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Robust Route Optimization for Gritting/Salting Trucks: A CERCIA Experience

Highway authorities in marginal winter climates are responsible for the precautionary gritting/salting of the road network in order to prevent frozen roads. Winter road maintenance is a truly challenging task that has a direct impact on both businesses and daily life of people all over the world. It also represents a global market costing many countries millions of pounds (or dollars) each year. In the case of UK, there are approximately 3,000 precautionary gritting routes that cover about 120,000 km or 30% of the entire road network. On nights with forecasted snow or ice, these routes require treatment to safeguard the road network, i.e., the safety of road users. Typically, the cost of maintenance for a winter season is from £200/lane km to £800/lane km [1].

For efficient and effective road maintenance, accurate road surface temperature prediction is required. However, this information is useless if an effective means of utilizing this information is unavailable. This is where gritting route optimization plays a crucial role. The decision whether to grit the road network at marginal nights is a difficult problem. The consequences of making a wrong decision are serious, as untreated roads are a major hazard. However, if grit/salt is spread when it is not actually required, there are unnecessary financial and environmental costs. The goal here is to minimize the financial and environmental costs while ensuring roads that need treatment will be gritted in time. Road Weather Information System (RWIS) has been used worldwide to aid this decision making, but it is imperative that gritting routes are planned in advance to make effective use of limited resources (e.g., trucks and salts) within the constraints (e.g., road conditions, budget and time).

In practice, optimization has traditionally been a manual task and is heavily reliant on local knowledge and experience. Currently, a 'static,' often paper-based, approach is used to optimize gritting routes within certain constraints, including the road network, vehicle capacity, number of vehicles and personnel. In this article, a Salting Route Optimization (SRO) system that combines evolutionary algorithms with the neXt generation Road Weather Information System (XRWIS) is introduced. The synergy of these methodologies means that salting route optimization can be done at a level previously not possible.

The neXt generation Road Weather Information System (XRWIS)

XRWIS is a high-resolution route-based forecast system which predicts road temperature for a 24-hour period. Instead of modelling road conditions at a single site and interpolating temperatures by thermal maps (literally a static map showing the variation of temperature across the road network), XRWIS models surface temperature and condition at thousands of sites in the road network. This is achieved by consider-

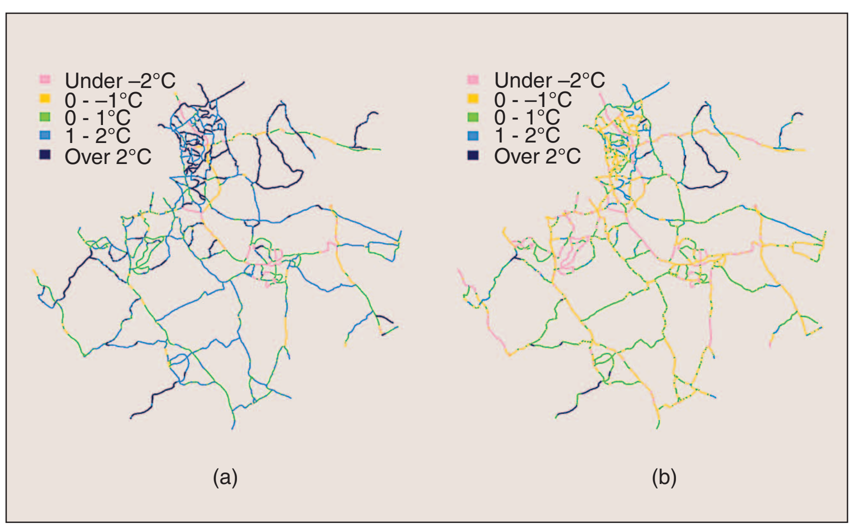

FIGURE 1 Temperature distributions for two nights in South Gloucestershire (UK): (a) on a cold night and (b) on a marginal night.

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ing the influence of local geography on the climatology of the roads. Data are collected along each gritting/salting route by conducting a survey of the sky-view factor (a measure of the degree of sky obstruction by buildings and trees) [2]. This is then combined with other geographical parameters (latitude, longitude, altitude, slope, aspect, road construction, thermal map residual temperature, land use and traffic volume) to produce a high-resolution geographical parameter database.

