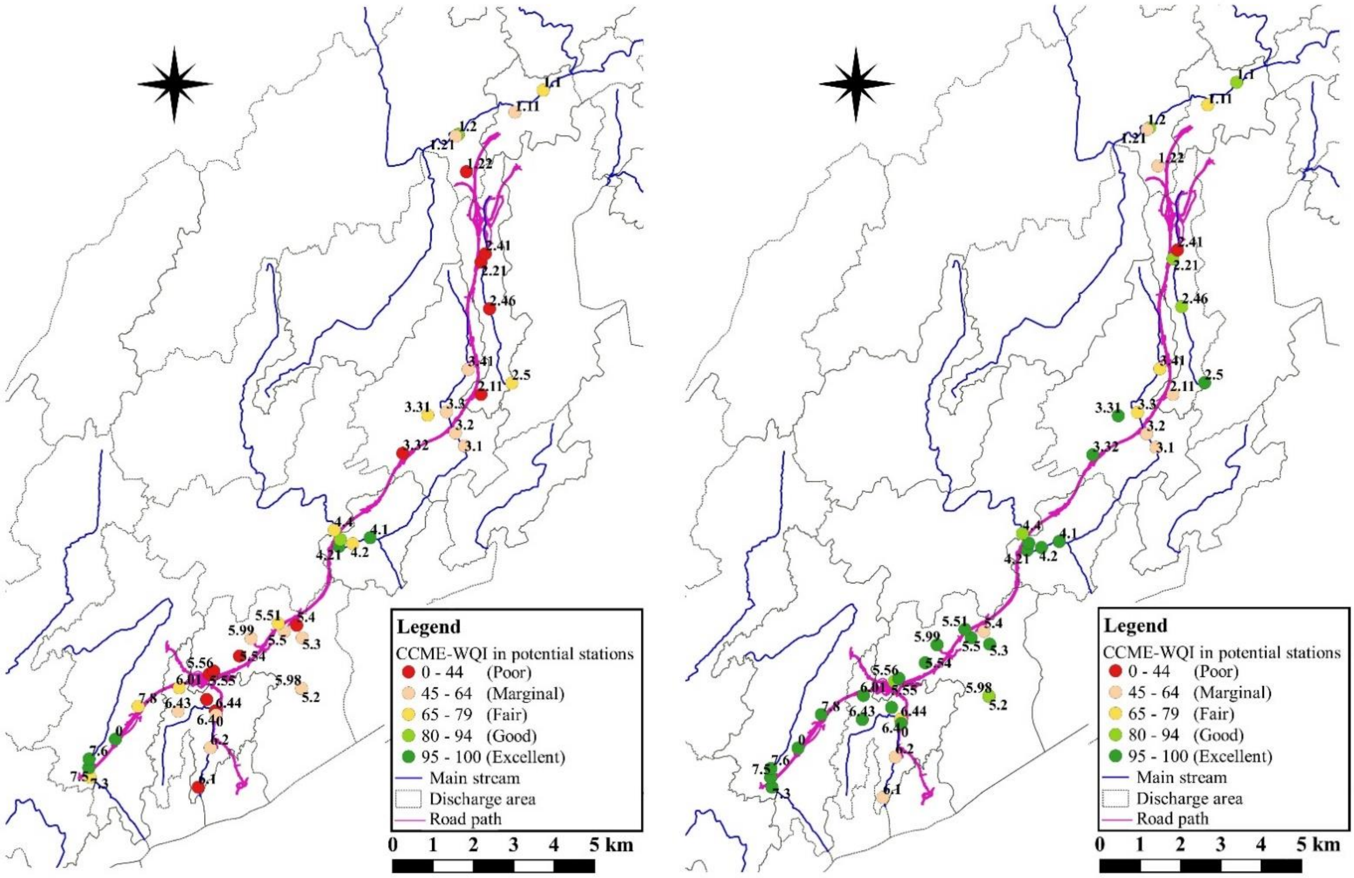
In this study, three MCDM models, including TOPSIS (Hwang and Yoon, 1981), PROMETHEE (Mareschal et al., 1984), and AHP (Saaty 1988) were utilized to reach the best WQMN among the alternatives on the trade-off curve. Besides, to evaluate the effects of weighing scenarios on results, different weighting scenarios were assigned to objectives by experts.

TOPSIS model attends the alternatives' distance from ideal and negative-ideal solutions, which both are achieved by normalizing the alternatives in the decision matrix and then weighing them based on the assigned weights to decision criteria. The best solution in this method has the lowest distance from the ideal solution (Mooselu et al., 2019). Also, PROMETHEE, as a flexible and straightforward decision-making model, is extensively applied in water resources management (Kuang et al., 2015; Pourshahabi et al., 2018a; Sapkota et al., 2018; Mooselu et al., 2019). PROMETHEE focuses on pairwise comparison in the ranking process. In this study, complete ranking (PROMETHEE-II) was employed, which ranks a set of alternatives $A = \{a_1, a_2, \dots, a_n\}$ given a set of criteria Z= $\{z_1, z_2, \dots, z_m\}$ in four steps (Zhang et al., 2009). First, the weighting of the criteria by expert's opinions that show their relative importance compared to one another. Then, preference function is adopted that conveys the priority of each pair of alternatives (e.g., $a_i, a_j$) in comparison to each other based on a single criterion such as $z_i$. In this study, the "V-shape with indifference preference function" was utilized, which provides a sensible pairwise comparison between alternatives. In the third step, for any pair in the set of alternatives ($A$) the global preference index, $\pi(a_i, a_j)$, is defined and indicates the preference of $a_i$over $a_j$. The higher value for $\pi(o_i, o_j)$, the more preference of $a_i$ compared to $a_j$. In the final step named outranking flows, for ranking the $a_i$ among other alternatives in the set of alternatives ($A$), the positive outranking flow or $\varphi^+(a_i)$ (the values of preference of $a_i$) and negative outranking flow or $\varphi^-(a_i)$ (not preferring of $a_i$ over the other alternatives) have to be computed. The alternative with the highest value of the net outranking flow ($\varphi(a_i) = \varphi^+(a_i)$- $\varphi^-(a_i)$) is selected as the best solution. More applications and information about PROMETHEE are provided by (Pourshahabi et al., 2018a; Mooselu et al., 2019).

