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Network design for surface water quality monitoring in a road construction project using Gamma Test theory

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ABSTRACT

Road construction has a negative environmental impact on the surrounding aquatic environment, requiring the continuous monitoring of surface water quality. Here, optimization of the water quality monitoring network (WQMN) is an essential step in supporting the sustainable development of road construction projects. This study introduces Gamma Test theory (GTT) as a practical method for optimizing the WQMN of surface waters during road construction. The water quality index (WQI) was computed in 48 monitoring stations for six monitoring periods from 2017 to 2019; data was acquired from a primary monitoring network over a new highway in southern Norway. Based on the results, it is possible to reduce the number of stations by 23% in comparison with the original empirical network. The proposed method could be useful to design the monitoring networks of projects with limited construction time and budget, as well as projects lacking enough data.

1. Introduction

One of the most important challenges of road construction projects is waste discharge due to various construction works, which negatively affects the physical, chemical, and biological quality of receiving surface water bodies. In addition, it may pose serious health and safety risks to consumers [1]. Over the course of a road construction project, the volume and quality of the waste discharge and its impacts on surface water bodies vary spatiotemporally due to road construction works, as well as the weather conditions in the catchment and construction areas. Therefore, the right design of a water quality monitoring network (WQMN) is needed to provide useful input on spatial-temporal variations of surface water quality during construction projects. This may support decision-makers in

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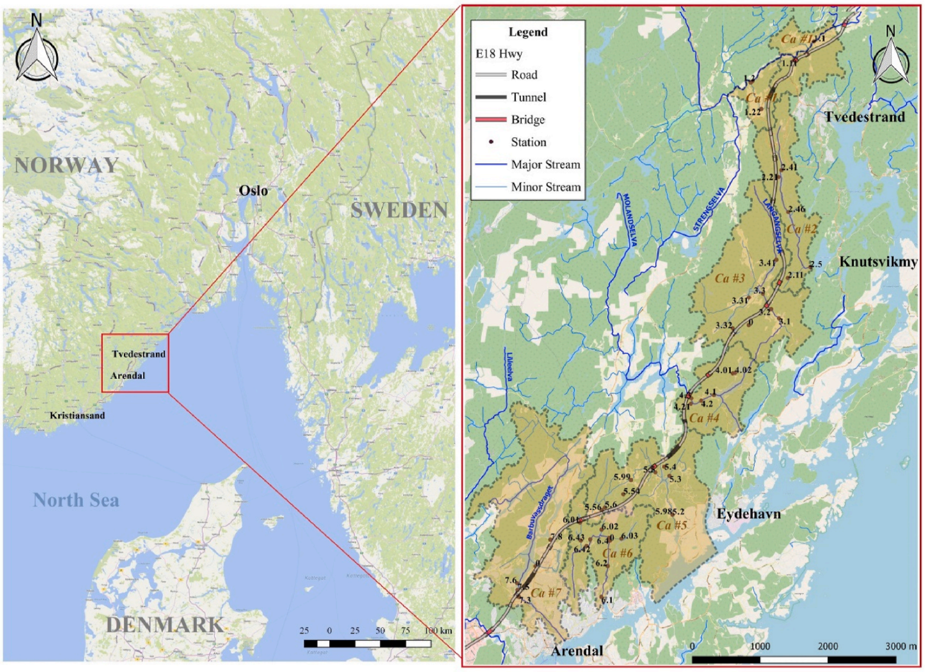

Fig. 1. Construction site of the Arendal-Tvedestrand highway with monitoring stations (Note: the first digit in the number of each station specifies the catchment number).

terms of managing the health risks of stakeholders, self-purification capacity of the environment, and implementation of remedial policies [2–5]; unfortunately, the optimal design of WQMN is a complicated process. Firstly, the uneven distribution of monitoring stations, or their insufficient number, provides a limited understanding of the surface water system of the study area [6]. On the other hand, if the number of monitoring stations is too large, additional information may be obtained, making the monitoring network costly and inefficient [6]. In road construction projects, sometimes after a long monitoring period and spending a lot of time and money, it becomes clear that the number of monitoring stations is large and consequently a lot of money has been wasted. In addition to this, the number of stations is insufficient, and the collected information gives a rudimentary understanding of the environmental impact of the construction works. Therefore, finding a method to determine the optimal number and location of stations after the first monitoring period gives valuable assistance to local authorities in managing the costs and environment.

The primary point for optimization of WQMN is designing a network with the maximum possible number of monitoring stations by empirical [7], statistical [4], and ranking methods [8]. For empirical methods, the WQMN is designed based on technical knowledge, the location of main streams and tributaries, and the distribution of pollution sources [9], while for statistical methods, different design scenarios are considered by assessing the ratio of explained data through the selected WQMN to the spatiotemporal variations of the water quality in the monitored catchment [10]. Finally, for ranking methods, the zoning layer of effective parameters in surface water quality is developed, and by weighing each layer and combining them, a monitoring priority map is then drawn [3]. After the initial design of the monitoring stations, the surface water quality is monitored for several periods and the monitoring network is then optimized using several methods, such as fuzzy clustering [8,11,12], genetic algorithms [13–16], multi-objective discrete particle swarm optimization [17], the value of information [18–20], entropy [20–23], optimal partition analysis [24], and strategic decision analysis [25]. However, there is evidence that most of the proposed methods are incapable to determine the optimal number of monitoring stations, and consequently, this number is often selected empirically or based on available data and related design limitations (e.g., project budget and the value of provided data) [15,25]. Furthermore, few studies have determined the optimal number of monitoring stations, in which the optimization process has been conducted using data of whole monitoring periods after the completion of the project [20]. In this condition, the results are less feasible to be applied since the authorities realize that the monitoring network presents issues once the project has been completed, and there is no way back to improve the monitoring network and data collection.

To solve these problems and determine the optimal number and location of monitoring stations after the first monitoring period, this paper presents the idea to apply Gamma Test theory (GTT), which is a nonlinear modeling tool that can be used to determine the minimum set of data needed to create a smooth model lacking in any knowledge of the equations that describes the phenomenon [26–28]. GTT was first introduced by Ref. [29] and it was examined and used in more detail years later by Ref. [30]. This study evaluates the ability of GTT to determine the optimal number and location of surface water monitoring stations in a construction project. For this purpose, the proposed method was applied to optimize a WQMN after the first monitoring period in the construction project of the Arendal-Tvedestrand highway in Norway. The construction of this highway took about three years, from 2017 to 2019.