The geographical data are combined with mesoscale meteorological data in an energy balance model to predict road conditions at typical spatial and temporal resolutions of 20 meters and 20 minutes, respectively. The output is displayed as a color-coded map of road temperature and condition that is then disseminated through the Internet to the highway engineer. Figure 1 shows example temperature forecasts of the road network in the South Gloucestershire, UK, for two nights. The colour of each point represents the temperature predicted by XRWIS, varying from dark blue for cold points to pink for warm points.

Salting Route Optimization (SRO) System

Figure 2 shows the overall architecture of our Salting Route Optimization (SRO) system. XRWIS in the system provides typical temperature distributions to the Evolutionary Algorithm module. After evolution, predicted temperature distributions are given to an acquired robust route to yield actual routes for daily operation. Temperature distributions presented by XRWIS are combined with 'commercial off the shelf' vector routing data before being translated into Capacitated Arc Routing Problem (CARP) instances [3]. Evolutionary Algorithms then find solutions that show the best performance for the CARP instances simultaneously. A Memetic Algorithm, which is based on a hybrid algorithm of Evolutionary Algorithms and local search methods, for finding robust solutions is used [4].

The main steps of the Memetic Algorithm include: selecting parents, reproducing offspring, applying local search to offspring, and replacing resultant offspring if the offspring is better than the worst individual in the population. A distinct feature of the proposed method is that a crossover operation and local search methods are applied to only one CARP instance at each generation while the fitness function is composed of an ensemble of evaluations of several CARP instances. That is, at the beginning of each generation, a CARP instance is selected for further evolutionary variations in this generation. This selection is based on weights, which are also used in fitness evaluation. By selecting one CARP instance at every generation, the Memetic Algorithm can concentrate on optimizing the selected CARP instance. The weights are updated for every predefined interval of generations as

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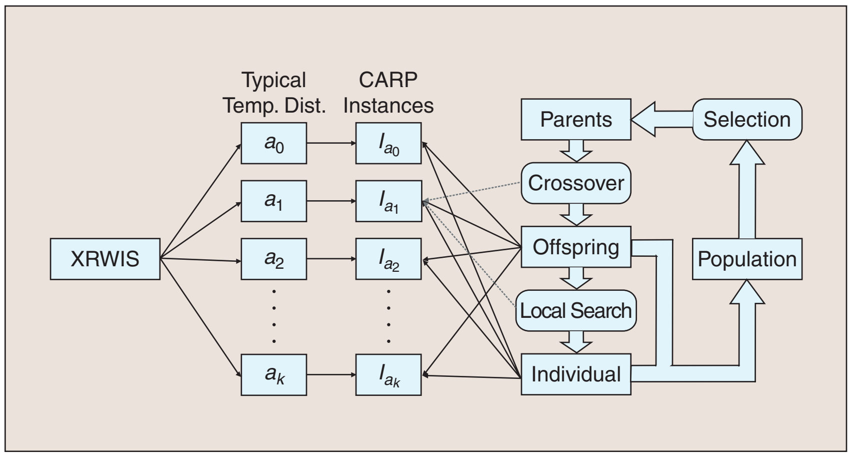

FIGURE 2 The system architecture of the Salting Route Optimization (SRO) System.

