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OPTIMIZING THE LOCATION OF ROAD WEATHER INFORMATION SYSTEMS (RWIS) STATIONS – A SAMPLING DESIGN OPTIMIZATION APPROACH

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ABSTRACT

This study presents an innovative approach to the design of a road weather information monitoring system (RWIS) that optimally combines spatial data on weather-related road surface conditions with data on traffic volume over a state-wide road network. The optimization method minimizes the spatially averaged ordinary kriging variance of hazardous road surface condition (HRSC) frequencies. Since it is desired that an RWIS should also be located at high traffic demand areas, road class data is implemented in the optimization process. Spatial simulated annealing (SSA) is used to search for the optimal RWIS network design by iteratively examining each possible location and accepting designs that ameliorate a weighted sum of average kriging variance and road class detection capability. This novel approach is applied in the optimization of Minnesota RWIS network to illustrate the distinct features of the proposed method, assess the effectiveness of the current location setting, and recommend new additional stations locations. The findings of the study suggest that the method introduced in this study is useful for determining the optimal RWIS station locations and placing a few in addition to the existing stations by incorporating key elements being considered in practice.

Keywords: Kriging, RWIS, Location Optimization, Geostatistics

1. INTRODUCTION

Wintery countries often experience a high frequency of inclement weather events, which can have a detrimental impact on the safety and mobility of motorists. Generally, road collision rates increase dramatically during inclement weather conditions due to degradation of visibility and traction on the roadway. A study by Liang et al. (1998) found that snow events can reduce the average operating speed by 18.13 km/hr, while Kyte et al. (2001) showed that snow can cause up to 50% reduction in speed. A comprehensive analysis by Agarwal et al. (2005) indicated that snow at various severity levels caused 4-22% and 4-13% reductions in capacity and average operating speed, respectively. More recently, Kwon et al. (2013) confirmed that winter weather events negatively affect the mobility of road users. Their findings suggest that snow-covered roads can reduce the free flow speed and capacity by 17.01% and 44.24%, respectively. In general, snow storms that typically result in poor road conditions are strongly related to high collision rates, reduced roadway capacity, and reduced vehicle speed.

To minimize the safety and mobility impacts caused by winter weather events, it is crucial to enforce systematic snow and ice control, which can be realized by integrating various winter road maintenance operations including snow plowing, sanding, and salting. Not only can efficient and effective winter road maintenance programs reduce the risk of vehicular collisions but they can also vitalize and promote traffic movement. Fu et al. (2005) showed with strong statistical evidence that lower rates of collisions on roads are associated with better road surface conditions, which could be the result of improved winter maintenance operations such as anti-icing, pre-wetting, and sanding. Qiu and Nixon (2008) explored direct and indirect causal effects of adverse weather and winter maintenance actions on mobility in the context of traffic speed and volume. Their findings confirmed that plowing and salting operations have significant positive effects on increasing the speed at which it is safe to drive.

While winter road maintenance is indispensable, it entails substantial financial costs and environmental damage. North American transportation authorities, for instance, expend more than $3-billion annually on winter road maintenance activities such as executing snow removal and applying salt and other chemicals for ice control. Use of these chemicals has become an increasing environmental concern because they contaminate the ground and the surface water, damage roadside vegetation, and corrode infrastructures and vehicles. To reduce the costs of winter road maintenance and the use of salts, many transportation agencies are seeking ways to optimize their winter maintenance operations and improve the safety and mobility of the traveling public.

While effective in providing valuable information, RWIS stations are expensive to install and operate and, therefore, can only be deployed at a restricted number of locations. Considering the immense road network that often needs to be monitored and the diverse road conditions that could develop any time during winter, RWIS stations must be placed deliberately to ensure they are most informative in providing the inputs required for stimulating competent winter maintenance operations. Currently, however, there are significant gaps in knowledge and methodology for effective planning of RWIS stations over a statewide road network. In practice, RWIS stations are placed through an ad-hoc and subjective process entailing a series of discussions and interviews with many individuals including meteorologists, traffic engineers, regional/local maintenance personnel, and other industry experts, requiring substantial amounts of effort and time. A few RWIS siting guidelines are available but they are limited to providing very general information and/or local site recommendations such as the availability of power and communication utilities (Manfredi et al., 2008). Therefore, it is of high necessity to develop an efficient and systematic approach to determining the RWIS location.

