Benefits of Mathematical Optimization and Machine Learning-Based Deterioration Modeling: A City of Calgary Case Study

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Abstract

Calgary's road network constitutes a major investment over many generations and plays a crucial role in the City's well-being by guaranteeing its citizens with full accessibility, ensuring safe travel, and providing a strong business competitiveness through an efficient movement of goods and services. This study identifies key limitations in current pavement network life cycle cost analysis processes by comparing the results of traditional prioritization approaches to a true multi-year multi-constraint optimization analysis. The results shows that the optimization solutions outperformed prioritization at all years showing an average 5.3% improvement over the planning horizon and 9.3% by the end of the plan. Monetization methods also arrived at significant cost savings via added performance over a 10-year planning horizon by switching to a mathematically optimized solution. To further improve modeling accuracy and reliability of results, this study investigates the quality of performance models used within the pavement management system and discusses the development of machine learning-based deterioration models using decision tree regression. The effects of more modern performance modeling methods on investment planning is examined by comparing various optimization scenarios using both the ML-based and the traditional age-based deterioration models. The paper shows the importance of condition-based predictive modeling and integrating accurate performance models into the current asset management system to provide more accurate information on monitoring the network's life expectations, capital investment plans, and vulnerable communities with accelerated pavement deterioration patterns.

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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 challenging task for governments under restricted funding programs. State and local governments in the United States spent $70 billion in 2014 alone on operation and maintenance activities (ASCE 2017). 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 entail 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. The 2019 CIRC (CIRC 2019) reports that since 2016 the situation has deteriorated with 39% of road assets currently in the Very Poor/Poor/Fair categories compared to 37% in 2016. With the continued downloading of road assets to lower-tier municipalities the increasing burden of operation and maintenance programs falls to municipal tax payers. 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).

Since the early 1990s the benefits of 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. 1999; 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 the idea is not supported or properly understood by the political decision-makers. This is on the contrast to the fact that 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.

As a national champion in infrastructure asset management and a leader in utilizing advanced technologies for better asset management, the City of Calgary is dedicated to improving its asset management practices. To support this initiative, formalization of asset management planning is taking place through coordinative efforts of Corporate Analytics and Innovation (CAI). One of the key objectives of the CAI is to develop a integrated lifecycle management and financial plan that aligns levels of service to asset performance for various asset classes. Development and implementation of a comprehensive lifecycle management requires considerations at both network and project levels. Effective network-level analysis requires a comprehensive process comprising a detailed network inventory, up-to- date 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 network to facilitate the allocation of the limited renewal funds available to the City of Calgary. This study investigates various analytical methods to determine effectiveness and optimum timing of preservation and rehabilitation treatments. It shows that improvements in investment efficiency achieved by better decision-making methods can be translated into millions of dollars in cost savings and signifies the importance of utilizing powerful and practical decision support tools. This study also investigates the effects of more modern deterioration modeling methods for investment planning to provide more accurate information on the network's life expectations, capital investment needs, and vulnerable communities.

DECISION-MAKING METHODS

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. Many researchers have investigated various analytical methods to determine effectiveness and optimum timing of preservation treatments. The traditional methods typically use a priority ranking process based on multi-criteria or cost-benefit analyses, while the more advanced optimization methods that use rigorous mathematical analysis to arrive at the best possible outcome based on defined criteria. (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, each with different implications and solution quality in terms of investment efficiency and network improvement effects.

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, which can range from the subjective opinion of road managers to ageor 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.

Another variant of the priority ranking approach is the decision tree method. If the priority policy or the decision criteria/rules have been optimized, the solution may not be very bad. The biggest problem of the current practice is that the priority policy/decision tree are determined with 'expert judgment' or subjective opinions, while those judgments or opinions are valid only at the project level at the best. The typical example is the worst-first policy. Many people feel this is native and intuitive. But it's not optimal. How to develop optimal decision criteria or prioritization rules that would automatically reach a network-optimum or near network-optimum is an interesting research question.

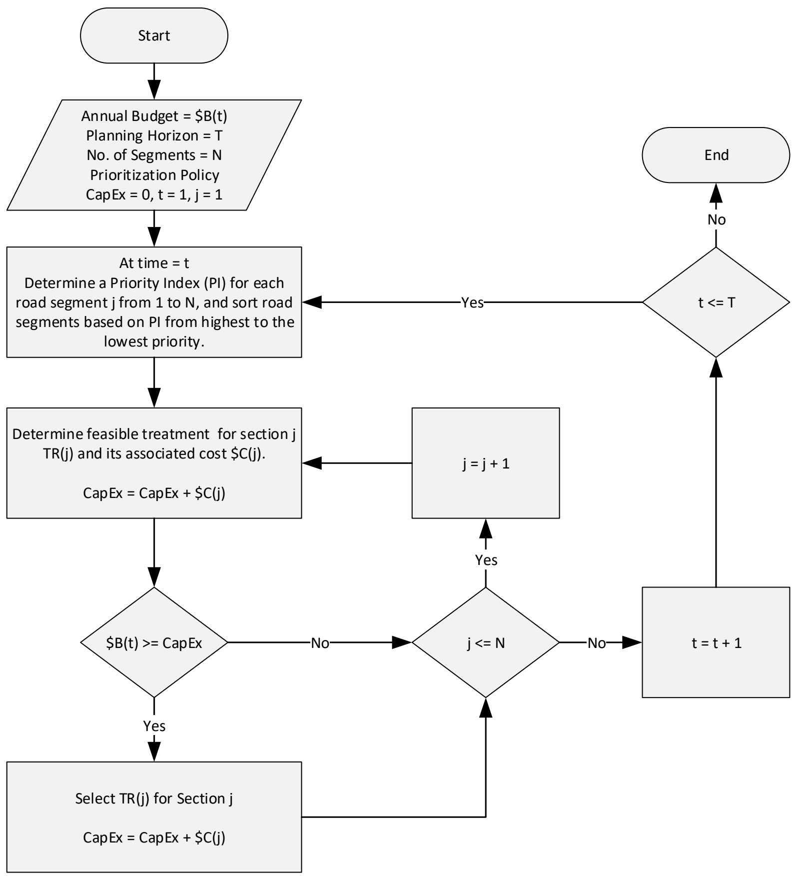

Figure 1: Schematic procedure for fund allocation using priority ranking

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 worst-first policy 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 and poor 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. On the contrary, preventive maintenance would be a more cost-effective strategy to improve network outcomes. Another problem with priority ranking is the fact that it is performed on a yearly basis.As a result, 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.