AHP is a suitable method for multi-objective analyses in discrete mode, which can enter qualitative and quantitative factors (criteria) in the decision model. It derives priorities among criteria and alternatives and simplifies preference ratings among decision criteria using pairwise comparisons (Satty 1988). The basic procedure in AHP consists of three steps, including 1) Developing the scores for each decision alternative for each criterion 2) Determining the weights of criteria and 3) Calculating the weighted average rating for each decision alternative. The details of AHP is presented in (Satty 1988).

## *3. Results and discussion*

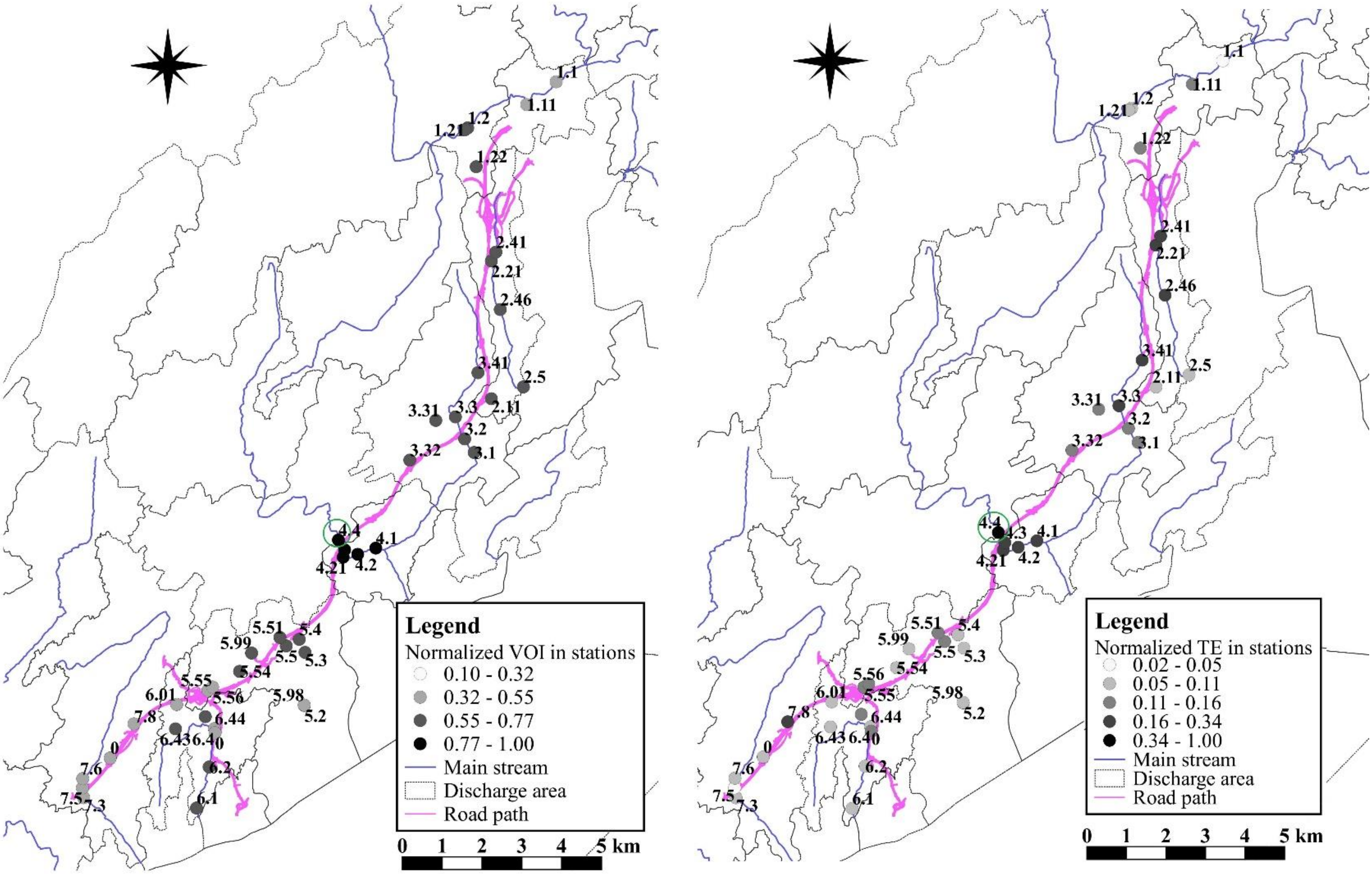
The CCME-WQI was computed for all potential monitoring stations and for all time steps during the construction period (2017-2019). The states of the potential monitoring stations in two different random time steps are presented in Fig. 3.




(a) (b)

**Fig. 3** The CCME-WQI values in all potential monitoring stations for a) Oct.2017, and b) Nov.2018

This figure clearly shows that a single station could have different states in various time steps, depending on different reasons such as weather situation (e.g., sampling conducted after a rain episode or after a longer dry period), and the type of activity being performed at the station. Hence, these issues will affect the water quality, and consequently, the prior probabilities resulting from CCME-WQI. Given the five categories in CCME-WQI (poor, marginal, fair, good, excellent), the value matrix was calculated, which is highly influential on the final results of the VOI method. Accordingly, VOI and TE were computed for all pairs of the potential monitoring stations, and the results were two square matrices (44×44) of $VOI_{i,j}$ and $TE_{i,j}$. Fig. 4a provides a graphical interpretation for $VOI_{i,j}$, in which the normalized values of VOI in station 4.4 ($VOI_{4.4,j}$) for detecting the state of all other potential monitoring stations is mapped. Besides, Fig. 4b demonstrates the redundancy of information given station 4.4 against all other potential monitoring stations ($TE_{4.4,j}$). Figure 4 clearly shows the concept of spatial distribution for TE and VOI given each monitoring station (here, station 4.4).