In this research, we introduce a systematic framework to optimize the spatial design of an RWIS network in a region, and demonstrate the value of the model using a real world case study. The work has made both methodological and practical contributions to the field of interest. Methodologically, the formulation of the RWIS location optimization problem is foundational with several unique features, including explicit consideration of spatial correlation of winter road weather conditions and travel demand. The model allows development of a balanced solution considering maintenance needs as well as the travelling publics. The practical value of the proposed model is demonstrated using a real world case study.

The remainder of this paper proceeds as follows. Section 2 describes the methods used in this study while numerical results on a case study are presented in Section 3. Section 4 is followed at the end to provide the conclusions.

2. METHODOLOGY

To optimize a monitoring network such as RWIS, it is critical to select a suitable criterion such that the fitness of any given design can be evaluated and quantified. An RWIS station typically consists of atmospheric, pavement, and/or water-level monitoring sensors that constantly (every 10-15 min) disseminate measurements including air and pavement temperatures; wind speed and direction, (sub)surface temperature and moisture, precipitation type, intensity and accumulation, visibility, dew point, and relative humidity (Manfredi et al., 2008). Furthermore, each RWIS station reports road surface condition status based on current observations: areas that experience hazardous road surface conditions (HRSC) are flagged for a prompt remedial winter maintenance action. These so-called hazardous surface conditions include snow/ice warning, snow/ice watch, and frost. As previously discussed, RWIS information makes it possible to perform proactive winter maintenance operations such as anti-icing (i.e., applying salt, mostly in liquid form, in advance of an event), which reduces the amount of time required to restore the roads to a clear and dry state at lower costs. Since a large portion of RWIS benefits lies in the use of information, it is critical to locate stations in such a way that produces the most accurate information on various hazardous events. This argument remains valid under the assumption that an increase in estimation or monitoring capability of hazardous conditions will contribute to improving the overall quality of winter road maintenance operations.

In order to model the monitoring capability of an RWIS network, this paper proposes to apply a popular geostatistical approach called kriging (described further below). Monitoring capability of given RWIS network can therefore be captured by summarizing the kriging variance (i.e., the expected estimation errors). A nice property of kriging variance is that these errors depend only on distance between sampling locations, assuming that the spatial correlation structure over the domain is known (Goovaerts, 1997). Because observed HRSC values are not required, RWIS stations can be moved and the effect of these movements on estimation errors can be evaluated. This means that kriging variance can be used as a criterion to optimize and evaluate an RWIS sampling design. In addition to this, another optimization criterion is introduced to reflect the needs of installing an RWIS station for covering the high travel demand areas. Incorporation of the said criteria has been decided based primarily on the findings from a survey dedicated to reviewing and examining the current best practices for locating an RWIS station in North America. In this survey, most participants responded that they would consider weather related hot-spots, such as those commonly encountered when roads are icy, snowy, or frosty, as posing the greatest potential danger to motorists. Equally important, they would also consider high traffic and accident-prone areas that serve a large number of travelers as key factors to consider in RWIS station placement. The following section provides a detailed description of the kriging method as well as the location optimization criteria.

2.1 Kriging estimation errors

The main idea behind kriging is that the predicted outputs are weighted averages of sample data, and the weights are determined in such a way that they are unique to each predicted point and a function of the separation distance (lag) between the observed location, and the location to be predicted. In addition, kriging provides estimates and estimation errors at unknown locations based on a set of available observations by characterizing and quantifying spatial variability over the area of interest (Goovaerts, 1997). Previous studies in a variety of different fields, mainly in hydrology and ecology, support the applicability and usefulness of geostatistics as a tool for an optimum selection of sites for monitoring environmental and meteorological variables. For example, numerous authors used geostatistic techniques to optimize groundwater observation wells by delineating the locations having maximum kriging variance (Nunes et al., 2004; Yeh et al., 2006; Brus and Heuvelink, 2007). Another study conducted by van Groenigen et al. (1999) employed a heuristic optimization approach namely simulated annealing (SA) to determine the optimal soil sampling schemes for obtaining the minimal kriging variance. Another study by Amorim et al. (2012) addressed the problem of planning a network of weather (air temperature) monitoring stations using geostatistical estimation error as a criterion. The authors used the geostatistical uncertainty of estimation in the location process for determining the optimal set of locations depending on the spatial arrangement of the stations.