Mathematical optimization is a branch of science in Operations Research (OR). Through a systematical evaluation of all possible feasible solutions, 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 a 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 system's behavior 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 cost-benefit analysis or priority ranking. These methods, however, cannot be categorized as formal mathematical optimization and are far less effective as compared to true optimization methods. Optimization, or prescriptive modeling "prescribes" a detailed course of action for an organization to best meet its goals. The ideal course of actions, or the "optimal" solution, is determined as a result of rigorous mathematical assessment of the optimization model, rather than using intuitive processes or on an ad hoc basis. Optimization models seek to find the value of decision variable that either maximize or minimize (i.e., optimize) an objective function under certain constraints that must be satisfied. Accordingly, optimization models have three main components:

- Objective Function: In the case of capital planning and pavement preservation programming, the objective function is typically defined as maximizing the overall road network performance or condition projection over the planning horizon. Other examples of objective functions are minimizing cost, minimizing network risk level, or maximizing return on investment. It is important to note that the objective functions can be combined to represent a multi-objective optimization process.
- Decision Variables: They are the variables that can be directly and freely changed by the decision maker and affect the performance of the system. In the case of capital planning, decision variables are typically defined at the network level as the timing of interventions and selection of road segments. At the project level, decision variables are concerned with selecting a treatment option among various possible alternatives. The optimized values of these decision variables answer the key questions about which road segment to be repaired with what treatment at what time.
- Constraints: In real life, only certain values for decision variable represent a practically feasible solution. Government agencies operate within a multitude of restrictions when planning future investments. These restrictions represent optimization constraints. In the case of capital planning problems, restrictions such as annual budget limits, minimum level of service requirements, operational considerations, resource and manpower limitations, and political requirements are examples of optimization constraints.

Formulating the network capital planning to an optimization is one thing, and solving the optimization is quite another challenging task. (Abaza, 2007). One of the key challenges is the exponential increase in solution space size as the number of road sections and consequently decision variables increase (Al-Bazi & Dawood, 2010). Renewal fund allocation represents a type of optimization, called 'combinatorial' problem that deals with finding the best possible solution amongst a large number of possibilities based on the combination of decision variables. 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 prohibitive processing time (Cook et al., 1997, Rashedi and Hegazy 2014). 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). Recent enhancement in advanced optimization technologies has led to the development of practical decision support tools that utilize true optimization capabilities to produce plans that result in the highest investment efficiency.

DECISION SUPPORT TOOLS

Decision support tools (DSTs) are software products developed to support decision makers in making better decisions, faster. Real-life decision-making process is complex even when decision makers understand that DSTs help to make connections between the data, improve information management processes, provide a better picture of the current state of infrastructure ad future expectations, combine advanced analytics with powerful predictions, and assist in finding the best possible course of action. To achieve the last objective, only decision support tools with a true mathematical optimization engine can grantee the best course of action to be identified. To perform a true optimization analysis, this study has used a commercial software provided by the Canadian company Infrastructure Solutions Inc., called Decision Optimization Technology (DOT)™ software (for more information visit www.infrasolglobal.com). The core analytical capabilities of DOT™ are based on over 10 years of doctorate level scientific research and development on infrastructure management decision support systems using componential intelligence and advanced mathematical optimization methods. DOT™ has been developed in collaboration with a large number of Canadian municipalities, engineering companies, construction firms, and academic institutions with a focus on infrastructure and pavement management systems. DOT™ provides a true mathematical optimization algorithm that calculates a multi-year, multi-constraint maintenance and capital plan that maximizes the overall performance of the network. The optimization algorithm finds an optimal budget allocation plan by maximizing an objective function defined by specified criteria, while also taking into account various ancillary requirements such as budget constraints, treatments and costs, level of service objectives, operational requirements, and alignment with other departments. Classic prioritization methods cannot guarantee an optimal outcome and only compare different alternative actions based on a priority index. DOT™ optimization on the other hand, finds the best possible outcomes in terms of a combination of actions, such as selection of assets, selection of treatment alternatives, and timing of interventions, out of millions and billions of possible combinations, within a very efficient and fast processing time using the latest optimization technologies. The outcome of the optimization, therefore, considers the trade-offs between delaying and accelerating interventions or alternative ways of allocating budget across all available options. The resulting plan is hence defensible as it is mathematically guaranteed to be the best possible solutions and results in a much more efficient investment strategy.

OPTIMIZATION VS. PRIORITIZATION

The City of Calgary's road network data was used in this study. The total road network size under analysis is 6,492.2 centerline kilometer consisting of 71,047 road segments. Current condition assessment results show an overall network condition of 5.8 weighted average by road length. Based on current data, 4.1% of roads are in very poor (PQI < 2) condition, 13.5% in poor (2 < PQI < 4), 36.1% in fair (4 < PQI < 6), 35.4% in good (6 < PQI < 8), and 10.9% in excellent (8 < PQI < 10) condition states. Data based on functional class shows that 51.8% of the network (3,365.2 km) consists of Local roads with 11% in poor and 7% in very poor condition. Collector roads represent 18.8% (1,223.2 km) of the network with 18% in poor and less than 1% in very poor condition states. Arterial roads represent 29.3% (1,903.8 km) of the network with 15% in poor and less than 1% in very poor condition states.

