Comparing Priority Ranking, Multi-Criteria Analysis, Cost-Benefit Analysis, and True Optimization Methods for Pavement Preservation Programing

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Abstract

Pavement preservation is described by the National Center for Pavement Preservation as “the application of engineering and fiscal management using cost-effective treatments and existing funds to control the future condition of pavement networks”. The implementation of an effective pavement preservation program at a network level requires a comprehensive process comprising a detailed network inventory, up-to-date pavement condition data, a catalogue of available preservation treatments, appropriate deterioration models for both “do-nothing” and with a range of treatment scenarios, and an estimation of costs and outcomes for all possible rehabilitation alternatives. These inputs are all used to formulate a detailed life cycle cost analysis model of the road network to facilitate the allocation of the limited renewal funds available. Fund-allocation decisions represent a major challenge for most municipalities and transportation agencies, where a small improvement in investment efficiency can be translated into millions of dollars in cost savings. In addition, the process for fund allocation needs to be transparent, defensible and technically robust. Different methods of decision-making can be used to arrive at a final fund allocation plan. These methods can range from priority ranking solutions typically based on the condition status of road segments, to more advanced multi-criteria analyses that consider multiple attributes of a road network to arrive at a decision, to cost-benefit analysis, or formal optimization methods that use rigorous mathematical analysis to arrive at the best possible outcome based on defined criteria. This paper discusses the fundamental assumptions and procedures used in each of these decision-making methods and compares their performance and quality of solution to identify the advantages and disadvantages associated with each method.

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INTRODUCTION

Municipal roads and highway systems are among the fundamental infrastructure assets that provide a foundation to the performance of all national economies by sustaining economic development and facilitating social interaction. Preserving and maintaining pavement assets has therefore been an important yet a challenging task for governments under restricted funding programs. The 2016 Canadian Infrastructure Report Card reports a $48 billion replacement cost for pavements currently in poor condition, and a further $75 billion replacement cost for those in fair condition (CIRC 2016). The report card states that roads present one of the largest gaps between current and target rates of reinvestment, with a current reinvestment rate of only 1.1% and a target recommended rate of investment at 2% to 3% as a percentage of asset replacement value. With the continued downloading of road assets to lower tier municipalities the increasing burden of operation and maintenance programs falls to city and county tax payers. State and local governments in the United States spent $70 billion in 2014 alone on operation and maintenance activities (ASCE 2017). Data from the Association of Municipalities of Ontario indicates that 67% of the roads in Ontario are under municipal jurisdiction, amounting to 140,000 km of pavement with a combined operating and maintenance budget in the range of $40 billion per year (AMO 2016).

When determining the cleverest way to spend an annual road budget, consideration must be given to the full toolbox of pavement preservation and rehabilitation treatments. Among various strategic approaches, preventive maintenance has received the most attention by highway agencies as a cost-effective method of extending the service life of a pavement network. Synthesis 153 on the Evaluation and Benefits of Preventive Maintenance Strategies (TRB 1989), defined Preventive Maintenance as, “A program strategy intended to arrest light deterioration, retard progressive failures, and reduce the need for routine maintenance and service activities.” More recent definition by the FHWA Pavement Preservation Expert Task Group and the National Center for Pavement Preservation emphasize more the benefits of long-term strategic preservation programs. FHWA defines pavement management as "a program employing a network level, long-term strategy that enhances pavement performance by using an integrated, cost-effective set of practices that extend pavement life, improve safety and meet motorist expectations” (FHWA 2017) while NCPP defines it as “the application of engineering and fiscal management using cost-effective treatments and existing funds to control the future condition of pavement networks” (NCPP 2019).

Some preservation treatments, such as thin resurfacing, are not intended to add to the structural capacity of a pavement. In fact in Canada, it is generally found that roads are built with high quality granular base and subbase materials and the loss in serviceability is more related to surface defects and deterioration of the upper hot mix asphalt layers. In the survey of Chiefs of Maintenance as part of the Synthesis 153 in 1989, the pavement maintenance treatments that received the highest ratings, in terms of cost-effectiveness, were pothole repair, surface treatment and then crack sealing. However, even the most highly regarded maintenance treatments only scored about 6 out of 10 with respect to implementation. There was a commonly held view at the time that maintenance could be deferred when there were funding constraints or other priorities were identified. Because the consequences of deferral are not immediately apparent, preventive maintenance tends to fall victim to funding shortages.

An attitude that was prevalent among road agencies in the 90s was that many preventative treatments, particularly thin resurfacings, were only suitable for medium and low volume roads and that high volume roads needed more intrusive and expensive treatments. There are now excellent performance examples that demonstrate that premium products like micro-surfacing and enhanced chip seals, deliver benefits even with high traffic volumes. Since the early 90s the message on road preservation has been clear and consistent, and backed up by extensive case studies and research, that a well-executed preservation program delivers cost effective solutions in terms of overall network performance (Hicks et al. 1981; Bausano et al. 2004; Labi and Sinha 2005). Although pavement preservation and its effectiveness has been promoted extensively for road networks, its implementation within capital plans faces considerable impediments (Peshkin et al. 2004; Rashedi et al. 2017). The predominant focus of many local and municipal governments is still a 'worst-first' philosophy that allocates the bulk of available funds to major rehabilitation and reconstruction. The prevailing attitude is that preventive maintenance is a luxury they cannot afford and it is not supported or properly understood by the political decision-makers. This is while even a small improvement on investment efficiency in road networks can be easily translated into millions of dollars in cost savings. Considering the substantial funds spent annually on road networks and the socio-economic challenges associated with capital planning for most municipalities and transportation agencies, the fund allocation process needs to employ effective decision-making methods that are transparent, defensible, and technically robust.