Over this time, 28 physical, chemical, and biological parameters were monitored every four months at 48 stations in the catchment area of this highway. Then, the water quality index (WQI) was computed for each station and monitoring period. Subsequently, GTT was applied to determine the optimal surface water monitoring network using the data of the first monitoring period. Finally, the proposed optimal monitoring network was systematically verified using the data from the second to the sixth monitoring period. The paper also contributes to addressing the knowledge gap in finding an optimal monitoring network for short- and mid-term projects in the shortest possible time via GTT.

2. Methods

The proposed methodology consists of two main steps: (i) determining the WQI in all stations based on the existing network, generating the required data for the second step; and (ii) optimizing the number and location of monitoring stations in different periods based on GTT.

2.1. Data collection

In the first step, qualitative information of surface water along the road construction site was collected. Fig. 1 illustrates the location of the construction site, which is a new 22-km long section of the Arendal-Tvedestrand highway in Norway. The drainage area of the highway (ca. 7180 ha) consists of seven catchment areas, including Storelva (#1), Vennevann (#2), Langangselva (#3), Sagene (#4), Mørfjær (#5), Songebekken (#6), and Longum/Barbu (#7). Fig. 1 also indicates the main and side streams of different catchments and their connections with the road. Various road construction works, including area cleaning, blasting, drilling, water management, asphalting, culvert work, and bridge construction, were carried out during the three years of construction between 2017 and 2019. Considering the requirements of the Department of Environment, County Governor of Aust-Agder (Norway) and based on the type of activities in different parts of the road, the surface water quality was monitored over different periods of the project. Accordingly, six time periods of one month each, at four-month intervals, were considered during the construction phase from 2017 to 2019. The first period (i.e., 4/2017) included preparation and mobilization steps. Most of the construction works were initiated from the second period (i.e., 10/2017); and by then, as the project progressed, one-month periods of monitoring continued, which were separated by four-month periods (i.e., 2/2018, 6/2018, 10/2018, 2/2019).

Different qualitative parameters, including physical properties (total suspended solids (TSS), turbidity, color, and pH), sum parameters (chemical oxygen demand, COD), alkalinity, and electrical conductivity, EC)), nutrients (total-N, total-P, and NO_3–N), minerals and ions (SO_4^{2-}, Mg^{2+}, Ca^{2+}, Na^+, Cl^-, and K^+), and heavy metals (Fe, As, Ba, Pb, Cd, Cu, Co, Mn, Hg, Cr, Ni, and Zn) were monitored at 48 stations in the catchment area of the highway. The monitoring stations in the primary WQMN (see Fig. 1) were established based on the catchment topography, the direction of main and side streams, and experts' experiences for evaluating the spatiotemporal variation in surface water quality during road construction.

2.2. Water quality index

The WQI is a management tool that makes a reasonable interpretation to assess water quality based on qualitative data [20]. In this study, the relative weighting method was applied to calculate the WQI in each station and monitoring period. Herein, the quantity rating scale (Q_i) was calculated according to Eq. (1) for all parameters, except for pH which was determined by Eq. (2) [31,32], as follows:

$$Q_i = \left(\frac{C_i}{S_i}\right) \tag{1}$$

$$Q_{i_{pH}} = \left[\frac{C_i - 7}{S_i - 7}\right] \tag{2}$$

where C_i represents the measured value for each parameter, and S_i corresponds to the maximum acceptable limit of each parameter. The value of S_i for all 28 parameters applied in this study (Table 1) was determined based on the WHO guidelines for drinking water (2017) [50,51], together with the regulations of water quality for the construction phase of the Arendal-Tvedestrand highway established by Department of Environment, County Governor of Aust-Agder (Norway).

Then, a normalized weight ranged from 1 to 4 for the lowest and highest negative impacts on water quality is assigned to each parameter based on experts' opinions. In this study, the normalized weight of each parameter was collected from various studies, and the average of the collected values ($\overline{w}_i$) was assigned as the normalized weight for each parameter (see Table 1). Afterward, the relative weight of each parameter (w_i), as reported in the last column of Table 1, was calculated according to Eq. (3):

$$w_i = \frac{\overline{\overline{w}_i}}{\sum_{i=1}^{28} \overline{w}_i} \times 100 \tag{3}$$

As observed in Table 1, specific parameters, such as As, Pb, and Cr with the relative weight of 5.3%, followed by Cu and Ni (5 and 4.9%, respectively), present the highest importance, while Total-P, Zn, and Mg^{2+} (1.2, 1.4, and 1.5%, respectively) have minor importance in water quality. Importantly, it is extremely needed to consider the negative effects of heavy metals with greater impact

Table 1
The maximum acceptable limits, normalized weights of parameters based on literature, and calculated relative weights.