There are several different types of kriging (simple kriging, ordinary kriging, and universal kriging), but we focus on one of the most well-known and established variants called ordinary kriging (OK).

Let's assume that the random function Z(x) satisfies with second order stationary (and thus intrinsic stationary), the covariance between any two random errors depends only on the distance that separates them, not their exact locations. Let x and x_i be location vectors for estimation point and a set of observations at known locations, respectively, with $i = 1, \dots, n$, and Z be a variable of interest. Based on n number of observations, we are interested in estimating a condition at any given location, denoted by $\hat{Z}(x)$. Hence, the OK estimator can be expressed as (Olea, 1999):

[1] $$\hat{Z}(x) = \sum_{i=1}^{n} \lambda_i(x)\, Z(x_i) + \left[1 - \sum_{i=1}^{n} \lambda_i(x)\right] m(x)$$

The unknown local mean is filtered from the linear estimator by forcing the OK weights λ to sum to 1. The OK estimator can then be written as:

[2] $$\hat{Z}(x) = \sum_{i=1}^{n} \lambda_i(x)\, Z(x_i) \quad with \quad \sum_{i=1}^{n} \lambda_i(x) = 1$$

The weights are determined such that the estimated variance is minimized under non-bias condition, $E\{\hat{Z}(x) - Z(x)\} = 0$. Minimization of variance subject to the unit-sum constraint on the weights calls the definition of a Lagrangian $L(x)$ which can be described as a function of the data weights, and a Lagrange parameter, $\Lambda(x)$:

[3] $$L = \sigma_E^2(x) + 2\Lambda(x)\left[1 - \sum_{i=1}^{n} \lambda_i(x)\right]$$

Taking the partial derivatives with respect to the weights and the Lagrange parameter and equating them to 0 will lead to the following system of equations:

[4] $$\begin{cases} \sum_{j=1}^{n} \lambda_j(x)\, C_R(x_i, x_j) + \Lambda(x) = C_R(x_i, x), \qquad i = 1,...n \\ \sum_{j=1}^{n} \lambda_j(x) = 1 \end{cases}$$

Once the OK weights and Lagrange parameter are determined by solving the system of equations, the OK error variance can be defined by Equation 5 (Olea, 1999):

[5] $$\sigma_{OK}^2\left[\hat{z}(x \mid Y)\right] = C(0) - \sum_{k=1}^{m} \lambda_k(x)\, C(x_k, x) - \Lambda$$

where Y denotes a set of observations at known locations. For a more compact display of the results, Equation 5 can be expressed in matrix form:

[6] $$\lambda_{OK}(x) = V_{OK}^{-1} v_{OK}$$

where

$$\lambda_{OK}(x) = \begin{bmatrix} \lambda_1 \\ \vdots \\ \lambda_1 \\ \Lambda \end{bmatrix}, \quad V_{OK} = \begin{bmatrix} C(x_1, x_1) & \cdots & C(x_1, x_n) & 1 \\ \vdots & \ddots & \cdots & \vdots \\ C(x_n, x_1) & \cdots & C(x_n, x_n) & 1 \\ 1 & \cdots & 1 & 0 \end{bmatrix}, \quad v_{OK} = \begin{bmatrix} C(x_1, x) \\ \vdots \\ C(x_n, x) \\ 1 \end{bmatrix}$$

Upon determination of OK weights, the OK error variance can be calculated as:

[7] $$\sigma_{OK}^2[\hat{z}(x \mid Y)] = C(0) - v_{OK}^T V_{OK}^{-1} v_{OK}$$

It is worthwhile to note that the method described above is used to solve the kriging system of equations in terms of covariances, instead of semivariances. This is primarily for convenience in handling the square matrices, despite the slight loss in generality (Olea, 1999). Under a second order stationarity assumption, both the covariance and semivariogram functions are related and their outputs are equivalent.