Many researchers also investigated various analytical methods to determine effectiveness and optimum timing of preservation treatments. Lamptey et al. 2008, for example, presented a case study for optimizing decisions in terms of the best combination of treatments and timings for a given highway section and determined that optimization can be a viable tool to support scheduling decisions for highway maintenance and to provide a rational and consistent basis for scheduling. Haider and Dwaikat 2011, also recommended the need for a rational methodology to evaluate pavement preservation alternatives to maximize project- and network-level benefits using optimization. These examples and many more show that different methods of decision-making can be used to arrive at a final fund allocation plan. This paper discusses the fundamental assumptions and procedures used in some of the more common methods of fund allocation including: priority ranking, multi-criteria analysis, cost-benefit analysis, and true optimization. Each method is discussed and compared with others in terms of performance and quality of solution to identify the advantages and disadvantages associated with each method using sample case studies.

CONDITION-BASED PRIORITY RANKING

Priority ranking has been suggested and used in many pavement management applications (Zimmerman et al. 2011; Wolters et al. 2011). Using ranking, projects are typically selected in order based on a calculated Priority Index (PI). Prioritization is generally performed based on agency policies and can range from the subjective opinion of road managers, to age-based, or to condition-based ranking methods. Indicators such as pavement condition index (PCI) can be used to prioritize road segments. Other attributes such as functional class, traffic, or minimum service standards can also be used to determine a PI. Figure 1 shows a schematic procedure that can be used for fund allocation based on a priority ranking approach. After determining a PCI for each road segment, the entire network is sorted from the highest to the lowest priority segment. Next, the highest priority segment is selected and the required treatment type and its associated cost are determined. If the available budget is adequate to cover the cost, the segment and the associated treatment is selected. The cost of treatment is subtracted from the available budget and the process is repeated until all segments are covered and the available budget has been used up. The algorithm then moves to the next year until the entire planning horizon is covered. The process is illustrated in Figure 1.

In order to investigate the application of priority ranking methods and to compare it with other fund allocation approaches, a sample of 10 road segments is used over a 3-year planning horizon assuming a $50,000 annual budget (Table 1). The small size of this example allows for easier investigation and comparison of treatment selection and timing based on each decision-making method.

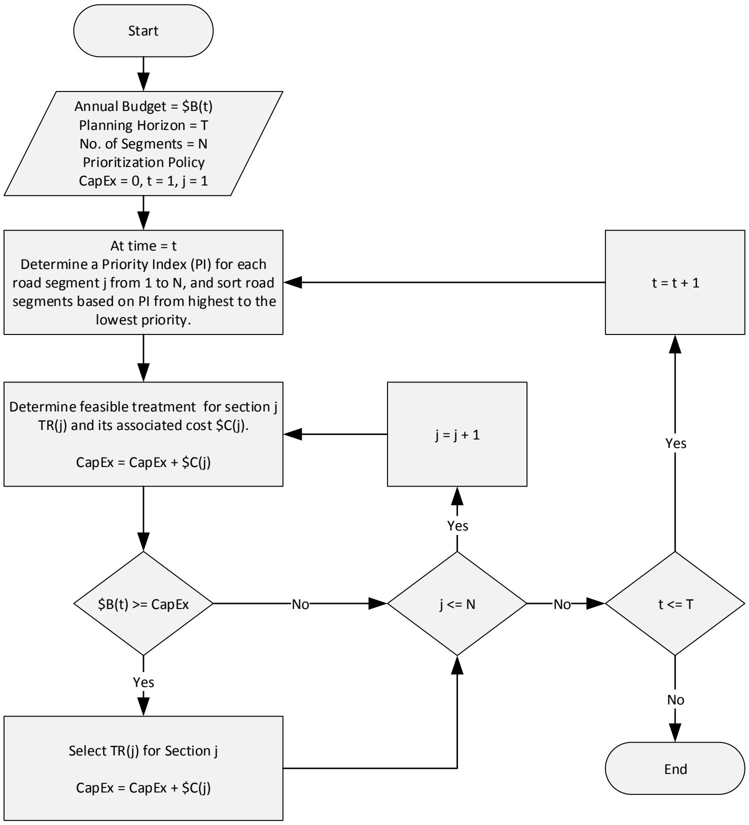

Figure 1: Schematic procedure for fund allocation using priority ranking

Table 1: Sample road network data

Section ID	Functional Class	MMS	AADT	Service Type	Surface Type	PCI
1	Local	5	50	RES	HMA	72
2	Local	5	160	RES	HMA	65
3	Local	5	215	RES	HMA	90
4	Local	4	85	RES	ST	80
5	Collector	3	590	RES	HMA	68
6	Collector	3	1100	RES	HMA	54
7	Collector	3	1000	RES	HMA	68
8	Minor Arterial	2	4850	COM	HMA	73
9	Collector	3	2100	RES	HMA	49
10	Local	5	210	RES	HMA	12.5

Annual average daily traffic (AADT) is recorded for each section. Minimum Maintenance Standards (MMS) are established based on in Ontario Regulation 612/06 and ranges from 1 to 6, with 1 representing the maintenance class with the highest importance. Service Types are categorized into residential (RES) and commercial (COM). The example is focused on hot mixed asphalt (HMA) paved and surface treated (ST) roads. Unpaved gravel roads can also be analyzed in conjunction with paved roads using methods beyond the scope of this paper as discussed in Rashedi et al. 2018. The derived fund allocation plan is summarized in Table 2 and illustrated in Figure 2.

The following observations are made after performing a condition-based priority ranking analysis using PCI.

- Road segments in the worst condition are getting immediate attention as expected. Section ID 10, for example, with current PCI of 12.5 (very poor) got selected immediately in the first year of the plan using a full-depth reclamation treatment with a total budgeted cost of $48,198. This section almost completely consumes the available budget in the first year. Section 3 receives a crack sealing treatment to utilize the remaining budget.
- Network performance is expected to improve from 58.2 to 86 by the end of the plan.
- By the end of the plan 20% of the network is expected to be in Fair condition and the rest (80%) in Good and Excellent conditions.