NO.	Parameters	Unit	Standard Limit Value	Assigned weights in different studies								
				[33]	[34]	[35]	[36]	[37]	[38]	[39]	[40]	[41]
1	SO_4^{2-}	mg / L	250	–	2.0	2.0	2.0	3.2	2.0	2.4	4.0	3.0
2	Mg^{2+}	mg / L	50	–	1.0	1.0	1.0	1.6	–	1.6	2.0	1.0
3	Ca^{2+}	mg / L	75	–	1.0	1.0	1.0	1.6	–	1.6	2.0	3.0
4	Fe	μg / L	500	–	–	–	–	3.2	–	1.6	4.0	–
5	pH	–	<7.5	1.0	1.0	1.0	1.0	3.2	4.0	2.4	4.0	1.0
6	SS	mg / L	2	–	4.0	–	4.0	–	–	–	–	–
7	Turbidity	(FNU)	10	–	–	4.0	2.0	–	3.0	–	–	–
8	Total-N	μg / L	750	–	3.0	3.0	3.0	–	2.0	–	–	–
9	Alkalinity	mmol / L	0.4	–	–	–	–	2.4	–	1.6	–	–
10	As	μg / L	5	4.0	–	–	–	–	–	–	4.0	–
11	Ba	μg / L	1000	–	–	–	–	–	–	–	–	–
12	Pb	μg / L	10	–	–	–	–	–	–	–	4.0	–
13	Color	mg Pt/ L	25	–	–	2.0	–	–	4.0	–	–	–
14	Cd	μg / L	0.53	3.0	–	–	–	–	–	–	–	–
15	K^+	mg / L	12	–	–	–	–	–	–	1.6	2.0	2.0
16	COD	mg / L	25	–	3.0	3.0	3.0	–	–	–	–	–
17	Cl^-	mg / L	250	–	1.0	1.0	1.0	2.4	2.0	2.4	3.0	4.0
18	Cu	μg / L	7	–	–	–	–	–	–	–	–	–
19	Co	μg / L	100	–	–	–	–	–	–	–	–	–
20	EC	mS/ m	100	–	1.0	4.0	2.0	–	4.0	2.4	–	2.0
21	Cr	μg / L	50	–	–	–	–	–	–	–	–	–
22	Hg	μg / L	0.005	3.0	–	–	–	–	–	–	–	–
23	Mn	μg / L	100	–	–	–	–	3.2	–	–	4.0	–
24	Na^+	mg / L	200	–	–	1.0	–	–	–	2.4	4.0	4.0
25	Ni	μg / L	20	–	–	–	–	–	–	–	–	–
26	Nitrate	mg / L	50	3.0	2.0	2.0	2.0	4.0	–	4.0	–	–
27	Zn	μg / L	77	–	–	–	–	–	–	–	3.0	–
28	Total-P	μg / L	25	2.0	1.0	1.0	1.0	–	1.0	–	–	–
Sum												

NO.	Assigned weights in different studies											Average Weights	Weights (%) (by Eq. (3))
	[31]	[39]	[42]	[43]	[44]	[44]	[45]	[46]	[47]	[48]	[49]		
1	3.2	–	–	3.2	3.2	3.2	–	–	2.4	2.4	–	2.7	**3.6**
2	1.6	1.6	–	1.6	1.6	1.6	1.6	2.0	–	1.6	–	1.5	**2.0**
3	1.6	1.6	–	1.6	1.6	1.6	2.4	–	–	1.6	–	1.7	**2.2**
4			–		3.2	3.2	3.2	–	2.4	–	2.4	2.9	**3.8**
5	3.2	2.4	–	3.2	3.2	3.2	3.2	–	3.2	–	1.7	2.5	**3.3**
6	–	–	–	–	–	–	–	3.0	–	–	–	3.7	**4.8**
7	–	–	–	–	–	–	–	–	–	–	–	3.0	**4.0**
8	–	–	–	–	–	–	–	–	–	–	–	2.8	**3.6**
9	1.6	1.6	–	2.4	2.4	2.4	2.4	–	–	1.6	–	2.0	**2.7**
10	–	–	–		–	–		4.0	–	4.0	–	4.0	**5.3**
11	–	–	1.6		–	–	3.2		–	–	–	2.4	**3.2**
12	–	–	4.0	4.0	–	–	4.0	4.0	4.0	–	4.0	4.0	**5.3**
13	–	–	–	–	–	–	0.8	3.0	–	–		2.5	**3.2**
14	–	–	4.0	–	–	–		4.0	4.0	–	2.4	3.8	**5.0**
15	–	1.6	–	–	–	–	1.6	–	–	0.8		1.8	**2.3**
16	–		–	3.2	–	–		–	–		–	3.1	**4.0**
17	2.4	2.4	–	2.4	2.4	2.4	1.6	–	2.4	2.4	–	2.2	**2.9**
18	–		1.6	–	–	–	–	2.0	1.6	–	1.6	1.7	**2.3**
19	–		–	–	–	–	–	3.0	–	–	–	3.0	**4.0**
20	4.0	2.4	–	–	–	–	2.4	3.0	4.0	–	–	2.8	**3.7**
21	–	–	4.0	4.0	–	–	4.0	4.0	–	–	–	4.0	**5.3**
22	–	–	–	–	–	–	–		–	–	–	3.0	**4.0**
23	–	1.6	3.2	4.0	3.2	3.2	3.2	2.0	–	2.4	2.4	3.0	**3.9**
24	0.8	2.4		1.6	–	–	2.4		–	2.4	–	2.3	**3.1**
25	–		3.2	–	–	–	4.0	4.0	–	–	–	3.7	**4.9**
26	–	4.0		4.0	4.0	4.0	4.0		4.0	4.0	1.8	3.3	**4.4**
27	–		0.8	–	1.0	0.8	1.6	1.0	–	–	1.6	1.4	**1.9**
28	–	–	–	–	–	–	–	–	–	–	–	1.2	**1.6**
Sum												**75.8**	**100**