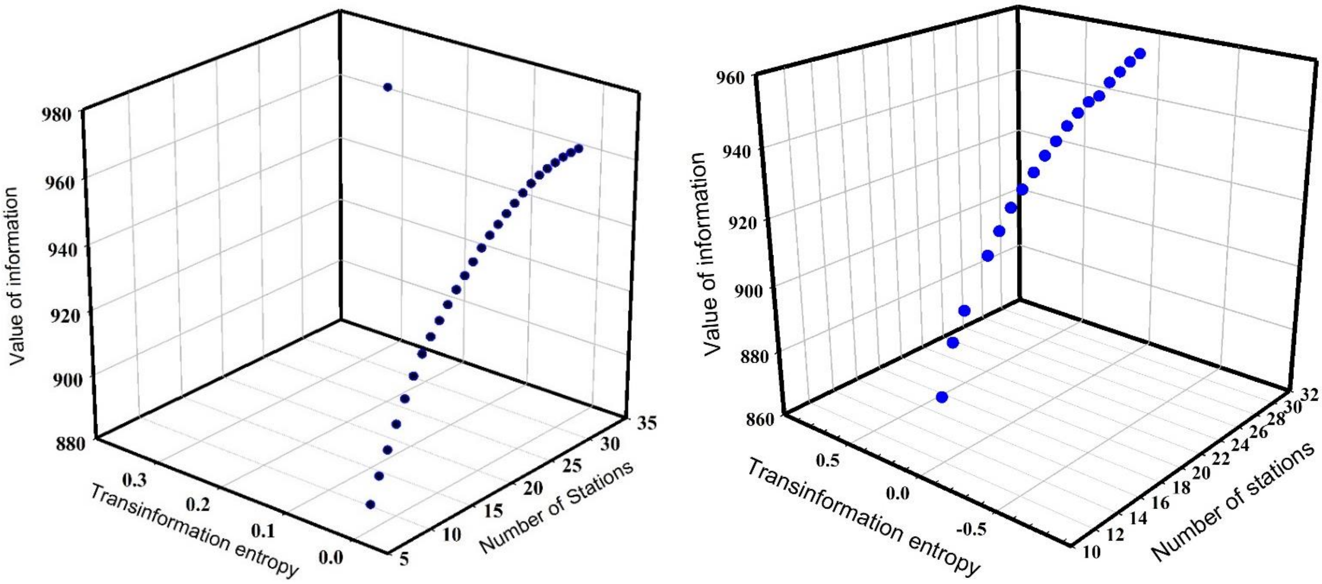



**(a)** **(b)**

**Fig. 4** The spatial distribution of normalized a) VOI, and b) TE values given station 4.4

$TE_{i,j}$ is measured between an origin station ($i$) and a goal station ($j$) and shows that how much information from station $j$ is achievable by the station $i$. The closer the values of normalized $TE_{i,j}$ to 1, the more accessible the information of the station $j$ through station $i$. By moving away from station 4.4, the VOI obtained from this station to determine the quality status of other stations will be reduced. The spatial distribution of TE in station 4.4 shows that for other stations in the same catchment area (e.g., 4.1, 4.2, 4.21, and 4.3), the amount of mutual information is more than other stations.

After that, running the optimization models for three objectives led to the trade-off curves composed of 27 and 18 optimal solutions for NSGA-II and NSGA-III, which are the best match for the selected objectives (Fig. 5).




Pareto optimal solutions of NSGA-II model　　Pareto optimal solutions of NSGA-III model

**Fig. 5** The Pareto optimal solutions resulted from the optimization models

NSGA-II uses crowding distance to keep uniform coverage of Pareto solutions, while NSGA-III takes advantage of the reference point mechanism as its selection operator to look at the solution space and preserve diversity (Deb & Jain, 2014). Comparing the results of the optimization models, the NSGA-II based optimization model provides optimal solutions with higher VOI and broader range for the number of stations in the WQMN. In contrast, NSGA-III based optimization model delivers more solutions with a minimum value of redundant information. From a decision-making perspective, it seems that NSGA-II is more applicable since it can offer more optimized alternatives to decision-makers. The values of normalized transinformation entropy in some of the optimal solutions (both NSGA-II and III) were zero. It is mainly because the third objective function of the optimization model is defined to minimize the summation of the normalized TE values between the selected stations in the optimized network (Eq. 9). Consequently, by selecting the minimum values for $TE_{i,j}$, the final value of this objective function would be zero. Therefore, the optimal solutions (selected set of stations) meet the objective of the problem (minimizing the redundancy between stations). However, the outlier point in the Pareto-front of NSGA-II model shows the optimal solutions that have a different value of $TE_{i,j}$. Both optimization models showed acceptable performance by providing the solutions that meet the selected criteria. The optimum alternative on the Pareto-front space was obtained by three different MCDM models, including TOPSIS, PROMETHEE, and AHP, for different weighing scenarios, which are assigned to criteria based on experts' opinions. In fact, the weighting scenarios show the priority of objectives in order to achieve optimum WQMN. Table 2 shows various weighing scenarios and corresponding solutions selected by TOPSIS and PROMETHEE models. Due to TE values in optimal solutions, which in the majority of the optimal solution is zero and shows the high performance of the model in minimizing the transinformation entropy, in most of the listed weighing scenarios, the assigned weight to this objective was adopted less than other two objectives.

**Table 2** Different weighing scenarios and selected solution by MCDM models

| **Weighing scenario** | **The weights of objectives*** | | | **Selected solution on the Pareto of NSGA-II** | | | **Selected solution on the Pareto of NSGA-III** | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{**}_1$ | $W_2$ | $W_3$ | TOPSIS | PROMETHEE | AHP | TOPSIS | PROMETHEE | AHP |
| 1 | 0.40 | 0.10 | 0.50 | 4 | 11 | 14 | 1 | 9 | 9 |
| 2 | 0.30 | 0.10 | 0.60 | 2 | 10 | 4 | 1 | 3 | 3 |
| 3 | 0.45 | 0.10 | 0.45 | 4 | 18 | 18 | 1 | 6 | 12 |
| 4 | 0.35 | 0.30 | 0.35 | 14 | 18 | 18 | 15 | 9 | 15 |
| 5 | 0.30 | 0.20 | 0.50 | 14 | 7 | 4 | 1 | 9 | 9 |
| 6 | 0.40 | 0.20 | 0.40 | 4 | 18 | 18 | 1 | 9 | 9 |
| 7 | 0.50 | 0.10 | 0.40 | 14 | 18 | 18 | 1 | 9 | 9 |
| 8 | 0.60 | 0.10 | 0.30 | 14 | 6 | 7 | 1 | 5 | 8 |
| 9 | 0.50 | 0.20 | 0.30 | 14 | 8 | 4 | 1 | 9 | 3 |
| 10 | 0.30 | 0.40 | 0.30 | 14 | 18 | 18 | 15 | 9 | 9 |