Table 2: Fund allocation plan using Priority Ranking

Intervention Time	Section ID	Treatment	Budgeted Cost
2019	3	HMA-Crack Seal	$164
2019	10	HMA-FDR & EAS & Ovly	$48,198
2020	2	HMA-Ovly	$7,456
2020	9	HMA-FDR & 2Ovly	$39,200
2021	1	HMA-ST	$3,570
2021	4	ST-SST	$4,505
2021	6	HMA-FDR & 2Ovly	$29,120
2021	7	HMA-Enh2Surf	$10,080

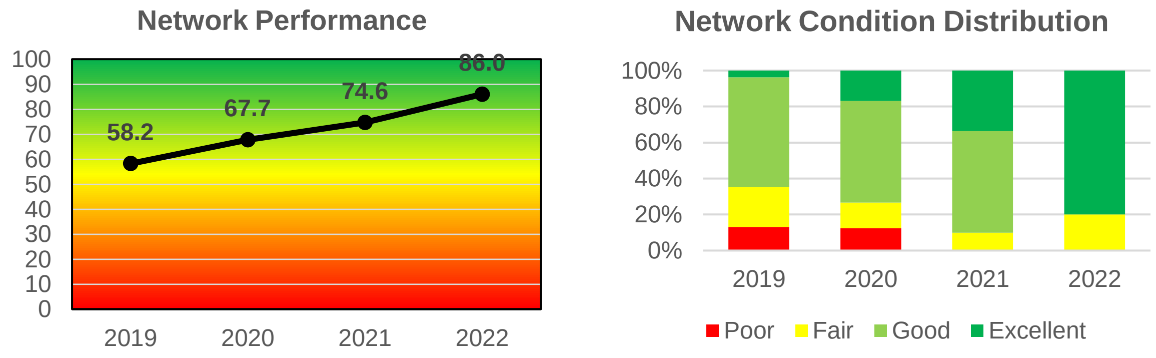

Figure 2: Network performance results using condition-based priority ranking

One of the main problems with using condition-based priority ranking for fund allocation is the resulting “worst roads first” approach. Under this strategy, the most deteriorated roads, which require major rehabilitation treatments, are a huge sink into which the largest proportion of municipal road budgets is poured. Unfortunately, this policy of worst first is like a dog chasing its tail, it is impossible to get caught up because while the worst roads are being reconstructed at huge expense, the good roads are rapidly deteriorating due to lack of maintenance and will become the worst roads in a few years. The large percentage of roads in fair condition by the end of the plan is an indication of this phenomenon. These sections will deteriorate further into poor condition at a higher rate (assuming that deterioration rates increase as condition decays) and will become future backlog. This is despite the fact that preventive maintenance if applied to these sections could be a more cost-effective approach to improve network outcomes. Another problem with priority ranking is the fact that it is performed on a yearly basis, therefore, it omits the time dimension of the analysis and does not have the capability to analyze the impact of time delays on the overall allocation of budget and network performance. Road network models need to be dynamic with the status being upgraded continually as maintenance work is performed. Another key limitation of priority ranking is its inability to incorporate multiple constraints into the analysis, when in reality agencies have to deal with a multitude of constraints.

MULTI-CRITERIA ANALYSIS (MCA)

Multi-criteria analysis (MCA) for decision-making is useful, particularly when dealing with decision-making problems that involve multiple objectives and constraints (criteria). A wide range of MCA methods were developed in 80s and 90s and since 2000 have become more widely considered in various domains. MCA techniques are diverse in both the kinds of problem they address and in the techniques they employ. Examples of some of the more widely used MCA methods include: Analytical Hierarchy Process (AHP) (Saaty 1990; Saaty 2008), fuzzy AHP (van Laarhoven and Pedrycz 1983), multi-attribute utility theory (Keeney and Raiffa 1993), and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) (Lai et al. 1994). In general, MCA methods are used to complement monetary evaluation methods such as cost-benefit analysis. MCA techniques can be employed to help overcome the limitations of human judgment by imposing a systematic and structured approach to evaluate criteria and their relative importance. To provide the ability to incorporate multiple criteria or conflicting objectives MCA can consider compensatory or dominance relationships among multiple attributes (Lai et al. 1994).

Analytical Hierarchy Process (AHP) is perhaps one of the most widely used MCA techniques for converting subjective assessments of the relative importance of a set of criteria into a set of numeric weights. AHP is easy to implement and requires answers to a series of simple questions regarding the importance of various criteria relative to each other. Based on the answers, a pairwise comparison matrix can be developed on the basis of a ratio scale to arrive at weights for the competing decision criteria. Table 3 shows the numeric preference scales used to develop a pairwise comparison matrix. For example, if a judgment is made that criterion A is moderately more important than B, then a preference index of 3 is assigned. The reciprocal of the index (i.e., 1/3) is assigned if B is determined to be moderately more important than A.

Table 3: Pairwise comparison preference weighting

How important is criterion A as compared to B?	Preference Index
Equally important	1
Moderately more important	3
Strongly more important	5
Very strongly more important	7
Extremely more important	9
Intermediate values	2, 4, 6, and 8

Using the AHP method, a hierarchical structure is developed to capture key criteria and their hierarchical relations to arrive at the desired outcome. In the case of pavement preservation programing, the main goal is to arrive at a priority index for each road segment. The rest of the fund allocation process can be similar to the process described in Figure 1 for priority ranking. Figure 3, shows an example of an AHP structure used for our sample pavement network. As shown in this figure, the ultimate goal at the top of the hierarchy is to assign project priorities. At the second level consideration is made towards the physical condition, section characteristics, and socioeconomic aspects of the decision. The next level of the hierarchy are attributes associated with each previous sub-goal such as PCI, Functional Class, or Strategic Plan. At the bottom of the hierarchy we show all the candidate sections which in the case of our sample network are a total of 10 road sections.