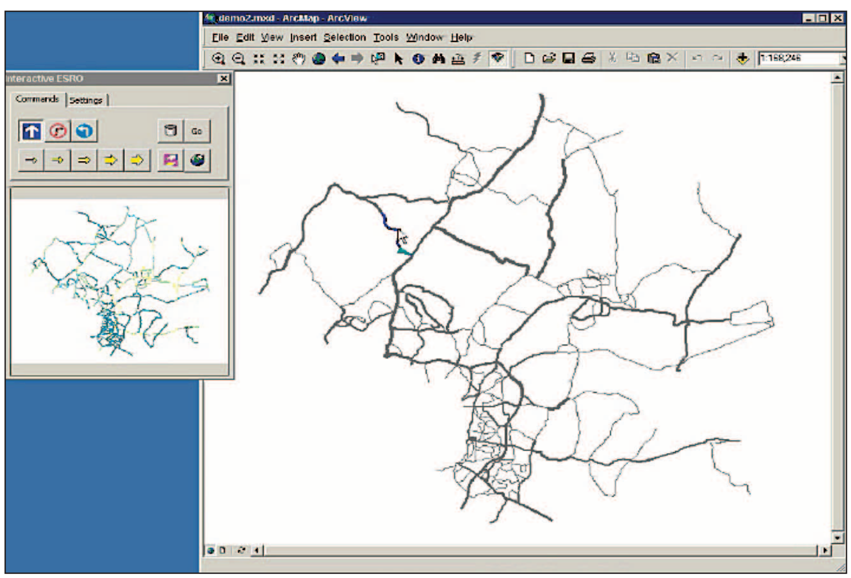

FIGURE 3 The graphical user interface of the Salting Route Optimization (SRO) System.

described in the "Weights and Their Update" section.

Since the SRO system is ultimately designed for practical use, an intuitive GUI, as shown in Figure 3, is developed to display the optimized and robust routes. The GUI is also used by highway authorities to incorporate into the SRO system additional local knowledge not available in 'commercial off the shelf' vector routing data, such as road preference by drivers, desirable turns, one-way roads, etc.

Robust Solutions for Salting Route Optimization

Searching for robust solutions is currently one of the most significant topics in evolutionary optimization in uncertain environments [5]. Robust solutions are needed for problems whose decision variables or environmental parameters[1] are subject to perturbation. We require the solutions to be as similar to each other as possible for different variables and parameters while pursuing optimality of the solutions. This is an important practical consideration because, as an example, it would be confusing to the highway authority and truck drivers if every different road temperature gave rise to an entirely different set of optimized routes.

In the case of Salting Route Optimization, robust solution can be represented by an optimal design value X for the following function:

$$F(X) = \int E(X, a) p(a)\, da, \qquad (1)$$

where X and a indicate design variables, i.e., gritting routes and possible temperatures. $E(X, a)$ denotes the distance of gritting routes X on temperature a. $p(a)$ indicates the temperature distribution.

Warmer and colder roads exist mainly as a result of microclimatological effects caused by the local geography. Although the distribution in temperature will vary daily across a road network, warmer sections are usually warmer than the rest of the road network and colder sections are usually colder. As a result, even on cold nights, some warmer sections of road may not require salting whereas colder sections of the road network may need treatment even on the least marginal nights. It is difficult to compute exactly equation (1) since the number of possible values of a is large and the probability distribution $p(a)$ is unknown. Hence, a number of typical temperatures are used in our SRO system in evolving robust solutions.

Let A_e be a set of temperatures used in evolution. The following function is useful for evaluating the robustness of salting routes:

$$\hat{F}(X) = \sum_{a_i \in A_e} \frac{1}{|A_e|} E(X, a_i). \qquad (2)$$

Chromosome Representation and Fitness Evaluation

A permutation encoding method is employed in our evolutionary algorithm. The chromosome of an individual is composed of several special symbols and edge IDs. Special symbols s_1 indicate the beginning of tours for each truck. For example, the following chromosome:

`2 6` s_1 `5 4 7 1` s_2 `8 3`

indicates tours for two trucks: $T_1 = \{5\ 4\ 7\ 1\}$ and $T_2 = \{8\ 3\ 2\ 6\}$.

Because our Evolutionary Algorithm tends to find solutions biased toward easier $E(X, a_i)$ in the case of equation (2), a normalized function $E_N(X, a_i)$ is employed in our fitness function:

$$\hat{F}(X) = \sum_{a_i \in A_e} w_i E_N(X, a_i), \qquad (3)$$

where w_i $(0 < w_i < 1, \sum_{a_i \in A_e} w_i = 1)$ denotes the weight for temperature a_i. The normalized function $E_N(X, a_i)$ is defined as follows:

$$E_N(X, a_i) = \frac{E(X, a_i) - E^*(a_i)}{E^*(a_i)}, \qquad (4)$$

where $E^*(a_i)$ is a real number indicating the difficulty of solving the CARP instance at temperature a_i, such as lower bounds and the distance searched by other algorithms. $E^*(a_i)$ is, in essence, defined as the shortest route distance for the CARP instance at temperature a_i searched in advance by using the Memetic Algorithm proposed previously [6].