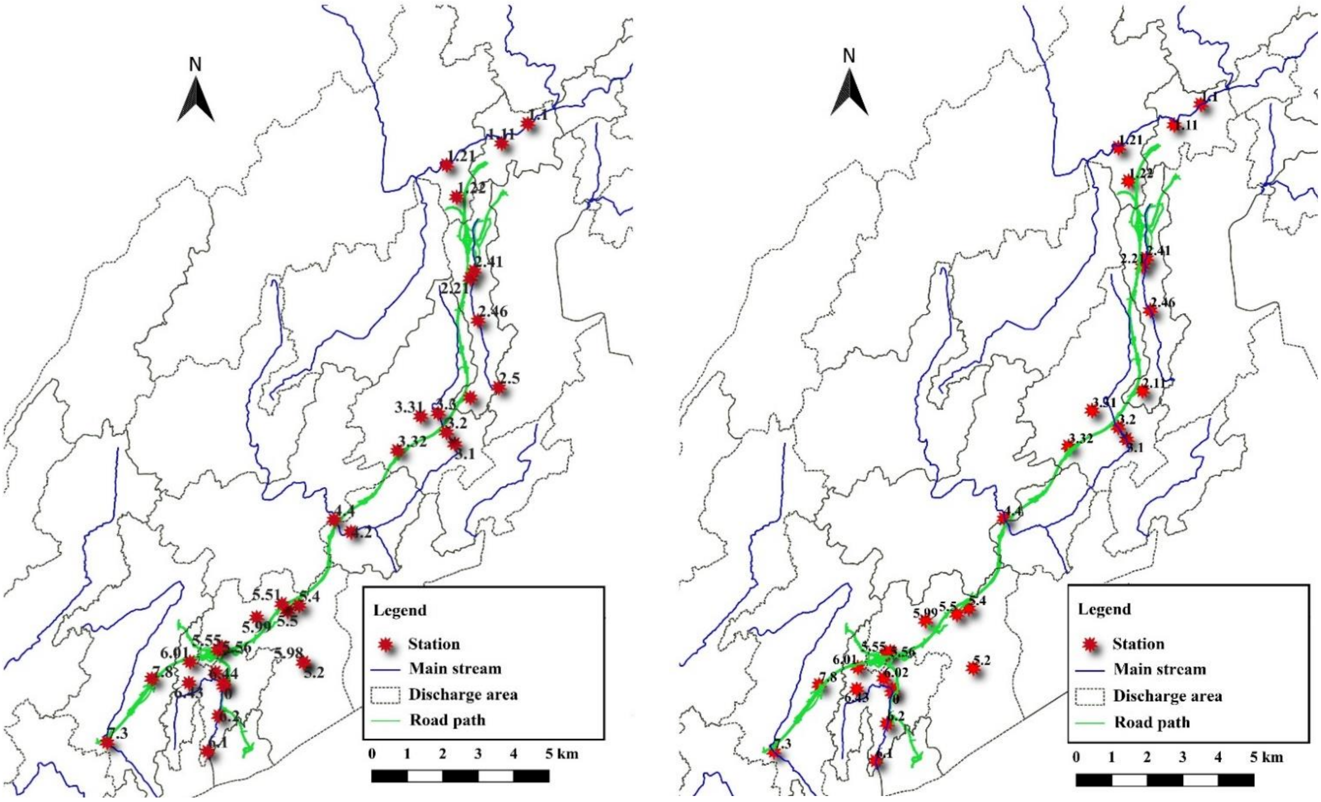
*Objectives: 1) the number of stations, 2) the VOI, and 3) normalized TE. $W_i$ ** is the assigned weight to the $i^{th}$ objective

As can be seen, for the results of the NSGA-II, if the objective function 1 (number of monitoring stations) receives more importance (e.g., weighing scenarios of 7, 8, and 9), TOPSIS selects solution #14 with 33 monitoring stations, while PROMETHEE and AHP pick three different solutions. When the first and third objective functions have the same importance (e.g., weighing scenarios of 3, 4, 6, and 10), PROMETHEE and AHP certainly chose the solution #18 with 28 monitoring stations, and TOPSIS has two different choices (solutions #14 and #4). If the experts prioritize the VOI as the most significant objective (e.g., weighing scenarios of 1, 2, and 5), all MCDM models deliver different solutions, depending on the assigned weights. Finally, solution #14, and #18 were recognized as the preferable solutions by MCDM models, respectively. For the Pareto optimal solutions of the NSGA-III based optimization model, the performance of MCDMs was different from that for the NSGA-II based model. In most of the weighing scenarios, TOPSIS selected solution #1 with 30 stations in the network, while PROMETHEE, as well as AHP, picked the solution #9 with 29 stations. The objective values in the selected solutions are presented in Table 3.

**Table 3** The objective values of the selected alternative by MCDM models

| **Optimization model** | **Solution number** | **The value of objectives** | | |
|---|---|---|---|---|
| | | No. of stations | Value of information (Eq. 8) | Normalized transinformation entropy (Eq. 9) |
| **NSGA-II** | 14 | 33 | 963.80 | 0.29 |
| | 18 | 28 | 962.70 | 0.00 |
| **NSGA-III** | 1 | 30 | 955.56 | 0.00 |
| | 9 | 29 | 954.08 | 0.00 |

The selected solutions provided the optimum WQMN during road construction, with the optimum number of stations and minimum redundant information among stations, while maximizing the value of information for the monitoring stations in WQMN. This network facilitates the situation for decision-makers to update their judgment about the quality of water in the road construction area. As an example, the selected WQMNs from the solutions of the NSGA-II model (solutions #14 and #18) are presented in Fig. 6.




**(a)** **(b)**

**Fig. 6** The selected monitoring networks from NSGA-II model a) solution #14, b) #18, (the first digit of the station labels shows the catchment area)

It is vivid that both WQMNs have a reasonable spatial distribution over the seven catchment areas, which provides a reliable evaluation of the impact of road construction activities on receiving streams. However, the reference stations were not considered in selected stations, and only affected potential stations were attended. In order to analyze the selected solutions based on provided VOI and TE, the union of the $VOI_i$ curves in the selected WQMNs, and TE among the selected stations in both optimum solutions (#14 and #18), are presented in Fig. 7 a,b and Fig. 7 c,d, respectively.