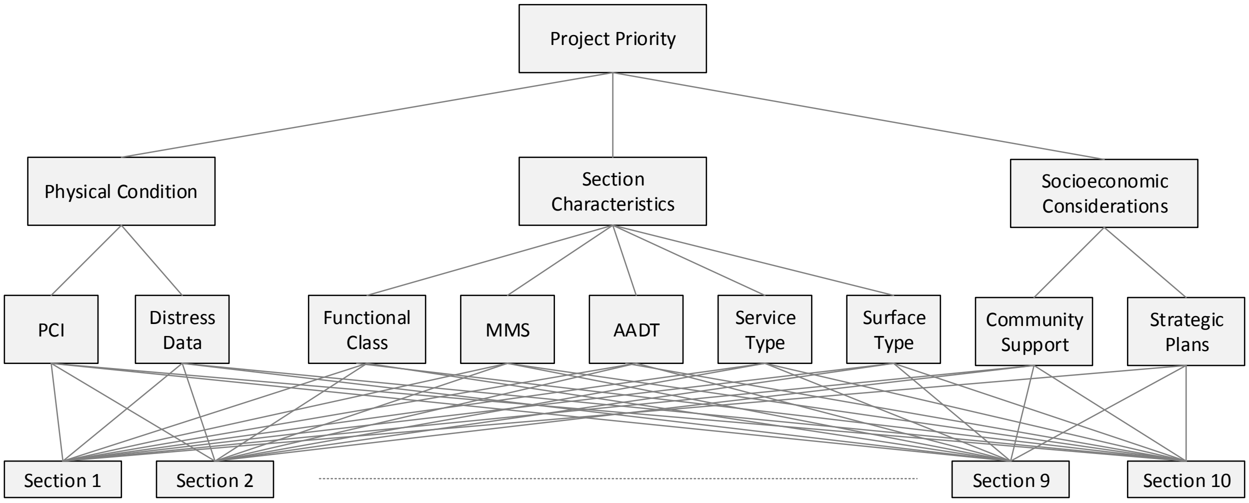

Figure 3: AHP structure for pavement preservation project prioritization

After the AHP structure is developed, the next step is to create the pairwise comparison matrix at each level for different sub-goals under consideration to determine appropriate weighting. To determine weights using AHP we need to solve the eigenvalue problem in Eq. 1, where A is the pairwise comparison matrix of *n* different criteria, λ_{max} is the maximum eigenvalue, and *w* is the weight vector ($w_1, w_2, \ldots, w_n$).

$$Aw = \lambda_{max} w \qquad (1)$$

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \qquad (2)$$

Rigorous mathematical calculations and matrix algebra can be employed to calculate the weights as the elements in the eigenvector associated with the maximum eigenvalue of the matrix. A simpler alternative approximation ca be used by first calculating the geometric mean (GM) of *A* and then estimate relative weights by normalizing the values. Figure 4 shows the pairwise comparison and AHP calculations for 5 criteria (a_1 to a_5) associated with section characteristics based on Figure 3, including Functional Class (a_1), MMS (a_2), AADT (a_4), Service Type (a_4), and Surface Type (a_5). As shown in the figure for *n* criteria only a total number of $\frac{1}{2}n(n-1)$ comparisons need to be made.

	a1	**a2**	**a3**	**a4**	**a5**	**GM**	**w**
a1	1	0.33	1	5	7	1.6345	0.222
a2	3	1	3	5	9	3.3227	0.450
a3	1	0.33	1	5	9	1.7188	0.233
a4	0.2	0.2	0.2	1	3	0.4743	0.064
a5	0.14	0.11	0.11	0.33	1	0.2259	0.031

n = 5 λ_{max} **5.22**
RI = 1.12 **CI** **0.06**
CR **0.05**

Figure 4: AHP calculations for section characteristic attributes

λ_{max} can then be calculated using Eq. 3, where *n* is the total number of criteria. A consistency ratio (CR) value is then calculated to determine if there are any inconsistencies in the pairwise comparisons. A 10% tolerance is used for human judgment errors, therefore, if CR is greater than 0.1, matrix *A* needs to be revisited. CR is calculated using Eq. 4, where RI is the random index determined based on the number of criteria being compared (Saaty 2008) and CI is the consistency index (Eq. 5). For the above example, CR is calculated at 0.05 suggesting a consistent comparison. The weigh vector *w* is also determined for all *n* criteria with the sum of the weight being equal to 1. This process should be repeated at all hierarchy levels to determine the relative weight of all criteria. Finally, a linear additive model can be employed to determine a priority index for each road section.

$$\lambda_{max} = \sum (Aw/w)/\, n \qquad (3)$$

$$CR = \frac{CI}{RI} \qquad (4)$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (5)$$

Table 4 and Figure 5 show the fund allocation results based on AHP analysis. The following observations are made:

- Road sections with higher priority index (PI) values receive more immediate attention. The PI ranges from 0 to 100 where 100 means the highest priority calculated using the AHP process. For example, Section ID 8, which is a Minor Arterial section with a traffic level of more than 4000 vehicles per day and a minimum maintenance standard level of 2, has the highest PI values of 65 as compared to other sections and is repaired immediately in year 1. This is in contrast to the case with condition-based priority ranking, where the same section is not selected at all since the current condition is relatively good. However, a thin resurfacing is applied using the MCA approach that will keep this section in good condition, which is more aligned with preventive preservation strategies.
- Network performance is expected to improve from 58.2 to 81.4 during the plan. Although the overall performance is lower at the end of the plan as compared to the ranking solution, it is important to note that the total cost is also 24% lower in the MCA case. One of the main reasons is that in the MCA case, Section ID 10 is not selected. A closer look at the results show that although Section ID 10 has a very low PCI, its overall MCA priority is lower than numerous other sections and sits at rank 5 in the middle of the list. Section 10 however requires a costly $48,000 major rehabilitation repair. The MCA logic therefore gives priority to other sections and leaves this section unrepaired.
- Condition distribution results show that by the end of the plan 87% of the network is in Excellent condition, and 13% of the network in Poor condition (Section ID 10).