The GIS data are in polyline format. To incorporate criticality related factors, all sections were tagged for Truck Route, Bus Route, Bikeway, School and Hospital access. Any number of these factors can be used to establish criticality settings, in addition to other physical attributes such as Functional Class, Roadside Environment, Service Type, etc. Condition Ratings were supplied based on the PQI (Pavement Quality Index) assessment method. Condition assessment data provided for the analysis were assumed to be updated by the City to 2020 numbers. PQI is used for the analysis as the main network performance indicator. Figure below shows the distribution of PQI values used in the analysis.

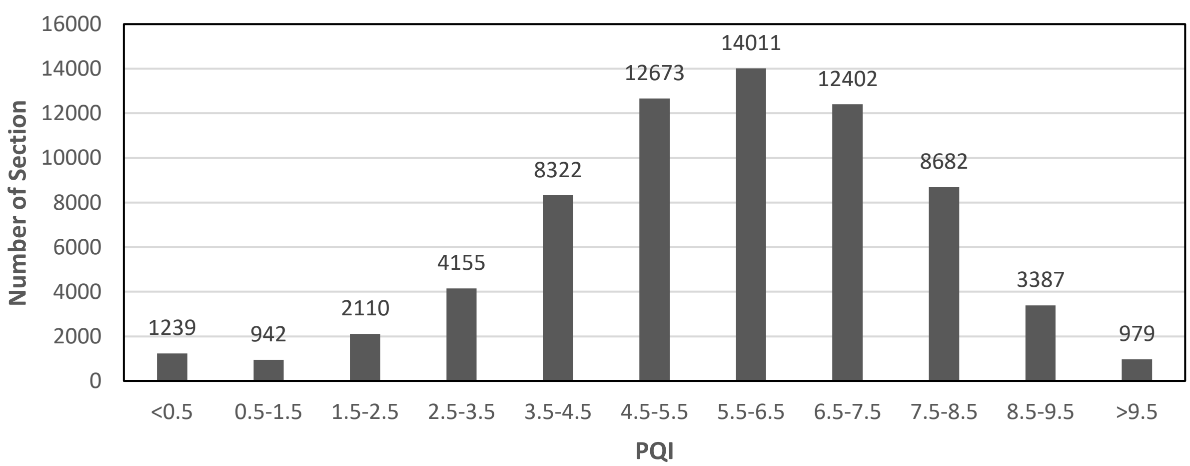

Figure 2: The 2020 Network PQI Distribution

The City's current prioritization process uses linear deterioration models. The expected service life of roads in different functional classes are set to 25 years for Arterial, 34 years for Collector, and 50 years for Local roads. The current models are based on an assumption of 0.2, 0.3, and 0.4 point reduction in PQI per year for Local, Collector, and Arterial roads, respectively. The result of the analysis uses a 0 to 100 scale for the PQI values. This study will further investigate the impact of a more accurate deterioration modeling process on the results. To have an apples-to-apples comparison, both the City's current prioritization methodology and ISI's optimization results ran through the exact same base models in terms of deterioration, treatment alternatives, decision rules, and prioritization factors. Both scenarios used a $40M annual budget constraint with a predefined distribution limit based on functional classes.

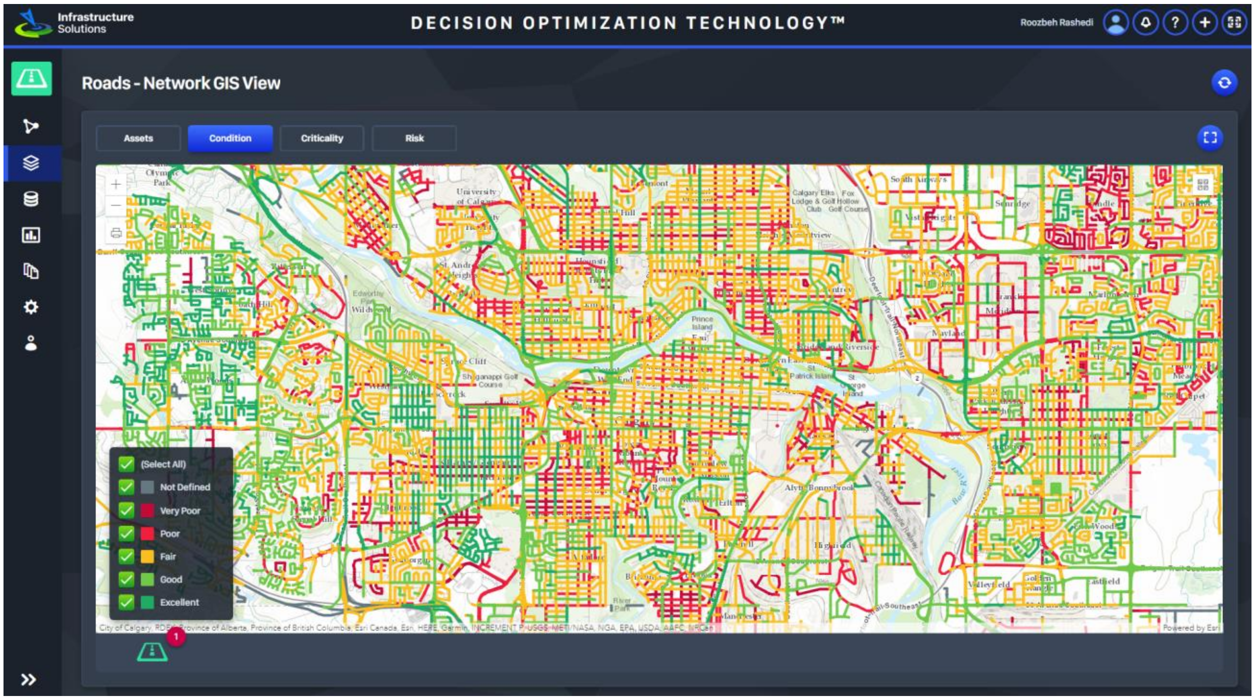

Figure 3: The City of Calgary's road network condition GIS view (DOT™ software)