Weights and Their Update

Weights in our system are used to balance the importance we give to route optimization at different temperatures. Weight updates correspond to changes in the direction of evolution driven by our Evolutionary Algorithm. For a predefined interval of generations L, the weight w_j is updated by using the best tour evaluation $E_N^b(X, a_i)$ found so far by the Evolutionary Algorithm:

$$w_j = \frac{\exp E_N^b(X, a_j)}{\sum_{k=1}^{m} \exp E_N^b(X, a_k)}, \qquad (5)$$

where m is the number of different temperatures considered by the algorithm.

Evolutionary variation operators, including crossover, and local search methods are applied to only one CARP instance in every generation. The EAX operation proposed by Nagata and Kobayashi [7], which utilizes distance information among edges, is employed as our crossover operator. The following probability distribution is used to randomly decide which CARP instance is subject to variation operators:

$$s_i = \frac{w_i}{\sum w_j}. \qquad (6)$$

We select one CARP instance at each generation because changing several CARP instances in a single generation is likely to pull evolution toward different and conflicting directions. Furthermore, easier CARP instances may be optimized faster, which may make the optimization of harder CARP instances more difficult because the evolution was led to a part of the search space, by the easier CARP instances, that are not amenable to finding near-optimal solutions to harder CARP instances. However, much future work needs to be done on this topic to fully understand the search dynamics.

[1] The environmental parameters indicate parameters that characterize the fitness function.

Comparison with Existing Solutions in the Real World

Robust solutions were evolved by using 10 different temperatures and then compared with the routes currently used by the South Gloucestershire Council. Two more temperature distributions that are not used in evolution are also employed. Figures 4 and 5 show routes on marginal and cold days, where gray lines, colored thick lines and colored thin lines denote routes with no trucks, routes with a truck, and deadheading edges, respectively. In comparison with the routes currently in use, our robust solution can provide more than 10% savings in terms of total distance travelled by trucks.

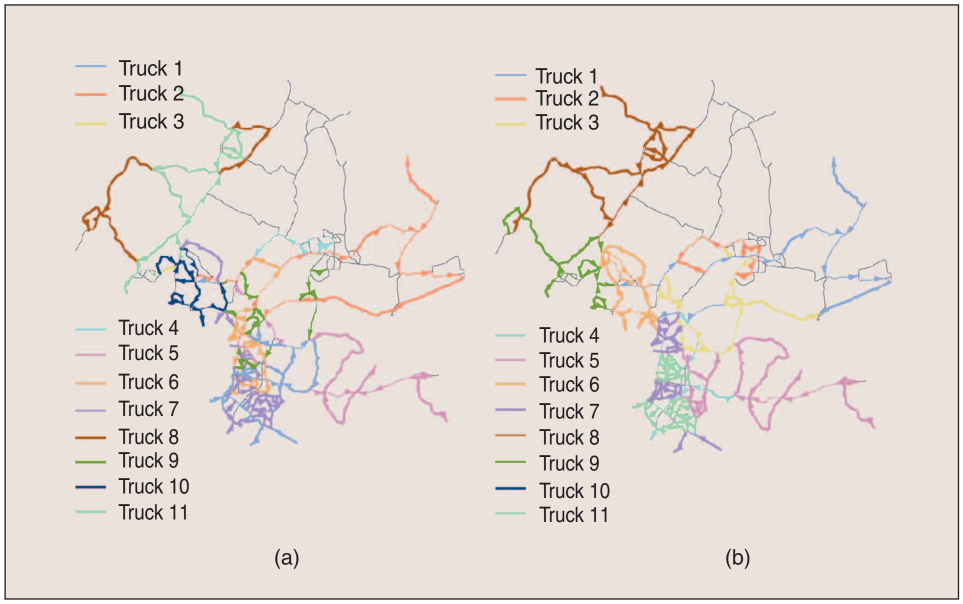

FIGURE 4 (a) Optimized robust routes by our SRO system and (b) the existing routes for a marginal temperature distribution.