Table 4: Fund allocation plan using MCA

Intervention Time	Section ID	PI (MCA)	Treatment	Budgeted Cost
2019	3	29.07	HMA-Crack Seal	$164
2019	8	65.20	HMA-EnhSurf	$7,560
2019	9	65.17	HMA-FDR & 2Ovly	$39,200
2020	2	36.57	HMA-Ovly	$7,456
2020	6	62.03	HMA-FDR & 2Ovly	$29,120
2020	7	57.83	HMA-Enh2Surf	$10,080
2021	1	31.21	HMA-ST	$3,570
2021	4	36.54	ST-SST	$4,505
2021	5	56.20	HMA-Enh2Surf	$13,311
Not selected	10	52.32	-	-

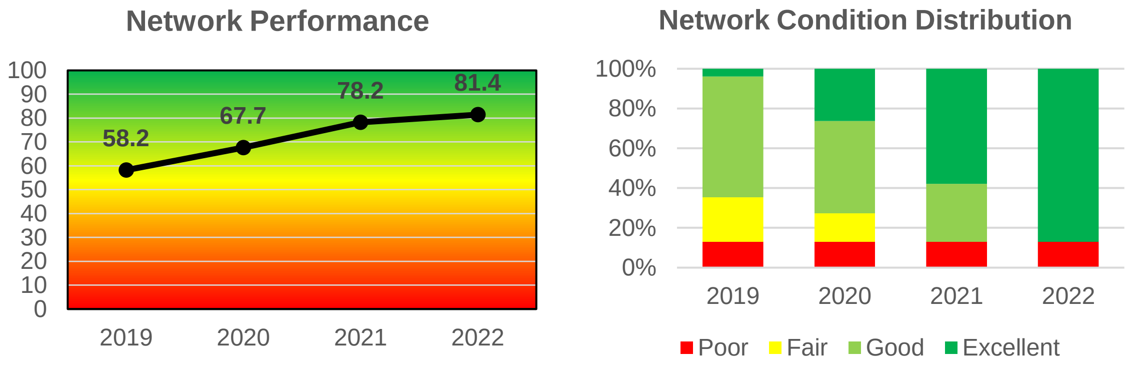

Figure 5: Network performance results using MCA

Although due to the smaller size of the sample network, the budget was not fully utilized under the MCA approach, the comparison with condition-based priority ranking suggests that MCA can help to better capture the variations in priority programing and results in more application of cost-effective preventive maintenance strategies. MCA is, however, not free of limitations and care must be taken when employing MCA methods. For example, the 1-9 scale has the potential to be internally inconsistent. As an example, if the section A preference index as compared to section B is 2, and B as compared to C is 5, then to be numerically consistent, section A must have a preference index of 10 over C, which is not possible using the 1-9 scale of AHP. Lack of a measurement scale for criteria can also contribute to vagueness when performing cross comparisons. A detailed review of AHP limitations can be found in French 1988. Although MCA is a better approach as compared to priority ranking and is a beneficial method in terms of focusing decision maker attention on developing a formal structure to the decision-making problem, it cannot guarantee that the best possible solutions are achieved.

COST-BENEFIT ANALYSIS (CBA)

Cost-benefit analysis (CBA) originated from the work of by two French engineers, Auguste Cournot and Jules Dupuit in the mid-19th century, who were known as the founding fathers of microeconomics (Arler 2006). CBA is a methodology to explicitly determine benefits and costs associated with a project in money terms (Thoft-Christensen 2012; Fraser and Jewkes 2013). CBA and be combined with MCA for a more comprehensive analysis when CBA assess the monetary or financial aspects of the problem and MCA those criteria that cannot be evaluated in monetary terms. Using the CBA method, an agency can prioritize projects based on the cost-effectiveness or the ratio of benefit over cost (B/C ratio) of a project. In general, an investment alternative is considered desirable when resulting benefit over cost ratio is greater than one, or in other words, the expected benefits exceed the expected costs. When a set of mutually exclusive alternatives exists, they can be raked based on their B/C ratio and a similar process to Figure 1 can be employed to arrive at the final solution. A variation to CBA method, called incremental CBA, looks at the incremental benefit gains and an alternative becomes more preferred than the current preferred one, if its incremental benefits are higher than its incremental costs (Fraser and Jewkes 2013).

Using present-worth method for cost calculations, the total present worth of cost when using treatment alternative R in year N for section j over an analysis period of t ($TPWC_{jt}^{RN}$) can be calculated using Eq. 6, where pwt_{it} is the present worth factor using discount rate i for t years ($pwf_{iN} = 1/(1+i)^t$); RC_j^{RN} is the rehabilitation cost of using treatment type R for section j in year N; and VOC_{jk} is the total vehicle operating cost for section j in year k.

$$TPWC_{jt}^{RN} = pwf_{iN} \times RC_j^{RN} + \sum_{k=1}^{t} pwf_{ik} \times VOC_{jk} \qquad (6)$$

The benefits are typically presented as the cumulative improvement effects form the selected rehabilitation decisions that increase the expected remaining life of the network or the overall network condition. This can be represented by the area under the condition projection curve which is one of the most effective and commonly used benefit measures in pavement management domain (Babashamsi et al. 2016). In this methods, the projected performance under no preservation strategy (do-nothing) is compared with using different alternatives and at different times over the planning horizon. Figure 6 shows a schematic example of comparing the performance benefit of using treatment alternative A1 in year T1 versus year T2 as shown by areas B_{A1T1} and B_{A2T2} with respect to the do-nothing deterioration curves and a minimum acceptable condition.