The prioritization scenario was performed under a $40M annual budget constraint. A predefined distribution based on functional class was also imposed to allocate maximum 50% of available budget to arterial, 40% to collector, and 10% to local roads. Results show an overall network condition deterioration over the 10-year plan from 5.8 in year 2020 to 4.3 in year 2030. The most significant deterioration can be found on Arterial roads as shown in the condition projection chart by functional class. Arterials are expected to deterioration from 5.9 in 2020 to 3.2 in 2030. Local roads are also deteriorating from 5.8 in 2020 to 4.4 in 2030. Collector roads, however, improve slightly from 5.5 in 2020 to 5.7 in 2030.

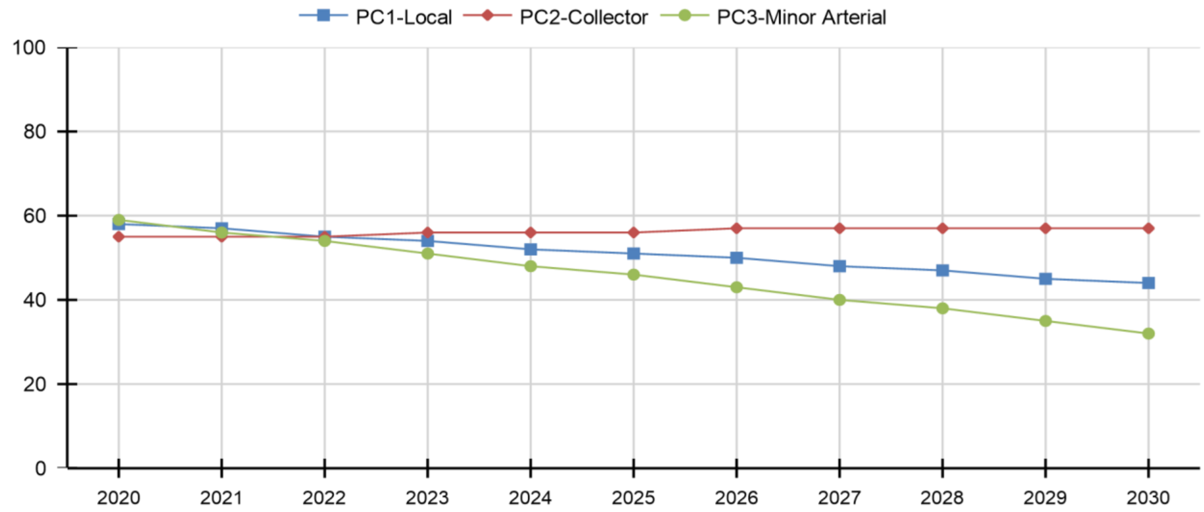

Figure 4: Condition projection based on functional class using prioritization

Network condition distribution results show that percentages of roads in poor and very poor conditions are increasing from 17% in 2020 to 51% in 2030. Consistent with the overall condition projections, Arterial roads show the most significant deterioration with 74% being in poor and very poor conditions by the end of the plan. The percentage of Collector roads in poor and very poor is expected to deteriorate from 20% in 2020 to 34% in 2030.

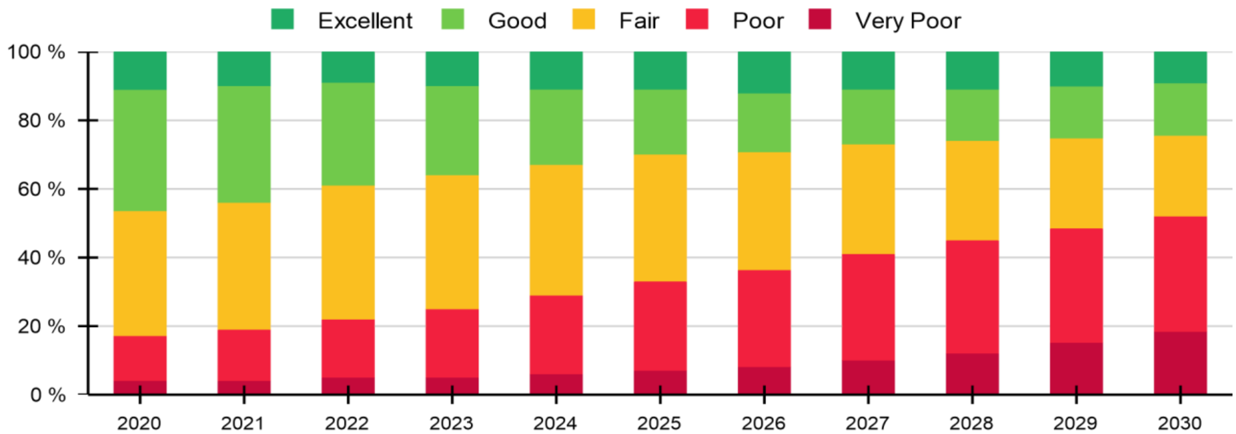

Figure 5: Network 10-year condition distribution using prioritization

Optimization scenario was performed under the exact same conditions as the prioritization scenario for an apple-to-apple comparison. Therefore, a $40M annual budget constraint with predefined distribution constraint to allocate maximum 50% of available budget to arterial, 40% to collector, and 10% to local roads. Optimization results show an overall network condition deterioration from 5.8 in year 2020 to 4.7 in year 2030. Arterials are expected to deteriorate from 5.9 in 2020 to 4.1 in 2030. Local roads are also deteriorating from 5.8 in 2020 to 4.4 in 2030. Collector roads improve from 5.5 in 2020 to 6.1 in 2030.