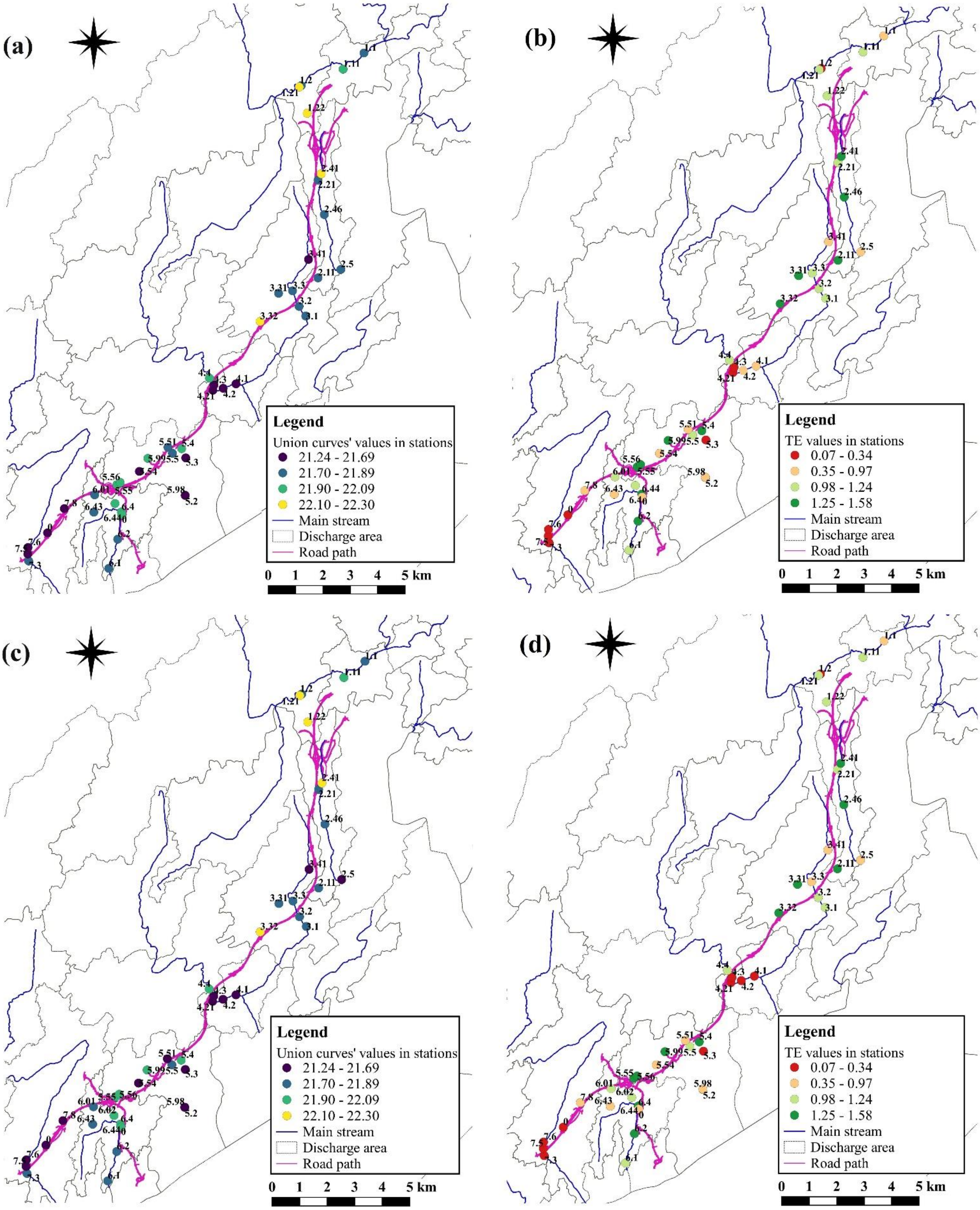



**Fig. 7** The union of the $VOI_i$ curves for solution number 14 (a) and 18 (c), and TE for solution number 14 (b) and 18 (d).

The best state of the monitoring system regarding the value of information is achieved by having all the potential stations in the final WQMN. Maximizing the value of VOI guarantees that the selected WQMN (with fewer stations) is approached to having the monitoring station in all potential points. However, the locations of the selected stations could have different distributions. Therefore, minimizing the TE secures that the selected stations have the best spatial distribution over the catchment areas.

As shown, both solutions have almost the same status in satisfying the objectives ($VOI_i$ and TE). Consequently, the same situation given $VOI_i$ and TE provides a suitable condition for the decision-maker to confidently select the best solution based on the number of stations. Hence, solution # 18, with 28 stations distributed in all seven catchment areas, is the final WQMN. With the same logic for the selected WQMNs from the NSGA-III, solution # 9, with 29 well-distributed stations, is the ultimate solution. The optimized WQMNs are the cost-effective solutions (with fewer monitoring stations) in comparison with the current monitoring program while provides reliable information on the water quality along the construction site.

## ***4 Summary and Conclusion***

This study proposed an applicable methodology for spatial multi-objective optimization of WQMN during a road construction project. Included are the CCME-WQI, the information-theoretic approaches (VOI and TE), NSGA-II and III, and MCDM models. The approach was applied to a monitoring program consisting of 44 potential monitoring stations in seven catchment areas, which received runoff from the construction of a 22 km long E18 highway in southern Norway. CCME-WQI was determined considering qualitative parameters in the time series dataset over the construction period. There were three main objectives, including *i*) minimizing the number of monitoring stations, *ii*) maximizing the value of information among stations, and *iii*) minimizing TE (redundant information) in the selected WQMN. Accordingly, the NSGA-II and NSGA-III based optimization models were utilized to achieve the Pareto-front of optimal solutions. Then, given different weighting scenarios (selected by experts' opinion) for objective functions, the best solution was found using the TOPSIS, PROMETHEE, and AHP multi-criteria decision-making methods. The application of the proposed methodology for optimizing WQMN during road construction provides feasible knowledge regarding the surface water quality and contributes to filling the information gap in utilizing CCME-WQI, a hybrid VOI-TE method, and NSGA-III, for optimization of the WQMN during the road construction project.