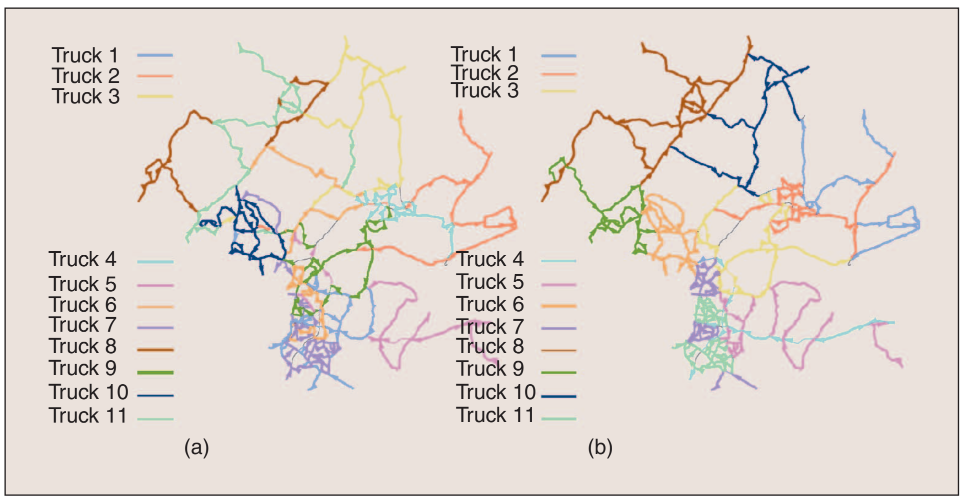

FIGURE 5 (a) Optimized robust routes by our SRO system and (b) the existing routes for a cold temperature distribution.

Conclusions

Route optimization for gritting/salting trucks during winter is a typical real-world problem that can benefit from powerful evolutionary algorithms, especially hybrid algorithms. Our SRO system has incorporated a number of new technologies from evolutionary computation and geography. Although the system was developed for finding optimized robust solutions for salting trucks, the core algorithms used can be adapted for many other real-world problems, e.g., waste collection and parcel delivery. In fact, many real-world problems in optimization and data mining have been solved successfully by CERCIA (http://www.cercia.ac.uk) using various computational intelligence techniques.

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References

[1] D. Cornford and J.E. Thornes, "A comparison between spatial winter indices and expenditure on winter road maintenance in Scotland," International Journal of Climatology, vol. 16, pp. 339–357, 1996.

[2] L. Chapman, J.E. Thornes, and A.V. Bradley, "Sky-view factor approximation using GPS receivers," International Journal Climatology, vol. 22, no. 5, pp. 615–621, 2002.

[3] P. Lacomme, C. Prins, and W. Ramdane-cherif, "Competitive memetic algorithms for arc routing problems," Annals of Operations Research, vol. 131, pp. 159–185, 2004.

[4] P. Moscato, "On Evolution, Search, Optimization, Genetic Algorithms and Martial Arts: Towards Memetic Algorithms, Caltech Concurrent Computation Program, C3P Report 826, 1989.

[5] Y. Jin and J. Branke, "Evolutionary optimization in uncertain environments," IEEE Trans on Evolutionary Computation, vol. 9, no. 3, pp. 303–317, 2005.

[6] H. Handa, L. Chapman, and X. Yao, "Dynamic salting route optimisation using evolutionary computation," Proceedings of the 2005 Congress on Evolutionary Computation, vol. 1, pp. 158–165, 2005.

[7] Y. Nagata and S. Kobayashi, "Edge assembly crossover: A high-power genetic algorithm for the traveling salesman problem," Proceedings of the 7th International Conference on Genetic Algorithms, pp. 450–457, 1997.