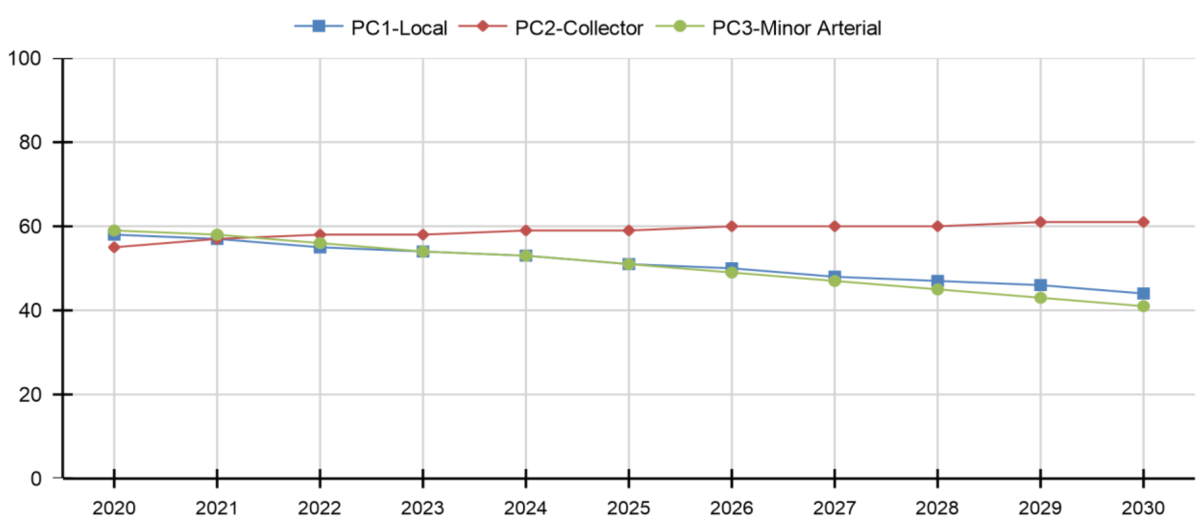

Figure 6: Condition projection based on functional class using optimization

Network condition distribution results show that by the end of the plan the percentage of roads in poor and very poor conditions is increasing from 17% in 2020 to 44% in 2030. Arterial roads deteriorate to poor and very poor condition from 16% in 2020 to 57% in 2030. The collector roads percentage of segments in poor and very poor slightly increases, however, the percentage in excellent and good condition significantly increases from 37% in 2020 to 61% in 2030, resulting in an overall improvement in their condition. Local roads deterioration to poor and very poor condition is from 18% in 2020 to 43% in 2030.

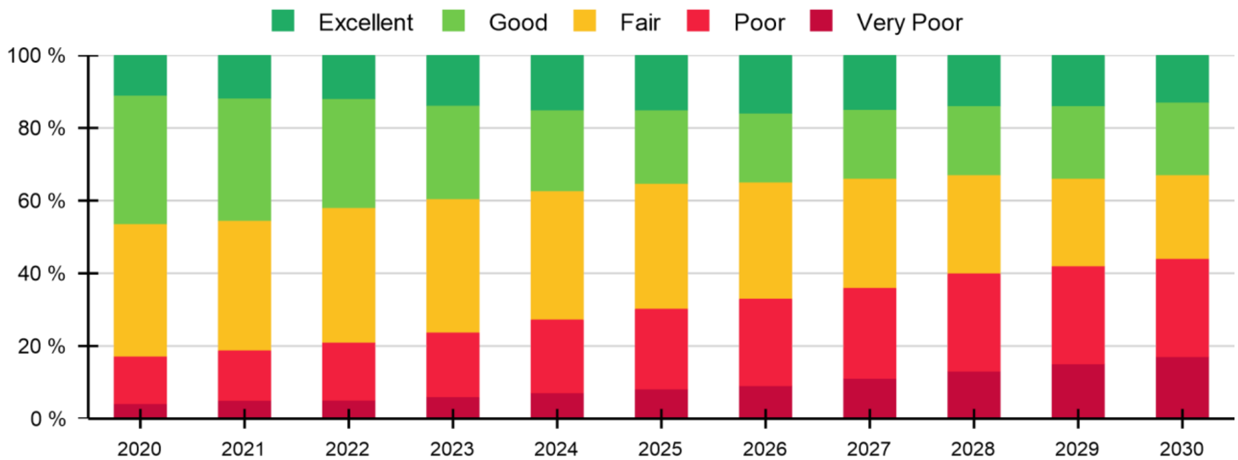

Figure 7: Network 10-year condition distribution using optimization

Average network condition over the 10-year planning horizon under the prioritization method is 49.5. Using the mathematical optimization method, the average condition over the plan is improved by 5.3% to 52.1 representing a globally optimum solution. Also, expected condition by the end of the plan is improved by 9.3% under the optimization from 4.4 to 4.7 PQI in year 2030. As shown in figure below, optimization outperforms prioritization at all years with higher network overall condition values. Average network improvement effect over the 10-year plan on Local, Collector, and Arterial roads are 0.4%, 5.3%, and 12.2%, respectively. End-of-plan network condition distribution results show that under the prioritization method 398 more kilometers of roads will be in poor and 62 more kilometers in very poor condition by the end of the plan, as compared to the optimization results. For Local roads, the optimization output maintains 55 more kilometers of roads in Good and Excellent conditions as compared to prioritization. For Collector roads, under the optimization scenario, 87 more kilometers of roads will be maintained in good and excellent conditions and 134 less kilometers in poor and very poor condition. For Arterial roads, optimization results in 273 more kilometers of roads in good and excellent conditions and 318 less kilometers of roads in poor and very poor condition. Figures below show the total length of roads in different condition states by the end of plan under optimization and prioritization cases for the network and each functional class.