The resulting extent of measurements has minimum redundancy and maximum value for the decision-making process. Having optimized the spatial part of WQMN (the distribution of monitoring stations), a temporal optimization and selection of an optimal sampling frequency could be the next steps. Besides, the Bayesian Maximum Entropy (BME) method (Hosseini and Kerachian, 2017) can be applied to get a reliable spatiotemporal fit of WQI. Also, the uncertainty in determining the WQI could be analyzed by interval number programming (Nikoo et al., 2013; Nikoo et al., 2016). CCME WQI needs the same time series for all qualitative parameters in each assessment, which in practice leads to a decrease in the number of parameters examined. Hence, the results of this study (using the CCME index) could be compared with other water quality indices such as the EU Water Framework Directive (WFD) or leachate pollution index (LPI).

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## Appendix 1. CCME-WQI

CCME-WQI was developed to facilitate the process of transmitting the qualitative data into qualitative information and then knowledge (Khan 2005). This index combines three measures of variance (scope; frequency; amplitude) to indicate the overall water quality as follow:

– Scope ($F_1$): the number of variables that violate the standards

$$F_1 = \left(\frac{Number\ of\ failed\ variables}{Total\ number\ of\ variables}\right) \times 100 \quad \text{1A}$$

– Frequency ($F_2$): the number of times that violation happens

$$F_2 = \left(\frac{Number\ of\ failed\ tests}{Total\ number\ of\ tests}\right) \times 100 \quad \text{2A}$$

– Amplitude ($F_3$): the magnitude of the violation. In order to compute $F_3$ , first, the excursion, which is the number of times by which an individual concentration is greater than (or less than), the water quality objective must be determined as follow:

when $i^{th}$ test value must not exceed the respective guideline (objective):

$$Excursion_i = \left(\frac{failed\ test\ value_i}{guideline_i}\right) - 1 \quad \text{3A}$$

when $i^{th}$ test value must not fall below the respective guideline (objective):

$$Excursion_i = \left(\frac{guideline_i}{failed\ test\ value_i}\right) - 1 \quad \text{4A}$$

Then, the Normalized Sum of Excursions (NSE) is calculated by Eq. 5A.

$$NSE = \frac{\sum_{i=1}^{n} excursion_i}{Total\ number\ of\ tests} \quad \text{5A}$$

After that, by scaling the NSE to the range of 0–100 (Eq. 6A), the amplitude ($F_3$) is calculated:

$$F_3 = \left(\frac{NSE}{0.01NSE + 0.01}\right) \times 100 \quad \text{6A}$$

Finally, the CCME-WQI is achieved by utilizing Eq. 7A:

$$CCME_{WQI} = 100 - \left(\frac{\sqrt{{F_1}^2 + {F_2}^2 + {F_3}^2}}{1.732}\right) \qquad 7A$$

The computed values of CCME-WQI are then transformed into rankings through the index categorization schema, which makes five categories of poor (0-44), marginal (45-64), fair (65-79), good (80-94), and excellent (95-100).

In this study, considering the length of the time series for the measured parameters, four parameters including Fe (iron), Turbidity, Suspended Solids (SS), and pH, which had a complete time series during the construction period were selected for the rest of analysis. The water quality regulations set by the discharge permit for the construction phase of E18 Arendal-Tvedestrand, released by the Environment Department of Agder County, Norway, was applied for every single station (see Table A1).

**Table A1** The water quality objectives in different stations

| Catchment | Station ID | Water quality objectives | | | |
|---|---|---|---|---|---|
| | | Fe (µg/l) | pH | SS (mg/l) | Turbidity (FNU) |
| 1 | **1.10** | 500 | 7.5 | 100 | 2 |
| | **1.11** | 900 | 8 | 100 | 8 |
| | **1.20** | 500 | 7.5 | 100 | 2 |
| | **1.21** | 900 | 8 | 100 | 8 |
| | **1.22** | 900 | 8 | 100 | 8 |
| 2 | **2.11** | 500 | 7.5 | 100 | 4 |
| | **2.21** | 500 | 7.5 | 100 | 4 |
| | **2.41** | 900 | 8 | 100 | 2 |
| | **2.46** | 500 | 7.5 | 100 | 5 |
| | **2.50** | 500 | 7.5 | 100 | 5 |
| 3 | **3.10** | 500 | 7.5 | 100 | 5 |
| | **3.20** | 500 | 7.5 | 100 | 4 |
| | **3.30** | 500 | 7.5 | 100 | 5 |
| | **3.31** | 900 | 8 | 100 | 4 |
| | **3.32** | 500 | 8 | 100 | 4 |
| | **3.41** | 900 | 8 | 100 | 4 |
| 4 | **4.10** | 500 | 7.5 | 100 | 2 |
| | **4.20** | 500 | 7.5 | 100 | 2 |
| | **4.21** | 500 | 7.5 | 100 | 2 |
| | **4.30** | 500 | 7.5 | 100 | 2 |
| | **4.40** | 500 | 7.5 | 100 | 1 |
| 5 | **5.20** | 500 | 7.5 | 100 | 4 |
| 5 | **5.30** | 500 | 7.5 | 100 | 4 |
| | **5.40** | 500 | 7.5 | 100 | 4 |
| | **5.50** | 500 | 7.5 | 100 | 4 |
| | **5.51** | 900 | 8 | 100 | 4 |
| | **5.54** | 900 | 8 | 100 | 4 |
| | **5.55** | 900 | 8 | 100 | 4 |
| | **5.56** | 900 | 8 | 100 | 4 |
| | **5.98** | 500 | 7.5 | 100 | 6 |
| | **5.99** | 500 | 7.5 | 100 | 6 |
| 6 | **6.01** | 900 | 8 | 100 | 8 |
| | **6.02** | 900 | 8 | 100 | 8 |
| | **6.10** | 500 | 7.5 | 100 | 4 |
| | **6.20** | 500 | 7.5 | 100 | 4 |
| | **6.40** | 500 | 7.5 | 100 | 4 |
| | **6.43** | 900 | 7.5 | 100 | 4 |
| | **6.44** | 900 | 7.5 | 100 | 1 |
| | **AF01-V** | 900 | 8 | 100 | 8 |
| 7 | **7.30** | 500 | 7.5 | 100 | 4 |
| | **7.50** | 500 | 8 | 100 | 4 |
| | **7.60** | 500 | 8 | 100 | 4 |
| | **7.7B** | 500 | 7.5 | 100 | 4 |
| | **7.80** | 500 | 8 | 100 | 4 |

CCME-WQI was calculated for 42 measurements in each station. The result was a matrix of 42×44, which applied for computing the value of information and the transinformation entropy.