2.2 Problem Formulation

A number of prior studies have suggested that an RWIS station should be located at high-travel-demand areas such that the benefits to road users can be maximized (Garrett et al., 2008; Buchanan and Gwartz, 2005; Mackinnon and Lo, 2009). For this reason, the majority of the North American transportation agencies (and other regions) are inclined to incorporate macro level traffic criteria such as collisions, traffic volume, and road class when deciding the RWIS station locations.

In this study, we use road class information to reflect the needs of installing an RWIS station at high travel demand areas. A primary reason for implementing the road class information is due to the fact that there is a considerable amount of variation in the range of traffic volume and collision data. Such a huge variation may produce a biased result when combined with other non- or less-skewed data (e.g., HRSC frequency). Hence, in addition to the first criterion representing HRSC frequencies, road class is added as another criterion to obtain a well-balanced optimal RWIS network.

As discussed in the previous section, average ordinary kriging variance is calculated to reflect the needs for installing RWIS stations for improved winter road maintenance operations (i.e., locations with higher errors require more attention than others with lower errors), and sum of average kriging variance should therefore be minimized. The traffic criterion pertaining to road class should also be minimized since an RWIS station should be located at high-travel demand areas (lower the road class is, higher the traffic volume is). Therefore, the two aforementioned RWIS station allocation criteria are included in the objective function as follows:

$$[8] \quad Minimize\ \left[HRSC \cdot w_{HRSC} + RC \cdot w_{RC}\right]$$

where *HRSC* and *RC* represent the average kriging variance of hazardous road surface conditions, and road class, respectively. The weighting terms w_{HRSC} and w_{SC} are included such that decision makers would have the freedom of choosing different weights depending on the needs of the traveling publics, winter road maintenance requirements, and their respective priority in locating RWIS stations. Note that the kriging variance term is root-squared so that estimation errors can be expressed in the same unit and magnitude as the observations themselves.

2.3 Optimization with spatial simulated annealing (SSA)

The problem defined previously is a non-linear integer programming (NIP) problem which is computationally intractable; heuristic techniques are often required to solve these types of problems in a realistic way. In this research, we applied a variant of one of the most successful techniques called spatial simulated annealing (SSA), which is a spatial counterpart to simulated annealing (SA, Kirpatrick, 1984). SSA is an iterative combinatorial optimization algorithm in which a sequence of combinations is produced by deriving a new combination from slightly and randomly modifying the previous combination (van Groenigen, 1999). In principle, by discretizing the region of interest, kriging variance for all possible combinations of the station locations could be evaluated, and the combination that produces the smallest value would be selected as the optimal solution. However, this is impractical as the number of combinations would be formidable, meaning that an exhaustive search over all possible outcomes is computationally infeasible. In the search process, SSA not only accepts improving solutions, but also worsening solutions, based on a certain probability that is defined to minimize the risk of falling prematurely into local minima (van Groenigen and Stein, 1998). Therefore, the algorithm is able to find high quality solutions that are not dependent on the selection of the initial solution compared to other local search algorithms. SSA has gained its popularity by numerous researchers praising its robustness and easy implementation, particularly for optimizing sampling schemes in situations where observations are spatially correlated in geographic space (van Groenigen et al., 2006; Brus and Huevelink, 2007; Sacks and Schiller, 1988; Melles et al., 2011). For more information on how the SSA algorithm works, readers are referred to a paper by van Groenigen and Stein (1998)

3. CASE STUDY

3.1 Study area and Data Description

The proposed approach is examined via Minnesota RWIS network, where there are a total of 97 RWIS stations currently in operation, and the number is expected to increase over the next few years. The current Minnesota RWIS network is depicted in Figure 1. To improve the computational efficiency, discretized network is used in this study.

Mn/DOT provided their regional RWIS data from a total of 62 RWIS stations which were collected at 15-min intervals over three consecutive winters (i.e., October to March) between 2010 and 2013. The data came stratified by individual stations each containing nearly one million rows of measurements including the variable of interest - surface condition status. There are a total of 15 surface status codes describing current representative surface conditions expressed in a descriptive format. These status descriptions are listed in order of severity and further classified into four different categories with the most critical category listed first. In this research, the top category representing so-called hazardous road surface conditions were considered, and they were snow/ice warning, frost, wet below freezing, and snow/ice watch. Each data entry was checked and counted if it reported anything that belonged to the top category under consideration. A VBA script was written to efficiently process over 58 million rows of data, returning a yearly average of HRSC frequency for each corresponding RWIS station.