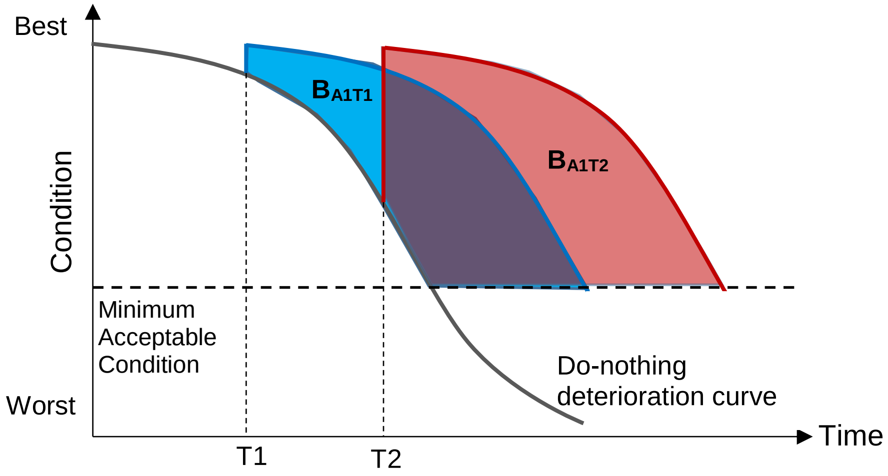

Figure 6: Performance benefit improvements of preservation alternatives

The derived fund allocation plan is summarized in Table 5 and illustrated in Figure 7. The following observations are made:

- Network performance is expected to improve from 58.2 to 81.6 by the end of the plan.
- Condition distribution results shows 13% of the network in poor condition and 87% in Good and Excellent conditions by the end of the plan. Similar to the MCA method Section ID 10 is not selected under the CBA method. The reason for not selecting Section ID 10, however, is different and mainly due to its large cost that brings down the B/C ratio for this treatment.

- Results from Table 5 show more focus on cost-effective preventive activities under the CBA method as compared to MCA and priority ranking.

Table 5: Fund allocation plan using CBA

Intervention Time	Section ID	Treatment	Budgeted Cost
2019	1	HMA-EnhSurf	$3,856
2019	2	HMA-Ovly	$7,456
2019	3	HMA-Crack Seal	$164
2019	4	ST-SST	$4,505
2019	5	HMA-EnhSurf	$7,987
2019	7	HMA-EnhSurf	$6,048
2019	8	HMA-EnhSurf	$7,560
2020	9	HMA-FDR & 2Ovly	$39,200
2021	6	HMA-FDR & 2Ovly	$29,120

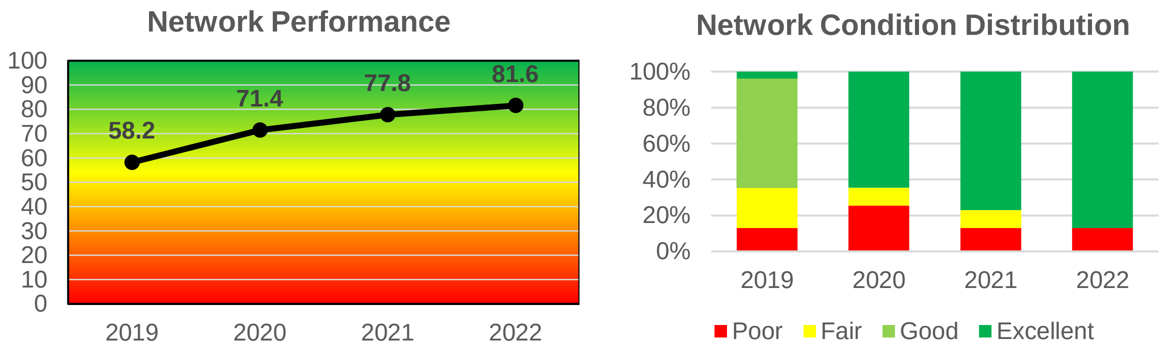

Figure 7: Network performance results using CBA

CBA is an effective method to determine monetary implications of project alternatives in terms of costs and benefits. This is, in particular, useful at the project-level analyses when a limited number of projects are compared for the upcoming construction season. CBA, however, has a number of limitations when it comes to effective network-level preservation programing. Although, some variations of CBA try to take into account time dimension of the analysis (i.e., accelerating or delaying treatment timings), it lacks the capability to analyze the impact of time delays or accelerations on the overall optimality of the results within a network of assets. Another key limitation of CBA, similar to MCA and priority ranking, is its inability to incorporate multiple constraints into the analysis. CBA generally looks at budgetary constraints or similar types of constraint that can be looked at sequentially and on an annual basis, but lacks the ability to incorporate more complex and non-linear types of constrains that are key in effective preservation programing. In reality, municipalities deal with fluctuating annual budgets, shifting strategic objectives, minimum levels of service objectives, safety considerations, input from the public, requirements for alignment with other projects (e.g., water/wastewater), and many other practical and operational constraints. Financial return on investment is only one component of the analytical process. Although CBA methods can get the decision-makers closer to a better solution, they cannot guarantee that the ideal or best possible solutions in achieved. Considering the monetary value of major infrastructure projects, the difference between an ideal (i.e., optimal solution) and a good solution can be translated into millions of dollars in cost savings.

OPTIMIZATION

Optimization is branch of science in Operations Research (OR). OR provides a scientific approach to decision making that seeks to optimize the performance of a system, usually under conditions requiring the allocation of scarce resources. OR originated during World War II when the British government recruited scientists from different disciplines to solve the operational problems of the war, such as the deployment of radar and the management of convoy, bombing, anti-submarine, and mining operations, which coined the term Operations Research. In the context of optimization, a system can be a collection of interdependent entities that work together to accomplish the goal of the system. For example, a corporation can be thought of as a system whose goal is to maximize its profit, while subjected to resource constraints and regulations governing its business activities. The focus of optimization is, therefore, to understand the complex operations of any system so as to predict its behavior over time and to identify the best course of action that leads to an ideal level of performance, or in other words, an ‘optimal’ solution. This scientific approach to decision making usually involves the use of mathematical models to represent the actual situation in terms of objective functions, decision variables, and constraints (Winston & Venkataramanan 2003).