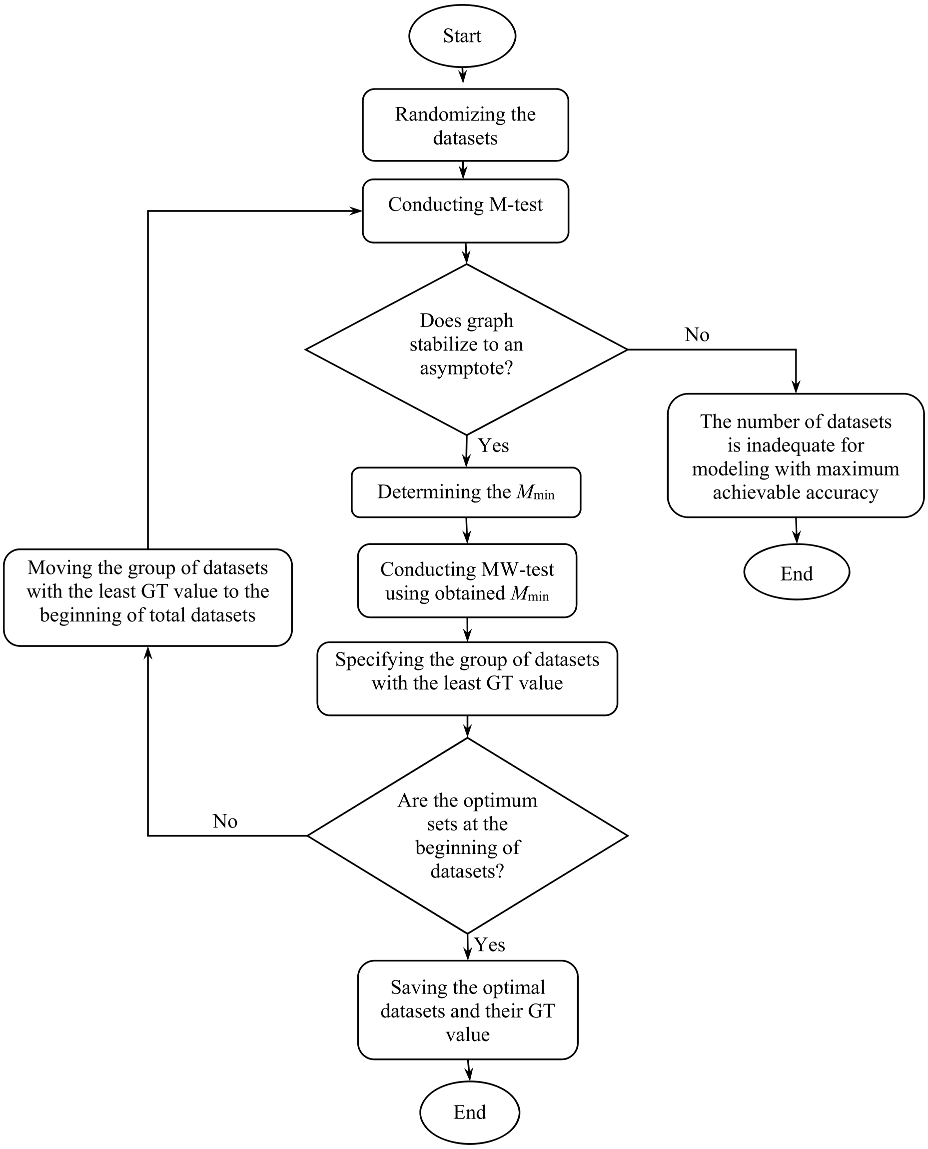

Fig. 2. Optimization algorithm towards WQMN in road construction using GTT.

than other parameters in water quality calculations.

Lastly, the WQI was calculated according to Eq. (4):

$$WQI = \sum_{i=1}^{28} w_i \times Q_i \tag{4}$$

In principle, the larger the WQI value, the lower the water quality. To determine the significance of the difference among the calculated WQI data in two different monitoring periods, the probability distribution of the WQI data in each monitoring period must be first determined using the Kolmogorov–Smirnov test (K–S test) [52,53]. If the data are normally distributed, the paired *t*-test can be used for specifying the significance of the difference among the WQI data in two periods [54]. Otherwise, data distribution must be normalized using transformation functions.

2.3. Gamma test theory

GTT is a statistical method of analysis used to specify three critical issues before developing a model; this method implies the following steps: 1) the adequacy of datasets to develop a causal model, 2) the maximum reachable accuracy of a smooth model to estimate a dependent variable, and 3) the best and minimum datasets applicable for training a model [55,56]. In this method, it is

Table 2
Evaluation statistics of all WQI values in each monitoring period.

Feature	Monitoring period					
	1st	2nd	3rd	4th	5th	6th
Maximum	302.8	1259.2	256.2	311.5	788.5	304.7
Minimum	21.8	25.1	24.0	23.2	26.6	26.0
Mean	60.0	99.3	61.8	75.6	83.8	63.4
Coefficient of variation (%)	84.6	187.9	69.2	82.2	139.2	74.4

supposed that if the two points are close together in the input space, their outputs should be close in the output space unless they contain noise. For GTT, data analysis is conducted based on the calculation of a statistic number, named gamma. Therefore, for each vector of independent variables, i.e., $X_i (1 \leq i \leq M)$, and scalar of the dependent variable (y_i), the nearest k^{th} neighbor for X_i (i.e., $X_{N[i,k]}$), must be determined. Then, the delta (δ) and gamma (γ) functions are calculated according to Eqs. (5) and (6), respectively:

$$\delta(k) = \frac{1}{M} \sum_{i=1}^{M} \left| X_{N[i,k]} - X_i \right|^2 (1 \leq k \leq p) \tag{5}$$

$$\gamma(k) = \frac{1}{2M} \sum_{i=1}^{M} \left| y_{N[i,k]} - y_i \right|^2 (1 \leq k \leq p) \tag{6}$$

where | | represents the Euclidean distance, M is the number of datasets, and $y_{N[i,k]}$ is the y value corresponding to $X_{N[i,k]}$, and i is the index of observations. In the previous equations, it is suggested to consider $10 \leq p \leq 20$ [55–57]. After that, a linear regression line ($\gamma = A\delta + GT$), which provides useful input about the datasets before developing a model, is fitted to the p points of ($\delta(k)$, $\gamma(k)$). The slope of the regression line (A) indicates the complexity of the relationship between dependent and independent variables. The higher the A value, the greater the complexity [55,58]. Furthermore, the intercept of the regression line ($\delta = 0$), which is equal to the gamma statistic (GT), shows the maximum reachable accuracy by smooth modeling tools. The higher the GT value, the weaker the modeling performance, which is mainly due to: 1) much noise in measured data, 2) a low number of datasets, and 3) the low number of independent variables in the model [59].

In theory, increasing the M in modeling leads to a rise in the degree of reliability. However, increasing the M above the minimum number does not increase the modeling accuracy [55,56]. M-test, as a GTT tool, determines the minimum required number of training datasets (M_{min}) in a given order of datasets to develop a model with maximum reachable accuracy, directly from the dataset [55,56]. For this purpose, GT is computed for an increasing number of datasets, and GT is then plotted against the number of datasets. As the number of datasets reaches the M_{min}, the graph is stabilized to an asymptote [60].

The moving window test (MW-test) is another tool in GTT, which indicates the variation of GT value for different subsets of the datasets displaying the same size [61]. In MW-test, a virtual window with the length of M_{min} is moved along the datasets with a special order, and the GT value is computed for the datasets in the window. Here, the datasets with the lowest GT value are selected as the best training set for modeling [61].