Different approaches can be utilized to determine the cost saving implications of the difference in results. As an example, in case of Arterial roads, one can calculate the estimated cost of rehabilitating the additional 318 kilometers of Arterials in poor and very poor conditions in the case of prioritization. Assuming treatment option MI120MM for very poor Arterials and MI100MM for poor Arterials based on the decision rules, and 9 meters average width for arterial roads segments (this was determined based on available GIS data), the total cost savings can be estimated at over $100 million dollars. Another approach is to determine how much more investment is required to get to the same level of performance as the optimization solution, by gradually increasing the prioritization scenario's budget. Optimization results under a $40M annual budget limit ($400M 10-year investment) showed a 10-year average condition of 52.1, while prioritization resulted in a 10-year average of 49.5. Increasing prioritization annual budget from $40M to $45M improved 10-year average condition from 49.5 to 50.5, and further increase to $50M improved condition to 51.2. It is important to note that although in some years prioritization scenarios with different investment levels show the same overall condition, the results are slightly better in higher budget scenarios. The effect on overall condition values in some years, however, is relatively small, considering the size of the network, and therefore not visible due to rounding effects. These improvements are verifiable by using condition distribution charts. As seen by these results and under both monetization approaches, the improvement effect of using a true optimization method can be translated into over a $100M in cost savings due to added performance that represents 25% of the $400M total 10-year investment.

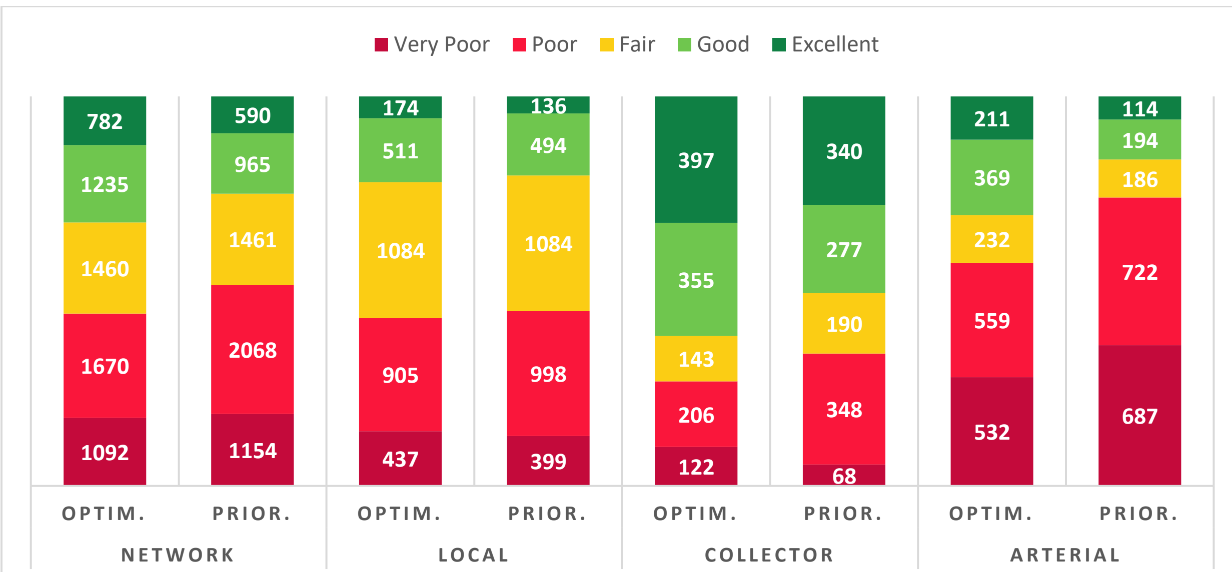

Figure 8: Kilometer of roads in different condition states by the end of plan (year 2030)

IMPACT OF DETERIORATION MODELLING

Different deterioration modelling techniques can be used to predict the expected conditions of road segments. Determination of the effectiveness and optimum timing of interventions requires the selection of a set of accurate deterioration models. The City's current prioritization process used a linear deterioration modeling approach based on expected service life (ESL) for roads in difference functional classes. Accordingly, ESLs of 25, 34, and 50 years were assigned to Arterial, Collector, and Local roads, respectively. The ESL determination is typically based on engineering judgement and the expected traffic volumes based on functional classes.

To investigate the sensitivity of the analysis and the capital planning outputs to the deterioration modeling methods, this study investigates the impact of a more rigorous deterioration modeling approach using decision tree regression analysis. The outputs of the decision tree model are compared with the linear ESL-based model. The decision tree regression is a non-parametric supervised machine learning approach that partitions datasets into different groups and provides the regression outcome for each group (Loh, 2002). The decision tree model analyzes pavement behavior considering a wider range of attributes including road class, community, district, bus route, truck route, school area, and the starting condition, as compared to the ESL model that is purely age-based. Due to the data limitations, the comparison analysis is conducted on a sub-set of the Calgary's road network data, representing 1,165 pavement sections representing 316.2 centerline kilometers or roads with a focus on Collector and Arterial roads only. Ten distinct deterioration models based on community data were developed using the decision tree regression process as shown in Figure 9. The 'Calgary Linear- ART' and 'Calgary Linear- COL' also show the ESL-based linear curves for arterial and collector roads, respectively. As shown in Figure 9, one of the key differences between the two modeling approaches is that the decrement of the condition index is fixed in the whole lifespan in the case of the linear ESL-based deterioration models, while the decision tree model predicts the decrements at each step to build the deterioration curve by deducting the decrements from the condition value of the previous step. The decision tree approach, therefore, results in a wider range of deterioration curves with a higher degree of variation in the expected service lives.