In the context of pavement management, or more generally, asset management, the term optimization has been used rather loosely for methods such as incremental cost-benefit analysis, MCA, or even priority ranking. These methods, however, cannot be categorized as formal mathematical optimization and are far less effective as compared to true optimization methods. Performing a true optimization analysis for the purpose of allocation of capital funds in pavement preservation programs represent a complex problem (Abaza, 2007). One of the key challenges associated with optimization modeling of pavement preservation programs is the exponential increase in solution space size as the number of road sections and consequently decision variables increase (Al-Bazi & Dawood, 2010). Pavement preservation programing represents a type of optimization, called ‘combinatorial’ problems that deals with finding the best possible solution amongst a large number of possibilities based on the combination of decision variables. To handle complex combinatorial problems, the trend in recent literature has been to use evolutionary optimization techniques, such as genetic algorithms (GAs) (Liu et al., 1997). In addition to GA, more rigorous mathematical methods such as mixed integer programming can also be employed in this domain (Winston & Venkataramanan 2003). GA-based techniques are inspired by the improved fitness of natural selection and the ‘survival of the fittest’ approach in living species. Using GAs, solutions (sets of values for the decision variables) are constantly generated and assessed based on a fitness function, which is derived from the objective function and the constraints, until the best solution is found (Goldberg, 1989). Many GA optimization models have been introduced for life cycle analysis and renewal planning in different asset domains, including pavements (de la Garza et al., 2011), bridges (Elbehairy et al., 2006), building facilities (Rashedi & Hegazy 2014), and groundwater remediation (Zou et al., 2009). While literature efforts provided useful models, their solution quality and speed greatly depended on problem size and model efficiency. Increasing problem size significantly affects the optimization results and degrades the performance, resulting in huge processing time (Cook et al., 1997, Rashedi and Hegazy 2014).

Recent enhancement in advanced optimization technologies has led to the development of practical decision support tools that utilize true optimization capabilities. The improvements achieved through an optimized solution can be translated into substantial cost savings and added performance. A capital planning tool with optimization capability can maximize the overall performance of a network in terms of performance over a multi-year analysis horizon while satisfying multiple constraints such as budget limits, level of service requirements, etc., all at the same time. The result is a best possible course of action in terms of timing and selection of different maintenance, rehabilitation, or reconstruction treatments considering all municipal goals and constraints. One of the most important advantages of optimization, beside cost savings and added performance, is the ability to arrive at a defensible capital plan. Using true optimization methods, a decision-maker can be assured that the final solution is the best possible solution and the most efficient way of investing the limited resources and in the case of public road networks delivers the best use of taxpayer money.

To perform a true optimization analysis on our sample network, a commercial optimization tool for capital planning called, DOT (Decision Optimization Technology)™, is used. DOT™ has the ability to optimize large-scale asset management problems to determine the best course of action in terms of timing and selection of a wide array of preservation treatments that results in the highest investment efficiency while satisfying a large number of constraints regarding serviceability criteria, socio-economic policies, budgetary limits, co-located projects, and operational efficiency. Although, our sample problem is relatively small and does not require all the advanced capabilities, still the optimization outcome, as shown in Table 6, is not an obvious answer that can be determined on an ad hoc basis or by employing non-optimal methods. Table 6 and Figure 8 show the fund allocation results based on a true optimization analysis. The following observations are made:

- Optimization completely outperforms other non-optimal methods of decision-making. In our sample problem, network performance is expected to improve from 58.2 to 91.1 arriving at the optimum solution.
- Condition distribution results also show superior performance by maintaining 95.7% of the network in Good and Excellent condition, and only 4.3% of the network in Fair condition, with no sections being in poor condition.
- Optimization makes a much better utilization of the available budget and considers alternative funding levels, in which to arrive at an optimal solution by cutting cost on one section to allow another section with a more severe deterioration behavior, to be funded.

Table 6: Fund allocation plan using optimization

Intervention Time	Section ID	Treatment	Budgeted Cost
2019	1	HMA-EnhSurf	$3,856
2019	5	HMA-EnhSurf	$7,987
2019	6	HMA-FDR & 2Ovly	$29,120
2019	8	HMA-EnhSurf	$7,560
2020	7	HMA-Enh2Surf	$10,080
2020	9	HMA-FDR & 2Ovly	$39,200
2021	3	HMA-EnhSurf	$1,767
2021	10	HMA-FDR & EAS & Ovly	$48,198