2.4. *Optimization of the surface water monitoring network using GTT*

The surface water quality monitoring network can be substantially optimized using GTT. For this, the minimum and the best-required number of monitoring stations (or datasets) is specified using M − and MW-tests. However, the results strongly depend on the order of datasets, while evaluating all possible permutations of orders is extremely complicated and time-consuming. Interestingly, a GTT-based optimization algorithm proposed by Ref. [62] (see Fig. 2) was applied to optimize the number and location of monitoring stations. The algorithm consisted of seven major steps. Initially, the total datasets are randomized to create a random order of datasets. In the second step, M_{min} is determined by the M-test tool. Then, the MW-test is conducted with the M_{min} to specify a group of datasets with the least GT value. In the fourth step, the specified group is located at the beginning of the rest of the datasets. After that, steps 2 to 4 are repeated to put the minimum number of stations (M_{min}) with the lowest value of GT at the beginning of the total datasets. This process is repeated several times by randomizing the datasets and changing the initial order of the datasets. Lastly, the group of datasets with the lowest number and GT value is selected as the optimal group. In this study, a GTT-based optimization algorithm was applied to optimize the number and location of surface water monitoring stations during the construction of the 22-km long highway in southern Norway. The latitude and longitude of stations were considered as independent variables while WQI was the dependent variable.

3. Results and discussion

3.1. *Water quality index from different stations*

As mentioned previously, the WQI was calculated based on 28 qualitative parameters of surface water at 48 monitoring stations in the catchment area of the Arendal-Tvedestrand highway for six monitoring periods. Over the highway construction project, WQI

Table 3
Water quality classification based on WQI and the number of stations in each class [63].

Water type	Value of WQI	Monitoring period					
		1st	2nd	3rd	4th	5th	6th
Excellent	<50	30	21	29	23	28	27
Good	50–100	11	18	11	16	10	14
Poor	100–200	6	6	7	5	6	6
Very poor	200–300	0	1	1	3	3	0
Polluted	300–400	1	0	0	1	0	1
Very polluted	>400	0	2	0	0	1	0

Table 4
K–S test results of the logarithmic transformed WQI data.

Transformed WQI data	Monitoring period					
	1st	2nd	3rd	4th	5th	6th
Number of data	48	48	48	48	48	48
Mean	1.69	1.79	1.72	1.78	1.76	1.73
Standard deviation	0.25	0.33	0.23	0.29	0.32	0.22
K–S Z	1.14	1.17	1.12	1.00	1.33	0.95
Asymp. Sig. (2-tailed)	0.15	0.13	0.16	0.27	0.06	0.32

Table 5
Paired *t*-test results of the different monitoring periods.

Pairs	Paired Differences			t	Degree of Freedom	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean			
1st – 2nd	0.10	0.32	0.04	2.23	47	0.03
2nd – 3rd	−0.07	0.24	0.03	−2.03	47	0.04
3rd – 4th	0.06	0.20	0.02	2.09	47	0.04
4th – 5th	−0.01	0.19	0.02	−0.66	47	0.51
5th – 6th	−0.03	0.20	0.02	−1.08	47	0.28

presents spatiotemporal variations depending on the type of construction works. The maximum value of WQI (ca. 1259) was recorded on 10/2017 at station #4.5 due to the explosions for tunneling. Due to construction works in the vicinity of this station, the concentration of TN, TSS, Mn, and EC in surface water increased by 200,000 (μg/L), 86 (mg/L), 600 (μg/L), and 161 (mS/cm), respectively. Table 2 reports the maximum, minimum, mean WQI values, and coefficient of variation (CV) for all calculated WQIs in each monitoring period. The CV, which is the ratio of the standard deviation of the mean, defines the degree of variation of two or more data series. As reported in Table 2, the highest average value (ca. 99.3) and degree of variation of 187.9 were recorded in the second period (i.e., 10/2017), indicating that this period had the highest range of variation in WQI and created the highest average pollution load to receiving streams compared to the other periods.

Table 3 presents the water classification based on WQI and the WQI classification for different water samples in six monitoring periods. By comparing the data reported in Tables 2 and 3, it becomes clear that during the road construction process, the average water quality in all monitoring periods was found as good, while in the second monitoring period, the average water quality was close to the poor category. During this period, two monitoring stations had very polluted quality, which led to an increase in the average WQI throughout the second period. In addition, the number of stations with excellent water quality was 21, which was the lowest in all periods. Compared to all monitoring periods, surface water in the first monitoring period had the best quality, which means the water from 30 monitoring stations had excellent quality. In the sixth monitoring period, which was related to the activities at the end of the project, the water quality in most of the stations was mostly rated from good to excellent, indicating a decrease in road construction works.

The paired *t*-test is used to evaluate the statistical significance of the difference between two related data series. Unfortunately, this test is limited to data with a normal distribution. Therefore, in this study, the normality of the WQI data of the six monitoring periods was first checked by means of K–S test. The results indicated that the WQI data did not have a normal distribution. As a consequence, a logarithmic transformation was applied to the WQI data to convert their distribution to a normal distribution. Once again, the K–S test was conducted. For instance, Table 4 reports the results of the K–S test coming from the logarithmic transformed WQI data in the six monitoring periods. It was observed that the Sig. parameter values from the first to sixth monitoring periods were 0.15, 0.13, 0.16, 0.27, 0.06, and 0.32, respectively. Since all these values are higher than 0.05, the logarithmic transformed WQI data possess normal distribution at a significant level of 0.05. Table 4 presents the mean, standard deviation, and K–S Z parameters of the logarithmic transformed WQI data for the six monitoring periods. The statistical significance and Sig. parameter values were determined by comparing K–S Z with standard values.