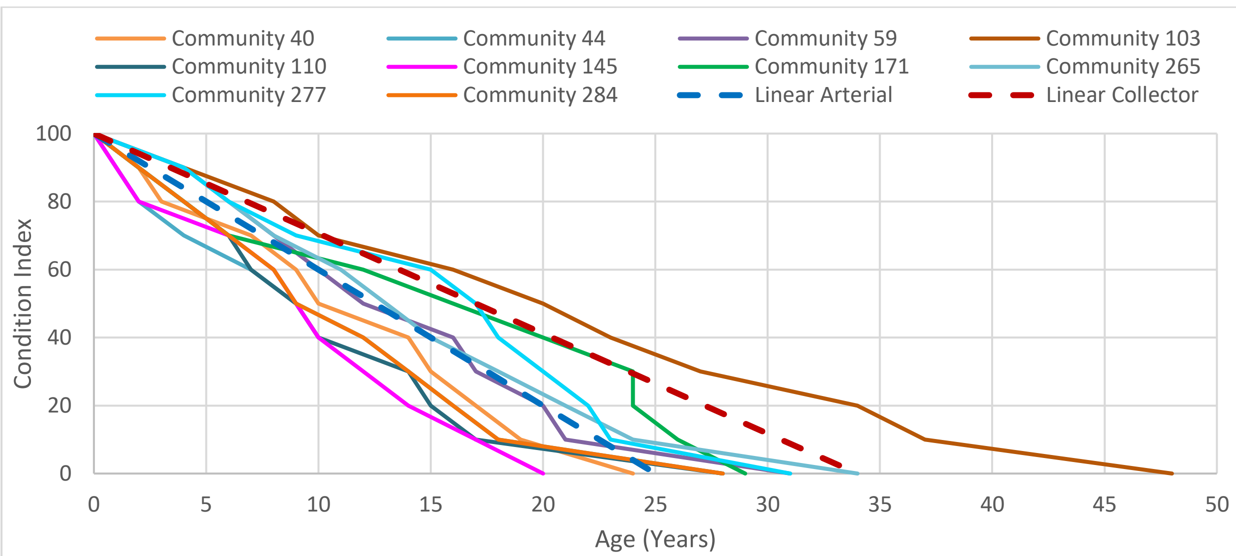

Figure 9: Decision tree and ESL-based deterioration curves

To perform a direct comparison between the two modeling approaches, all inputs including treatment alternatives, decision rules, and prioritization factors, are kept the same, and only the deterioration models are changed. Three scenarios have been designed to investigate the impact of the two deterioration modeling approaches under different circumstances. First, a 'Do-Nothing' scenario is designed to investigate the difference between the expected network condition decay over a 10-year planning horizon under each deterioration modeling approach. Next, a 'Maintain Current' scenario is designed to investigate the difference in investment needs to maintain the current condition of the network using the linear and decision tree models. Finally, a 'Fixed Budget' scenario is designed to investigate the expected level of service attainable under each case with an annual budget limit of $2.5M. Under the 'Do-Nothing' scenario, the condition of the network deteriorates from 59 at the beginning of the plan, to 25.5

and 22.2 by the end of plan using the linear model and the decision tree model, respectively. Do-Nothing results show a more optimistic projection under the linear model, with a significant difference of 57% in project condition for Collector roads as shown in Figure 10.

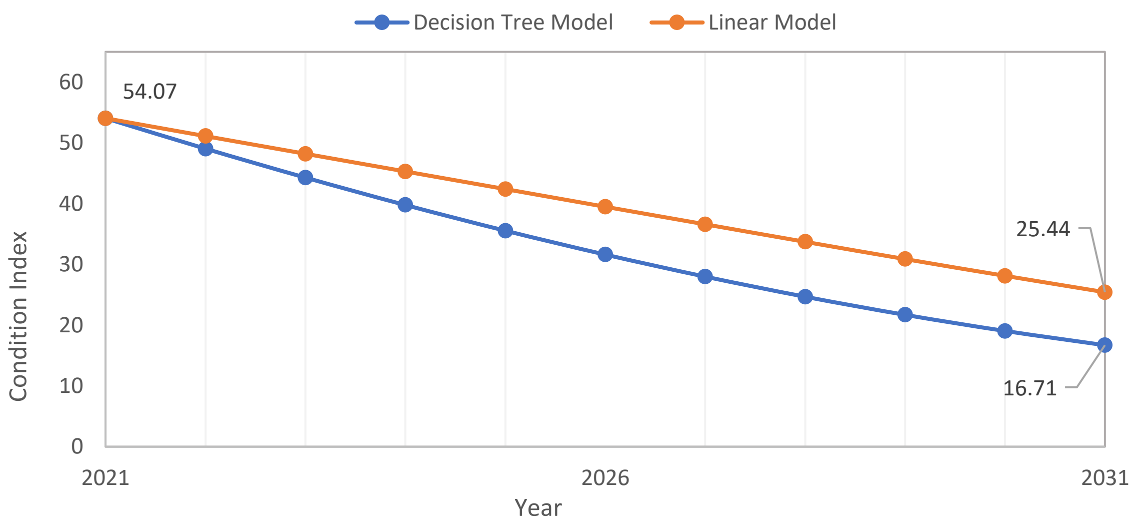

Figure 10: Do-Nothing deterioration projection for Collector roads

Under the 'Maintain Current' scenario the level of service is set to be the same throughout the planning horizon. As shown in Figure 11, under the linear model, the average 10-year investment need is estimated at $2.3M, while the decision tree model projects a $2.6M average annual investment need, showing a $3M difference over a 10-year planning horizon. Considering that the analysis is only looking at a sub-set of the network data, extrapolation of the results would suggest a significant backlog if the financial plan was based on the predictions of the linear ESL-based model.