As pointed out in previous sections, a fundamental assumption of implementing geostatistics is the existence of spatially correlated data, which describes the commonly held notion that near-by measurements will have similar values and degree of dissimilarity increases as a function of distance. Since the assessment of such spatial correlation is a prerequisite to further pursue and apply kriging, it is critical to model the semivariogram based on the information provided by the attribute of interest – the hazardous road surface conditions. The processed data were subsequently fed into constructing a semivariogram, a model characterizing the spatial autocorrelation of HRSC measurements to be used in estimating the kriging variance in the objective function. Modelling of a semivariogram entails selection of the most adequate model type and the determination of its parameters. Assuming an isotropy, the semivariogram was fit with the exponential model given an estimated nugget variance of zero, a partial sill (sill minus nugget) of 0.94, and range of 95,000 m. Ordinary kriging was then performed using R. The square root of kriging variance discussed in Section 2 was implemented as the first criterion in the objective function.

Another set of data provided by Mn/DOT was traffic volume (AADT) collected over a 10 year period. Since we are interested in incorporating road class information, the road class classification scheme of Mn/DOT was used to convert the traffic volume data to its corresponding road class. Since the minimum spatial unit was 3 kilometers, numerical values representing the road class data were aggregated and averaged over a 9-km^2 gridded surface so that the traffic portion of the optimization criterion could be evaluated.

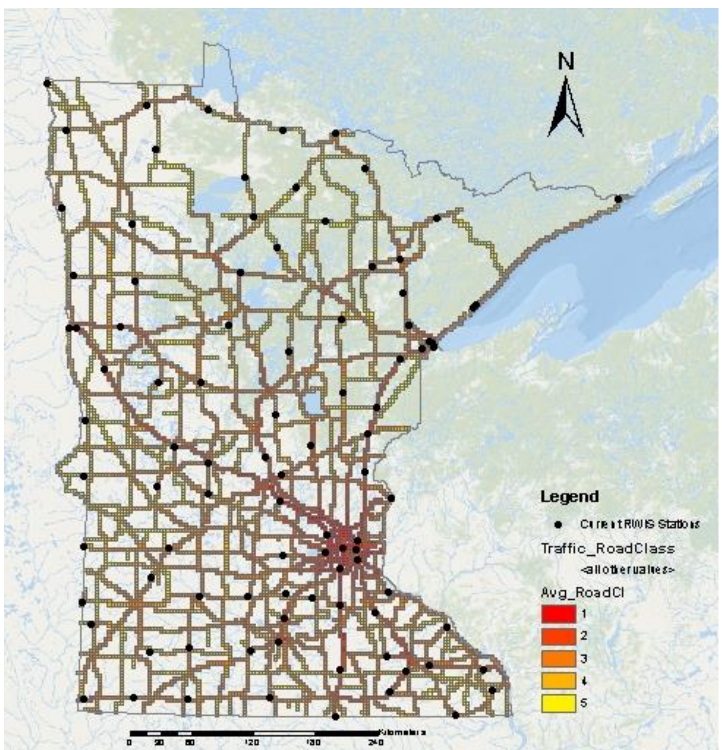


Figure 1: Minnesota road and RWIS networks

3.1 Optimal Minnesota RWIS Network

The proposed model was implemented in designing an optimal RWIS network using the dual criteria discussed earlier. First, as there are currently a total of 97 RWIS stations in Minnesota, the optimization algorithm was run to obtain an all-new 97 RWIS station design using different weights to better appreciate different network design scenarios. The optimized and existing RWIS networks were then compared by determining a numerical value reflecting the performance (i.e., objective function value) of each network design to demonstrate the superiority of the optimized network. In addition, RWIS network expansion scenarios were proposed by delineating a new set of 10 and 20 additional RWIS stations in the existing RWIS network of Minnesota. When running the optimization with the SSA algorithm, the initial temperature was chosen such that the average acceptance probability was 0.80 (accepting worsening designs $p \leq 0.2$) to avoid being trapped in local minima. This probability of accepting a worsening design was set to exponentially decrease as the optimization progresses to ensure convergence. The optimization was run over a total of 6,000 fixed iterations in generating each optimal network design solution. Analyses were performed on a windows operating desktop computer equipped with a 3.39 GHz processor and 8.00 GB of RAM, and a series of functions coded in R was used in this study.