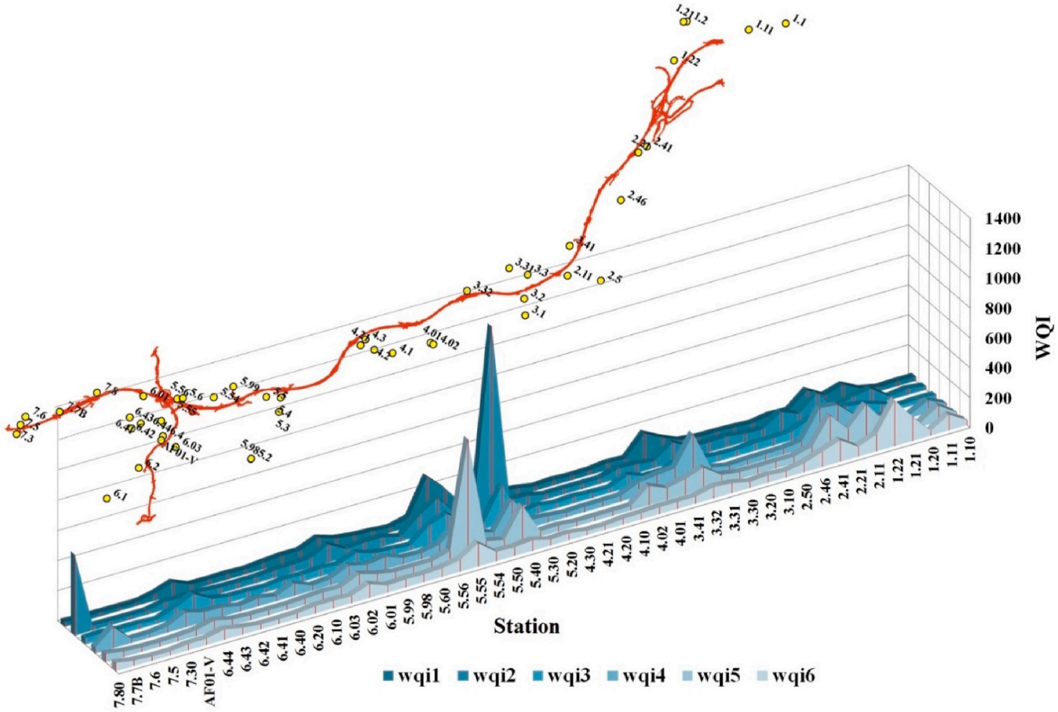

Fig. 3. Spatiotemporal variation of WQI along the road construction route.

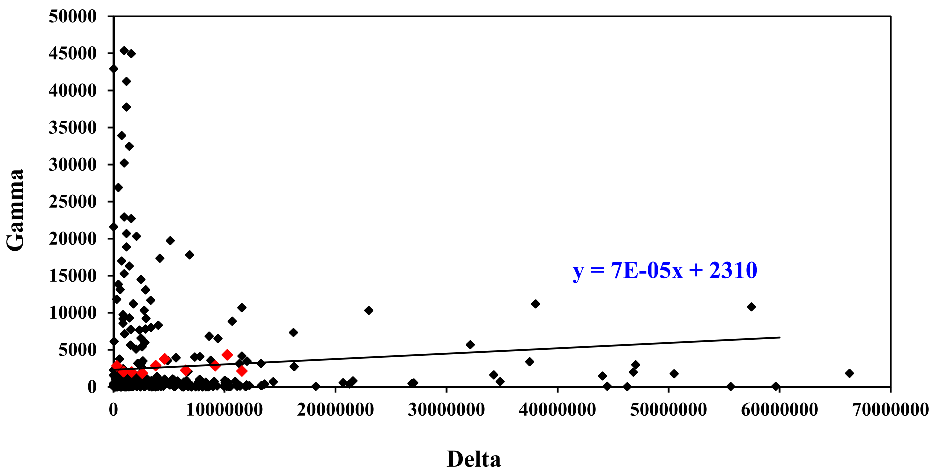

Fig. 4. GTT results for the data from the first monitoring period (4/2017).

Since the transformed WQI data in the six monitoring periods had a normal distribution, the paired *t*-test was then used to determine the statistical significance of the difference, as shown in Table 5. If the Sig. parameter value is greater than 0.05, the difference between the two data series will be insignificant. According to Table 5, there are significant differences between the first and second, second and third, and third and fourth monitoring periods, while the differences between the fourth and fifth, and fifth and sixth periods, are insignificant. From April 2017 to June 2018, there were several changes in road construction works, leading to significant differences in surface water quality. In contrast, during the fourth, fifth, and sixth monitoring periods (from June 2018 to February 2019), different construction works did not show any significant difference in surface water quality. Table 5 also presents the mean ($\overline{d}$), standard deviation (S_d), and standard error means ($S_{\overline{d}}$) of the paired differences, as well as t statistic ($\frac{\overline{d}}{S_{\overline{d}}}$), and degree of freedom (i.e., number of data series minus one). Sig. parameter of the paired *t*-test was determined by comparing the calculated t statistic with standard t value to 47 degrees of freedom. Fig. 3 illustrates the spatiotemporal variation of WQI during the six monitoring periods.