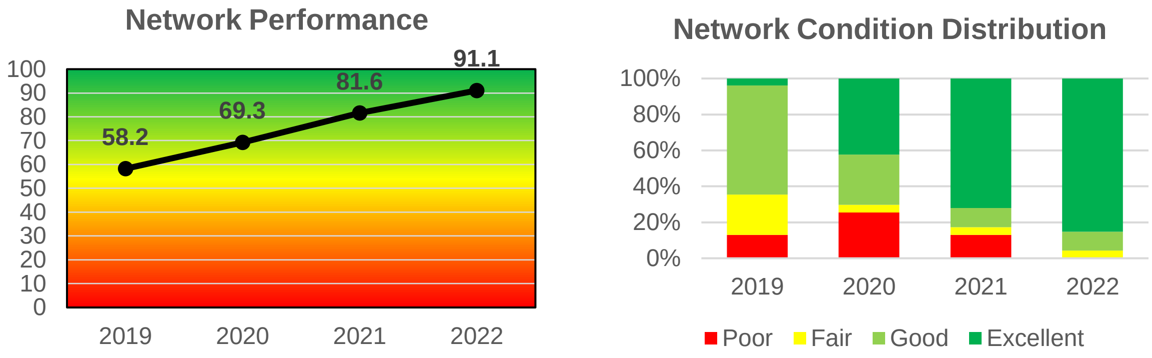

Figure 8: Network performance results using optimization

Figure 9 shows a closer comparison among all the methods discussed in terms of the percentage of performance improvement at each year over the 3-year planning horizon. As shown by the figure, optimization outperforms all the other methods. On average, optimization results in 27.6%, 25.3%, and 19.9% higher performance gains over the entire plan as compared to MCA, condition-based priority ranking, and CBA, respectively. In real-life cases with thousands of assets, a wide array of treatment alternatives, multitude of constraints, and longer planning horizons (typically 10 years), the significance of optimization improvements are more dramatic. Government agencies spend millions of dollars on pavement preservation programs and asset management in general. Even a small improvement in performance can be easily translated into millions of dollars in cost savings at local government level, and more significant savings can be achieved at the provincial and federal levels. A number of real-life case studies from Canadian municipalities who are using DOT™ software for their capital planning shows that savings on average from 7% to 17% can be made just by switching to an optimized solution (Rashedi et al. 2017). Percentage improvements by using optimization can be much higher if previous fund allocation was done on an ad hic basis or following a worst-first approach.

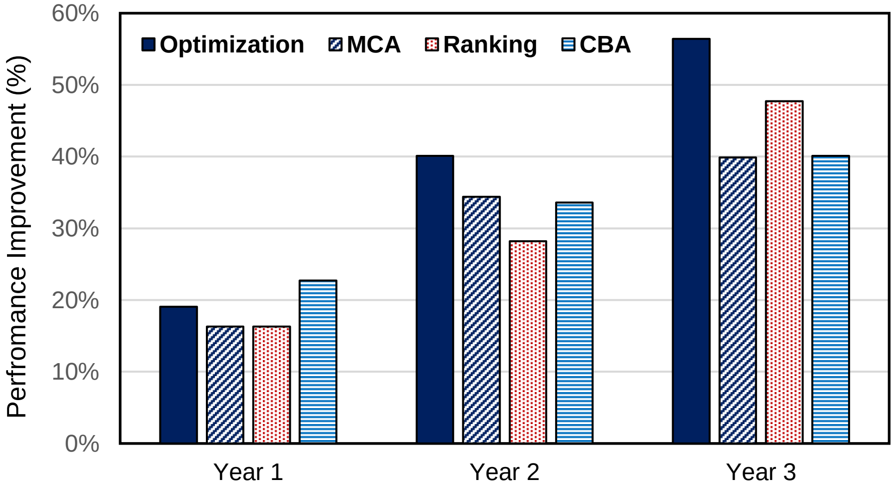

Figure 9: Performance comparison of Optimization, MCA, CBA, and Ranking methods

In addition to cost savings, optimized preservation programing enables public works and asset managers to develop defensible capital plans. A multitude of parameters and criteria can be incorporated in the analysis that ensures all expectations are satisfied in the best way possible while considering the existing resource limits. Optimization ensures that all municipal constraints and objectives are satisfied at the same time, while the highest possible levels of service are achieved for the community, and the tax payer money is spent in the wisest possible manner using a scientific approach to decision-making. This can result in a much higher support from the community, political council, and other stakeholders

Practical application of optimization in the municipal domain, however, is not free of challenges. Optimizing real-life complex and large-size infrastructure networks is not an easy task. In the context of combinatorial optimization, even a small network with only hundreds of assets is considered a large-size optimization problem, due to the enormous increase in the number of possible combinations and therefore solution space. The other challenge associated with practical application of optimization, is the inherent complexity of formulating and developing mathematical optimization models. Optimization modeling requires expertise and technical understanding in the field of Operations Research that makes it somewhat unfamiliar and complicated for most mainstream applications in the municipal domain. To overcome these challenges, advanced powerful optimization technologies are needed that can effectively handle large-scale complex problems in the municipal domain, while providing a user-friendly interface and an easy-to-understand application framework that requires no specific expertise beyond a basic understanding of asset management. New emerging technologies, such as DOT™ (Decision Optimization Technology) software, which was used in this study, are starting to become available at an affordable price to provide powerful capabilities that can be effectively applied in real-life settings by municipalities, big and small, across North America.

CONCLUSIONS

Pavement preservation is defined as the application of engineering and fiscal management using cost-effective treatments and existing funds to control the future condition of pavement networks. The implementation of an effective pavement preservation program at a network level requires a comprehensive process comprising a detailed network inventory, up-to-date pavement condition data, a catalogue of available preservation treatments, appropriate deterioration models, and an estimation of costs and outcomes for all possible rehabilitation alternatives. These inputs are all used to formulate a detailed life cycle cost analysis model of the road network to facilitate the allocation of the limited renewal funds available.

This paper discussed the fundamental assumptions and procedures used in four main decision-making methods in the area of pavement preservation programing, and in general in asset management domain, including: 1) condition-based priority ranking; 2) multi-criteria analysis (MCA); 3) cost-benefit analysis (CBA); and 4) optimization. The paper discussed and compared the performance and quality of solutions to identify the advantages and disadvantages associated with each method. In order to perform the comparisons, a sample road network over a 3-year planning was used. The small size of the sample data allowed for an easier investigation and comparison of treatment selection and timing based on each decision-making method.

The results clearly showed that mathematical optimization outperforms all the other methods. On average, optimization resulted in 27.6%, 25.3%, and 19.9% higher performance gains over the entire plan as compared to MCA, condition-based priority ranking, and CBA, respectively. In real-life cases the expected improvements and the significance of optimization improvements can be even more dramatic. Government agencies spend millions of dollars on pavement preservation and asset management programs. Even a small improvement in performance can be easily translated into millions of dollars in cost savings. Practical application of optimization, however, requires advanced powerful optimization technologies that can effectively handle large-scale complex problems in the municipal domain, while providing a user-friendly interface and an easy-to-understand application framework. New emerging technologies, such as DOT™ (Decision Optimization Technology) software which was used in this study, are starting to become available at an affordable price to provide powerful capabilities that can be effectively applied in real-life settings by municipalities, big and small, across North America.

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