## ***Reference***


Alfonso, L., & Price, R. (2012). Coupling hydrodynamic models and value of information for designing stage monitoring networks. *Water Resources Research*, *48*(8).

Alfonso, L., Mukolwe, M. M., & Di Baldassarre, G. (2016). Probabilistic flood maps to support decision-making: Mapping the value of information. *Water Resources Research*, *52*(2), 1026-1043.

Alilou, H., Nia, A. M., Keshtkar, H., Han, D., & Bray, M. (2018). A cost-effective and efficient framework to determine water quality monitoring network locations. *Science of the total environment*, *624*, 283-293.

Alilou, H., Nia, A. M., Saravi, M. M., Salajegheh, A., Han, D., & Enayat, B. B. (2019). A novel approach for selecting sampling points locations to river water quality monitoring in data-scarce regions. *Journal of hydrology*, *573*, 109-122.

Alizadeh, Z., & Mahjouri, N. (2017). A spatiotemporal Bayesian maximum entropy-based methodology for dealing with sparse data in revising groundwater quality monitoring networks: the Tehran region experience. *Environmental Earth Sciences*, *76*(12), 436.

Alizadeh, Mohammad Reza, Nikoo, Mohammad Reza, Rakhshandehroo, Gholam Reza, 2017. Developing a multi-objective conflict-resolution model for optimal groundwater management based on fallback bargaining models and social choice rules: a case study. Water Resources Management 31, 1457–1472, 5. doi:https://doi.org/10.1007/s11269-017-1588-7.

Alizadeh, Z., Yazdi, J., Moridi, A., 2018. Development of an entropy method for groundwater quality monitoring network design. Environ. Process. 5 (4), 769–788.

Alfonso, L., & Price, R. (2012). Coupling hydrodynamic models and value of information for designing stage monitoring networks. Water Resources Research, 48(8).

Alizadeh, Z., Yazdi, J., & Moridi, A. (2018). Development of an entropy method for groundwater quality monitoring network Design. *Environmental Processes*, *5*(4), 769-788.

Behmel, S., Damour, M., Ludwig, R., & Rodriguez, M. J. (2016). Water quality monitoring strategies—A review and future perspectives. *Science of the Total Environment*, *571*, 1312-1329.

Boyacioglu, H. (2010). Utilization of the water quality index method as a classification tool. *Environmental monitoring and assessment*, *167*(1-4), 115-124.

Deb, Kalyanmoy, Amrit, Pratap, Agarwal, Sameer, Meyarivan, T. A. M. T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE transactions on evolutionary computation 6(2), 182– 197. doi:10.1109/4235.996017.

Deb, K., & Jain, H. (2014). An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: Solving problems with box constraints. *IEEE Transactions on Evolutionary Computation*, 18, 577–601. doi:10.1109/TEVC.2013.2281535

Grayson, Charles Jackson, 1960. Decisions under uncertainty: drilling decisions by oil and gas operators. Ayer.

Hosseini, M., & Kerachian, R. (2017). A Bayesian maximum entropy-based methodology for optimal spatiotemporal design of groundwater monitoring networks. *Environmental monitoring and assessment*, *189*(9), 433.

Hosseini, M., & Kerachian, R. (2017). A data fusion-based methodology for optimal redesign of groundwater monitoring networks. *Journal of Hydrology*, *552*, 267-282.

Hwang CL, Yoon KS (1981) Multiple attribute decision making: methods and applications. Springer-Verlag, Berlin.

Jain, H., & Deb, K. (2014). An Evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach, part II: Handling constraints and extending to an adaptive approach. *IEEE Transactions on Evolutionary Computation*, 18, 602–622. doi:10.1109/TEVC.2013.2281534

Jha, R., & Singh, V. P. (2008). Evaluation of riverwater quality by entropy. KSCE Journal of Civil Engineering, 12(1), 61-69.

Karamouz, M., Nokhandan, A. K., Kerachian, R., & Maksimovic, Č. (2009). Design of on-line river water quality monitoring systems using the entropy theory: a case study. *Environmental monitoring and assessment*, *155*(1-4), 63.

Keum, J., Kornelsen, K. C., Leach, J. M., & Coulibaly, P. (2017). Entropy applications to water monitoring network design: a review. *Entropy*, *19*(11), 613.

Khan, H., Khan, A. A., & Hall, S. (2005, June). The Canadian water quality index: a tool for water resources management. In *MTERM International Conference, AIT, Thailand* (pp. 06-10).

Khorshidi, M. S., Nikoo, M. R., & Sadegh, M. (2018). Optimal and objective placement of sensors in water distribution systems using information theory. Water research, 143, 218-228.

Khorshidi, M. S., Nikoo, M. R., Taravatrooy, N., Sadegh, M., Al-Wardy, M., & Al-Rawas, G. A. (2020). Pressure sensor placement in water distribution networks for leak detection using a hybrid information-entropy approach. Information Sciences, 516, 56-71.

Krstanovic, P. F., & Singh, V. P. (1992a). Evaluation of rainfall networks using entropy: I. Theoretical development. *Water Resources Management*, *6*(4), 279-293.

Krstanovic, P. F., & Singh, V. P. (1992b). Evaluation of rainfall networks using entropy: II. Application. *Water resources management*, *6*(4), 295-314.

Kuang H, Kilgour DM, Hipel KW (2015) Grey-based PROMETHEE II with application to evaluation of source water protection strategies. Inf Sci 294:376–389.

Lee, C., Paik, K., & Lee, Y. (2014). Optimal sampling network for monitoring the representative water quality of an entire reservoir on the basis of information theory. *Journal of Water and Climate Change*, *5*(2), 151-162.

Mahjouri, N., & Kerachian, R. (2011). Revising river water quality monitoring networks using discrete entropy theory: the Jajrood River experience. *Environmental monitoring and assessment*, *175*(1-4), 291-302.