3.1.1 All-new optimal RWIS network

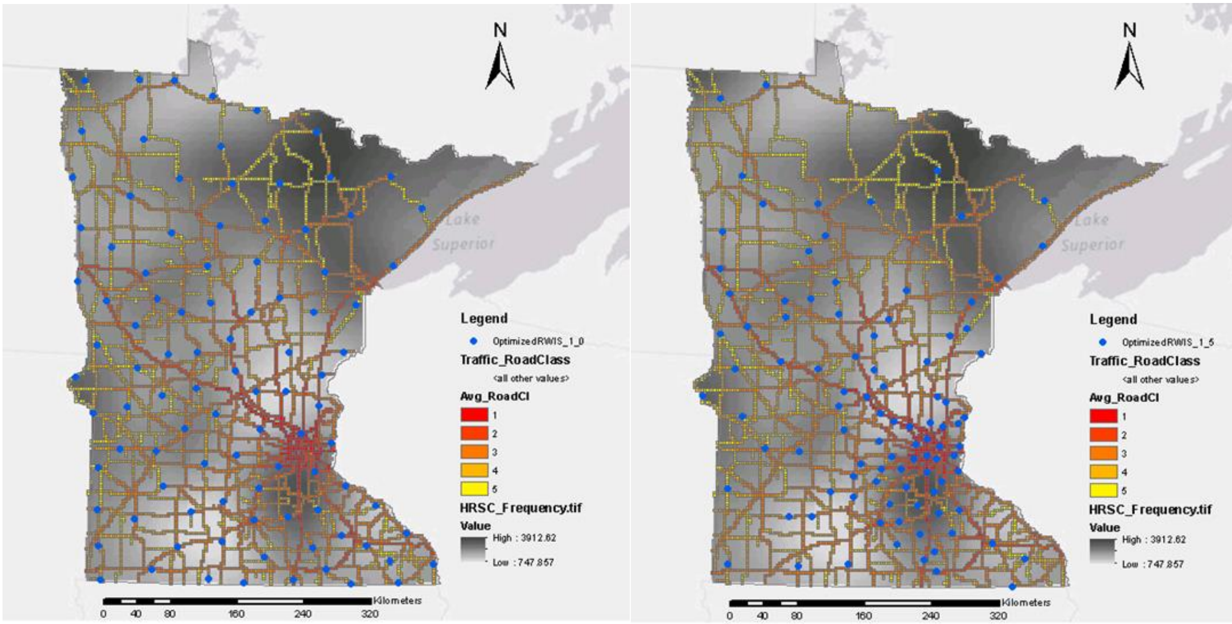
Relocating the entire set of existing RWIS stations may not be possible due to economical infeasibility, but evaluating the current network of 97 stations in relation to an optimal design provides valuable information with which to assess the current location setting, and simulates how optimal locations will change when assigning different weights to the two different criteria considered in this study. As discussed earlier, the greatest benefit of the proposed approach is its ability to simulate and optimize RWIS station locations under any given settings that users define. This surely is an advantageous option, which is never possible in real world situations because costs associated with establishing any monitoring stations are very high (Chang et al., 2007). Likewise, it provides decision makers with the freedom to choose different weights depending on the needs of the traveling public, winter road maintenance requirements, and their respective priority in locating RWIS stations.

As such, the RWIS network optimized under two different weights is presented in Figure 4. The aggregated road classes and kriged HRSC measurements are superimposed on the same map to help better appreciate and recognize how assignment of varying weights could contribute to deciding the optimal location for an individual RWIS station. In this figure, RWIS stations are represented by blue circles. It is worthwhile to note that for each weighting scheme, the optimization was run three times and the outputs were visually compared to confirm that the optimization outputs were very similar and comparable to each other. The intent of multiple tryouts was to ensure that the SSA algorithm had reached a (near) optimal solution without being trapped in local minima; an inherent problem of the SSA algorithm and all other metaheuristic algorithms currently available today.