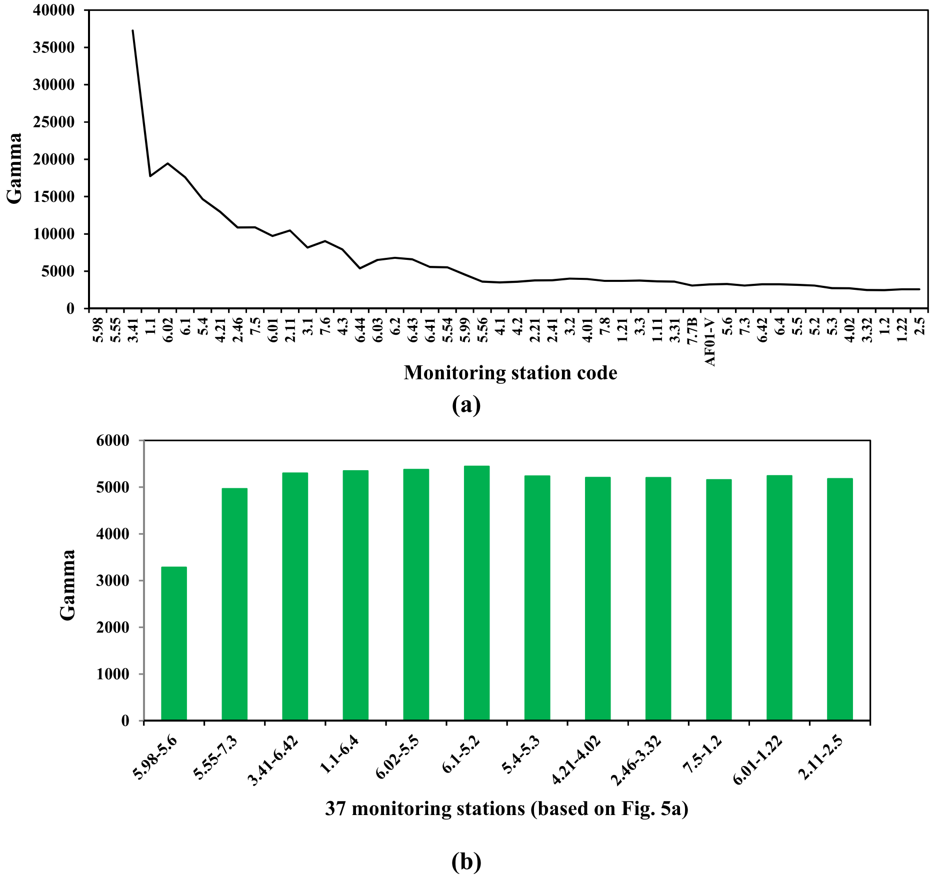

Fig. 5. a) Results of the M-test based on the data of the first monitoring period (4/2017), b) Results of the MW-test including 37 stations for the best order of stations.

3.2. Determination of the optimal WQMN using GTT

To achieve the optimal WQMN with the best spatial distribution using the minimum amount of available data, WQI data in the first monitoring period (i.e., 4/2017) was analyzed. First, 48 datasets, including latitude and longitude of stations as independent variables, and WQI as a dependent variable, were amassed. Then, GTT was conducted on the datasets. Fig. 4 shows the scatter plot and the regression line fitted to the points with coordinates of ($\delta(k)$, $\gamma(k)$). In the scatter plot, the black dots indicate the Euclidean distance of each monitoring station from each neighboring station. The red dots represent the average Euclidean distance of the monitoring stations from the surrounding stations as the neighborhood radius increases. The gamma statistic (GT) is equal to the intercept of the regression line fitted to the red dots ($\delta = 0$). Since the regression line does not present a steep slope, creating an expected modeling function is not difficult and does not need a large number of WQI data. Importantly, the scatter plot should have no input data with small $|X_i - X_j|$ values and large values of $|y_i - y_j|$, as corresponding output (the upper left corner of the δ- γ scatter plot), since they reflect relatively high intrinsic noise of the data and thus negatively affect developing a smooth model. As shown in Fig. 4, some points are in the upper left corner of the δ- γ distribution diagram, displaying the noise in WQI data from monitoring stations.

To find the optimum number and location of monitoring stations, M − and MW-tests were performed on the datasets of the first monitoring period, and a group of datasets, which could best represent the total condition, was placed at the beginning of the total datasets using the proposed method, as shown in Fig. 2. In this way, the M-test chart tends to be asymptotic faster, and the MW-test chart rises, showing the lowest GT in the initial data. Fig. 5a displays the GT variation for the best order of data. Since the GT tends to be asymptotic, the number of monitoring stations is more than the optimum number. Based on Figure 5a and 37 stations were selected as the optimum stations to monitor the WQI and hence determine its spatial distribution. Additionally, Fig. 5b indicates the result of the MW-test for 37 monitoring stations based on Fig. 5a. As can be seen, the first 37 stations present the lowest GT, and consequently, they were selected as the optimum monitoring stations, as depicted in Fig. 6.

The selection process of the number of monitoring stations and location was performed simultaneously. For GTT, the optimal number and location of stations resulted from the data analysis of the first monitoring period, which must also provide the spatial distribution of WQI with appropriate accuracy in other monitoring periods. Hence, to validate the results, M − and MW-test were conducted on WQI data coming from the selected 37 stations in the other five periods (see Fig. 7).

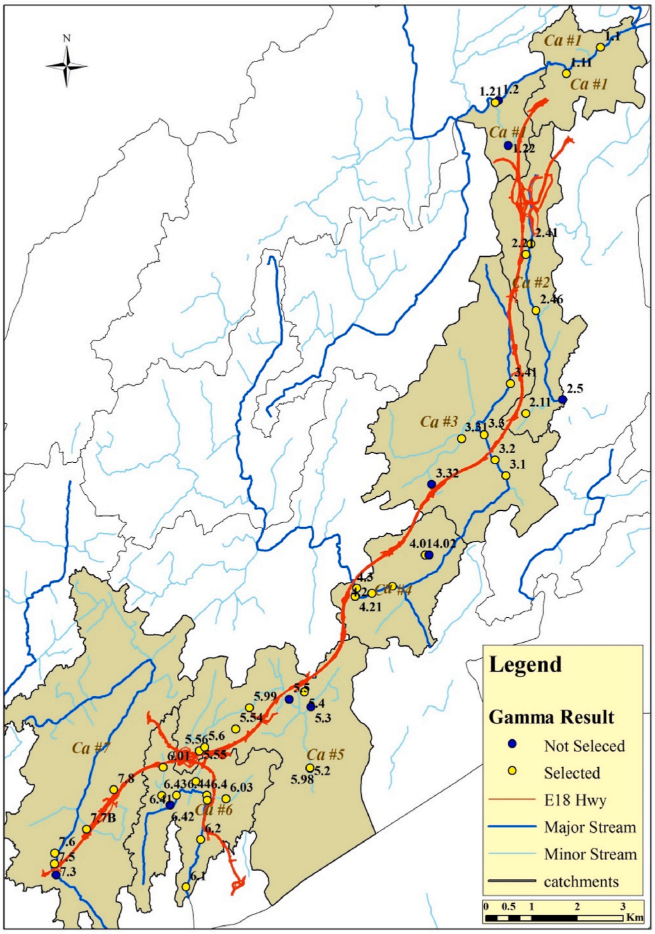

Fig. 6. The best WQMN derived from the M-test conducted on the data of the first monitoring period (4/2017).

According to Fig. 7a–e, GT tends to be asymptotic, confirming that the selected number of stations is optimum in all periods, and there is no need for more stations. By comparing GT and the asymptote location from the different periods, it can be concluded that it is possible to have a smaller number of monitoring stations for developing an optimal WQMN. However, given the M-test results in the 6th monitoring period (Fig. 7e), at least 37 stations are required to achieve an asymptote in this period. Therefore, after the first monitoring period, the initial asymptotic threshold is not necessarily the optimal number of monitoring stations in other periods.