Masoumi, F., & Kerachian, R. (2010). Optimal redesign of groundwater quality monitoring networks: a case study. *Environmental monitoring and assessment*, *161*(1-4), 247-257.

Maymandi, N., Kerachian, R., & Nikoo, M. R. (2018). Optimal spatio-temporal design of water quality monitoring networks for reservoirs: application of the concept of value of information. *Journal of hydrology*, *558*, 328-340.

Memarzadeh, M., Mahjouri, N., & Kerachian, R. (2013). Evaluating sampling locations in river water quality monitoring networks: application of dynamic factor analysis and discrete entropy theory. *Environmental earth sciences*, *70*(6), 2577-2585.

Mogheir, Y., De Lima, J. L. M. P., & Singh, V. P. (2009). Entropy and multi-objective based approach for groundwater quality monitoring network assessment and redesign. *Water Resources Management*, *23*(8), 1603-1620.

Mondal, N. C., & Singh, V. P. (2012). Evaluation of groundwater monitoring network of Kodaganar River basin from Southern India using entropy. *Environmental earth sciences*, *66*(4), 1183-1193.

Mooselu, M. G., Nikoo, M. R., Latifi, M., Sadegh, M., Al-Wardy, M., & Al-Rawas, G. A. (2020). A multi-objective optimal allocation of treated wastewater in urban areas using leader-follower game. *Journal of Cleaner Production*, 122189.

Mooselu, M. G., Nikoo, M. R., Rayani, N. B., & Izady, A. (2019). Fuzzy Multi-Objective Simulation-Optimization of Stepped Spillways Considering Flood Uncertainty. *Water Resources Management*, 1-15.

Munna, G. M., Chowdhury, M. M. I., Ahmed, A. M., Chowdhury, S., & Alom, M. M. (2013). A Canadian water quality guideline-water quality index (CCME-WQI) based assessment study of water quality in Surma River. *Journal of Civil Engineering and Construction Technology*, *4*(3), 81-89.

Mahagamage, M. G. Y. L., & Manage, P. M. (2014). Water quality index (CCME-WQI) based assessment study of water quality in Kelani river basin, Sri Lanka. International Journal of Environment and natural resources, Mahidol university, Thailand, 1, 199-204.

Mareschal B, Brans JP, Vincke P (1984) PROMETHEE: a new family of outranking methods in multi-criteria analysis (no. 2013/9305). ULB–Universite Libre de Bruxelles.

Nikoo, M. R., Kerachian, R., Malakpour-Estalaki, S., Bashi-Azghadi, S. N., & Azimi-Ghadikolaee, M. M. (2011). A probabilistic water quality index for river water quality assessment: a case study. *Environmental monitoring and assessment*, *181*(1-4), 465-478.

Nikoo, M. R., Karimi, A., & Kerachian, R. (2013). Optimal long-term operation of reservoir-river systems under hydrologic uncertainties: application of interval programming. *Water resources management*, *27*(11), 3865-3883.

Nikoo, M. R., Beiglou, P. H. B., & Mahjouri, N. (2016). Optimizing multiple-pollutant waste load allocation in rivers: an interval parameter game theoretic model. *Water resources management*, *30*(12), 4201-4220.

Nikoo, M. R., & Mahjouri, N. (2013). Water quality zoning using probabilistic support vector machines and self-organizing maps. *Water resources management*, *27*(7), 2577-2594.

Nikoo, M. R., Pourshahabi, S., Rezazadeh, N., & Shafiee, M. E. (2016). Stakeholder engagement in multi-objective optimization of water quality monitoring network, case study: Karkheh Dam reservoir. *Water Science and Technology: Water Supply*, *17*(4), 966-974.

Owlia, R. R., Abrishamchi, A., & Tajrishy, M. (2011). Spatial–temporal assessment and redesign of groundwater quality monitoring network: a case study. *Environmental monitoring and assessment*, *172*(1-4), 263-273.

Pourshahabi, S., Talebbeydokhti, N., Rakhshandehroo, G., & Nikoo, M. R. (2018**a**). Spatio-temporal multi-criteria optimization of reservoir water quality monitoring network using value of information and transinformation entropy. Water resources management, 32(10), 3489-3504.

Pourshahabi, S., Nikoo, M. R., Raei, E., & Adamowski, J. F. (2018**b**). An entropy-based approach to fuzzy multi-objective optimization of reservoir water quality monitoring networks considering uncertainties. *Water resources management, 32*(13), 4425-4443.

Roberts, M. J., Schimmelpfennig, D., Livingston, M. J., & Ashley, E. (2009). Estimating the value of an early-warning system. *Review of agricultural economics*, *31*(2), 303-329.

Saaty, T. L. (1988). What is the analytic hierarchy process?. In *Mathematical models for decision support* (pp. 109-121). Springer, Berlin, Heidelberg.

Sapkota M, Arora M, Malano H, Sharma A, Moglia M (2018) Integrated evaluation of hybrid Water supply systems using a PROMETHEE–GAIA approach. Water 10(5):610.

Shannon CE (1948) A mathematical theory of communication. Bell Syst Tech J 27:623–656.

Stosic, T., Stosic, B., & Singh, V. P. (2017). Optimizing streamflow monitoring networks using joint permutation entropy. *Journal of hydrology*, *552*, 306-312.

Terrado, M., Barceló, D., Tauler, R., Borrell, E., & de Campos, S. (2010). Surface-water-quality indices for the analysis of data generated by automated sampling networks. *TrAC Trends in Analytical Chemistry*, *29*(1), 40-52.

Verkade, J. S., & Werner, M. G. F. (2011). Estimating the benefits of single value and probability forecasting for flood warning. *Hydrology and earth system sciences*, *15*(12), 3751-3765.

Vikan, H., & Meland, S. (2013). Purification Practices of Water Runoff from Construction of Norwegian Tunnels—Status and Research Gaps. In Urban Environment (pp. 475-484). Springer, Dordrecht.

Zeng, D., Gu, L., Lian, L., Guo, S., Yao, H., & Hu, J. (2016). On cost-efficient sensor placement for contaminant detection in water distribution systems. *IEEE Transactions on Industrial Informatics*, *12*(6), 2177-2185.

Zhang K, Kluck C, Achari G (2009) A comparative approach for ranking contaminated sites based on the risk assessment paradigm using fuzzy PROMETHEE. Environ Manag 44(5):952.