Fig 4 (a) represents a case when OK variance is solely used in the objective function to minimize the spatially averaged kriging variance. In this figure, it is evident that RWIS stations are well spread across the entire state, providing the maximum RWIS coverage in term of its monitoring capability of hazardous road surface conditions. In fig (b), the traffic criterion, representing road class, has been added to the first criterion with equal weights. As can be seen clearly, incorporation of the traffic criterion was able to capture high travel demand areas, providing an improved balance. Such a difference in its pattern is well manifested; a higher number of RWIS stations have been allocated to areas exposed to high traffic demand areas.

As for the iteration schedule of the performed optimizations, Figure 5 illustrates the decrease of the dual objective function as number of iterations increases. It is apparent after around 5,000 iterations, the objective function for all runs starts to level off and slowly reaches its minimum value as evidenced by the lower value obtained at the 6,000th iteration. As explained previously, the SSA algorithm has a mechanism that reduces the risk of falling prematurely into local minima, provided that there is a certain probability and a decaying function controlling how fast the objective function converges. Such behavior is well presented by the continuous fluctuations and peaks observed until it stabilizes at around 6,000 iterations. In terms of computational efficiency, optimization converged slowly and took an average running time of 9 + hours for optimizing a single network.

To evaluate the overall efficacy of each optimized network with respect to the existing network, the objective function was used to calculate its corresponding numerical value for all individual outputs as well as the current RWIS network. This evaluation metric is simply the lowest value obtained at the end of each optimization. For the existing network, a comparable yet equivalent approach is exercised by adding the averaged OK variance and road class given the current RWIS station locations. As a result, the percent differences in the objective function values between the existing and the optimized network, which can also be interpreted as perceived benefits, were found to be 17.30% for Fig. 4(a) and 20.05% for Fig. 4(b), signifying that the optimized networks are "better" in terms of monitoring capabilities of various hazardous road surface conditions while considering the needs of serving the traveling publics, as defined in the objective function.



(a) (b)

Figure 4: All new 97 optimized RWIS station locations using the combined criterion using $w_1 = 1$ combined with (a) $w_2 = 0$ and (b) $w_2 = 1$

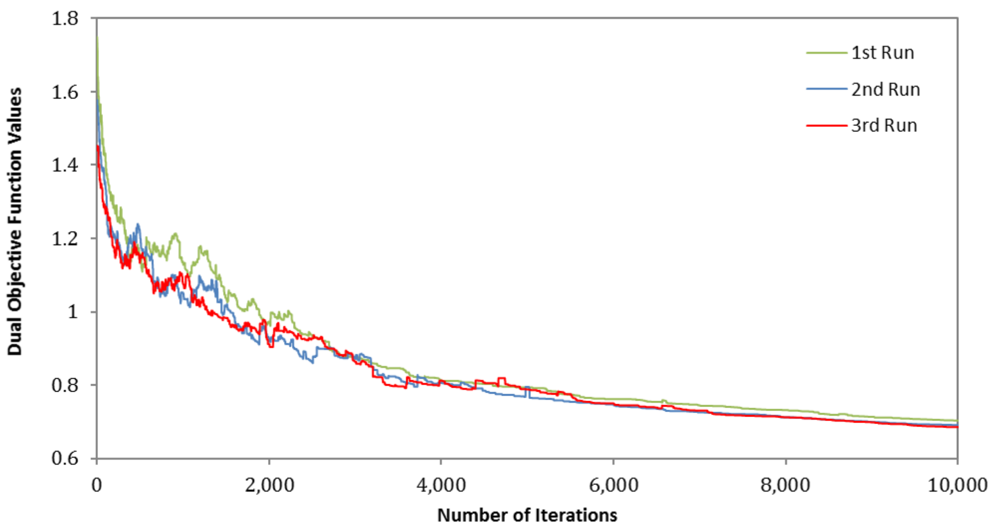
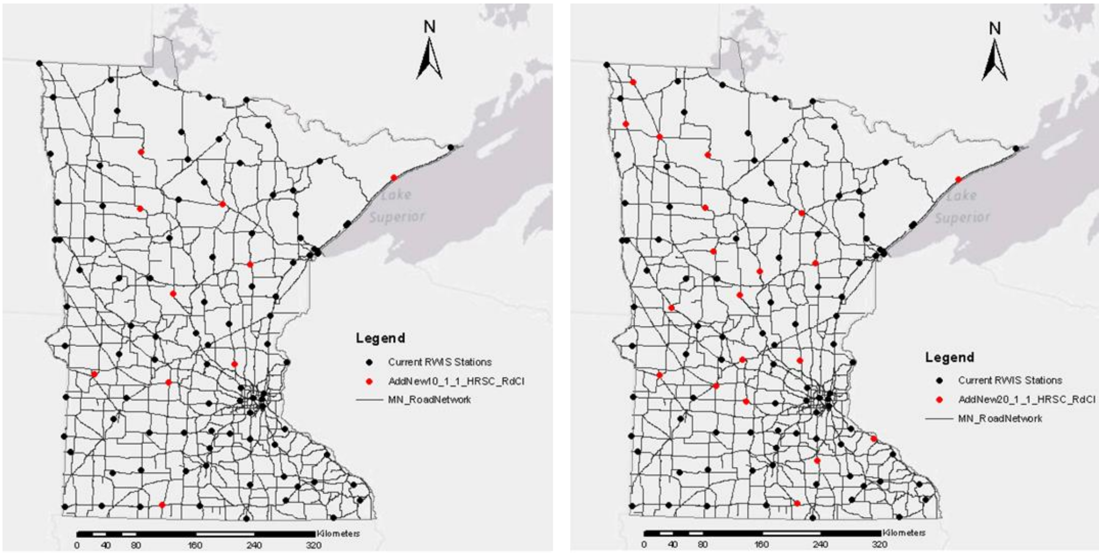