The application of GTT has not been documented in the literature to determine the optimal monitoring network. However [20], successfully applied the transinformation entropy technique and value of information to achieve the optimum surface water quality monitoring network by using the data of multiple monitoring periods. In general, their selected network consisted of 33 stations that provided the minimum redundant information among stations while maximizing the value of information for the monitoring stations. Our best results, which were obtained using the data of the first monitoring period, revealed 37 stations for the monitoring network, covering the same stations as reported by Ref. [20]; along with four more stations, which are well distributed in all catchment areas.

4. Conclusions

The design and optimization of a surface water quality monitoring network in construction projects is a serious concern of decision-makers. This becomes even more relevant when it comes to projects with limited time and budget as well as projects with the lack of enough data for the optimal design of a monitoring network. The main goal of the current study was to evaluate the ability of GTT in determining the optimal number and location of surface water monitoring stations in a road construction project. The proposed method was successfully applied to optimize WQMN after the first monitoring period in the construction project of the Arendal-Tvedestrand highway in Norway. A primary monitoring network containing 48 stations was established based on the hydro-geological feature of the highway catchment, while the surface water quality was monitored in six periods. The water quality index (WQI), calculated based on the 28 physical, chemical, and biological parameters, was used to assess the quality of surface water. Then, the M − and MW-tests were performed on data coming from the first monitoring period to achieve the optimum number and location of monitoring stations. The results reveal that 37 monitoring stations (23% less than the number of stations in the primary WQMN) are

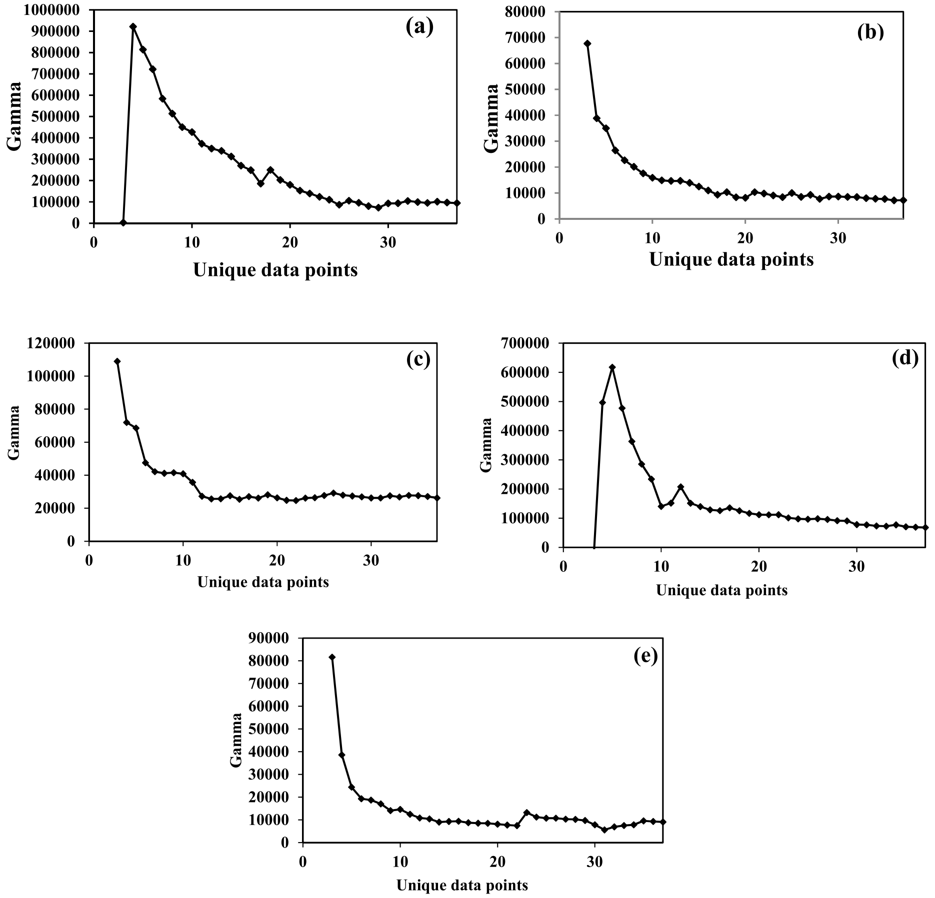

Fig. 7. Results of the M-test, graphs from a) to e) correspond to the 2nd to 6th monitoring period, respectively.

enough to assess WQI with sufficient accuracy. Additionally, they present an optimal distribution over seven discharge areas.

The proposed monitoring network was verified using the monitoring data of the next five monitoring periods. The results indicated that the optimal number and spatial arrangement of monitoring stations in a road construction project can be determined using the data of one monitoring period. In particular, some uncertainties, such as large changes in the location and type of construction works or variation of precipitation patterns in different periods, can make a difference in the results. Therefore, the proposed method is feasible to establish a WQMN in short- and mid-term construction projects, such as road construction, tunneling, and mining. Definitely, further research must be carried out to establish a basis for GTT in different environmental impact assessment (EIA) projects and design of monitoring networks in urban projects dealing with air pollution, quantitative and qualitative quality of surface water, groundwater, and soil. Finally, this study confirmed that the developed approach allows to significantly minimize the costs needed for effective environmental monitoring.

CRediT authorship contribution statement

Design of a surface water quality monitoring network in a road construction project using Gamma Test theory.

Sama Azadi: Investigation, Formal analysis, Conceptualization, Methodology, Validation, Data Curation, Writing - Review & Editing. Hamid Amiri: Investigation, Formal analysis, Conceptualization, Methodology, Validation, Data Curation. Mehrdad Ghorbani Mooselu: Data collection, Validation, Writing - Original Draft. Helge Liltved: Formal analysis, Validation, Data Curation, Writing - Review & Editing, Supervision, Project administration. Xun Sun: Writing - Review & Editing. Roberto Castro-Muñoz: Writing - Review & Editing. Grzegorz Boczkaj: Conceptualization, Methodology, Validation, Formal analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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