Figure 5: Decrease of the combined objective function as a function of iterations

3.1.2 Expansion of current RWIS network

In the previous section, the proposed method was applied to delineate optimal locations for the entire existing set of RWIS stations. However, this may be not a realistic option from a practical standpoint since it is extremely costly to relocate the entire network. Hence, a more feasible option is to expand the current RWIS network as described below. The optimization problem has therefore been modified to reflect the changes in the base condition. The objective function is evaluated at each iteration considering that there are permanently fixed 97 RWIS stations throughout the entire optimization process. Identical optimization parameters and weighting schemes ($w_1 = w_2 = 1$) were used to locate 10 and 20 additional RWIS stations (red circles) as depicted in Figure 6.

As can be seen in this figure, minimization of sum of averaged kriging variance, featured in the objective function, effectively prevented new stations from being closely located in the vicinity of existing stations. From a visual inspection, it can be asserted that new stations fill gaps in the existing RWIS network. In addition, evaluation of objective function values show that the current network improved by 11.5% and 16.3% with the placement of 10 and 20 additional stations, respectively.



(a) (b)

Figure 6: Expansion of current RWIS network with (a) 10, and (b) 20 additional stations

4. CONCLUSIONS

In this research, an innovative framework was introduced for the purpose of locating RWIS stations over a regional highway network. In the proposed method, the weighted sum of average kriging variance of hazardous road surface conditions (HRSC) was used to determine the optimal RWIS network design. This method relies on a sensible assumption that minimizing the total estimation error would, in due course, contribute to improving the global effectiveness and efficiency of winter road maintenance operations. Road class data were also incorporated and weighted to provide a balanced network that considers demands of the traveling public. The spatial simulated annealing (SSA) algorithm was employed to solve the combinatorial optimization problem ensuring convergence. Case study based on Minnesota, US exemplified two distinct scenarios –redesign and expansion of the existing RWIS network. Findings indicate that optimally redesigned RWIS networks are, on average, 18.90% better than the existing RWIS network. The study further revealed that the deployment of 10 and 20 additional RWIS stations would improve the current network by 11.5 % and 16.3%, respectively. The findings of our study show that the new approach is easy and convenient to implement, thus appropriate for real-world applications by integrating key features (road weather and traffic) considered in practice. In addition, Finally, we have presented the results to the Mn/DOT and received overwhelming positive feedback regarding the reasonableness of the solutions identified by our model. They have also confirmed that these solutions will be considered as the primary input to their decision on the location of their future RWIS stations.

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