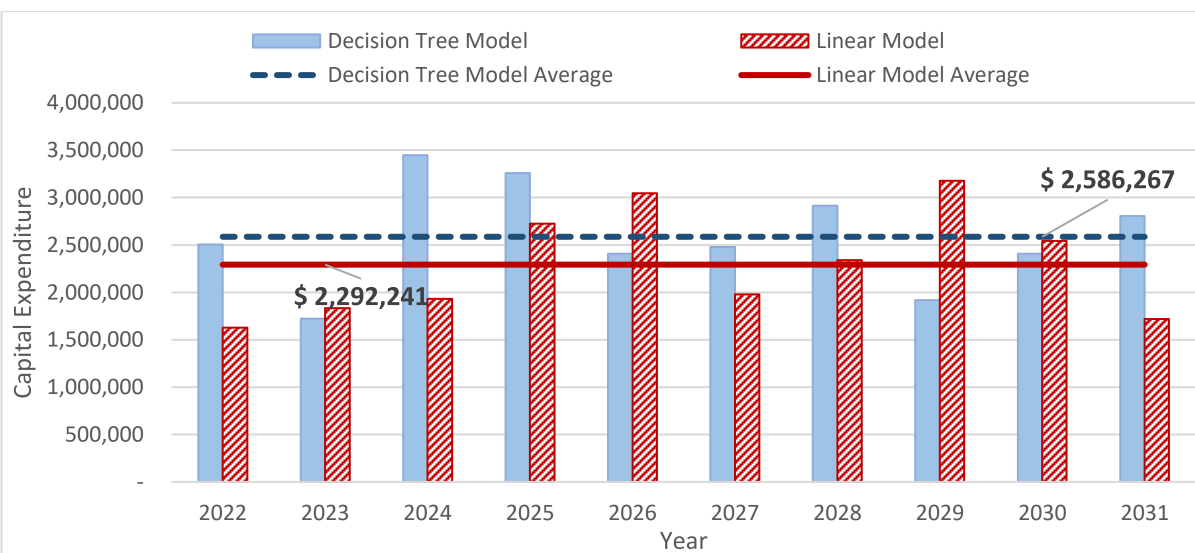

Figure 11: 10-year investment needs under decision tree and ESL deterioration models

Under the 'Fixed Budget' scenario with an annul budget limit of $2.5M, the overall condition index of the network increased from 59 to 62.8 and 67.2 using the decision tree and the linear models, respectively. The condition distribution results show a larger portion of the network in the poor and very poor condition states under the decision tree model confirming that the linear ESL-based models underestimate the deterioration rates throughout the planning horizon.

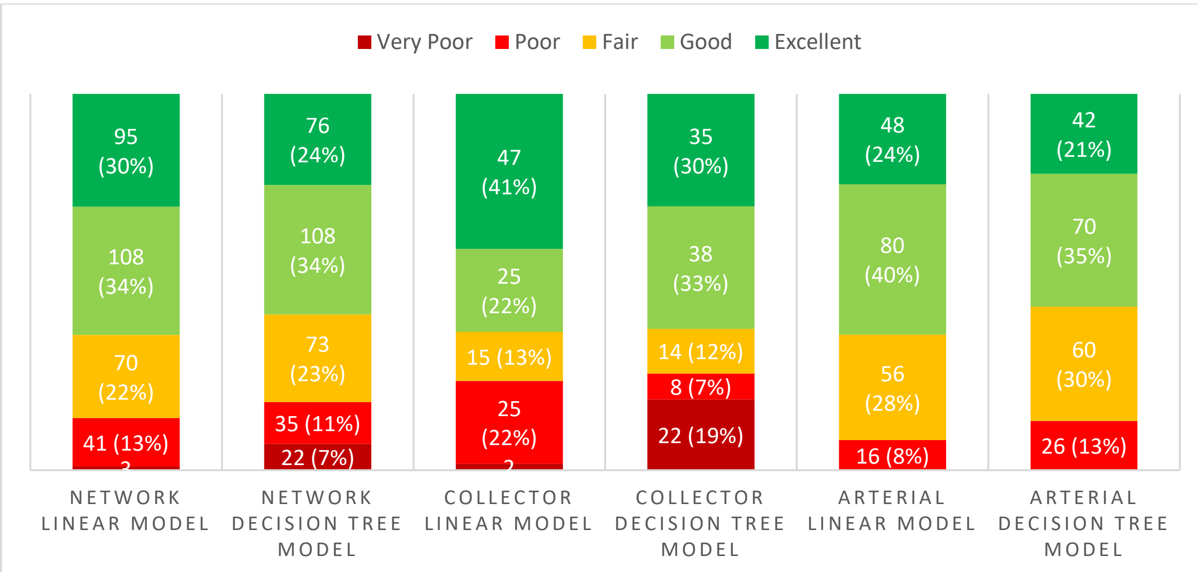

Figure 12: Kilometer of roads in different condition states by the end of the 10-year plan

CONCLUSIONS

This study compared the results of a prioritization approach and a true mathematical optimization approach for investment planning using the City of Calgary's road network data. The results showed that the average network condition over the 10-year planning horizon deteriorates under both prioritization and optimization methods. Optimization, however, outperformed prioritization at all years showing an average 5.3% improvement over the planning horizon and 9.3% by the end of the plan. Monetization methods arrived at an estimated $100M cost savings via added performance over the 10-year planning horizon by switching to a mathematically optimized solution.

One of the main problems with using condition-based priority ranking methods is the resulting "worst first" plan. Under this strategy, the most deteriorated roads are a huge sink into which the largest proportion of budgets is poured for major rehabilitation. 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. 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 agencies like the City of Calgary deal with a multitude of constraints. This study also investigated the sensitivity of outcomes to the deterioration models used within the pavement management system and compared machine learning-based deterioration models using decision tree regression with linear ESL-based models. The comparison results showed that the linear ESL models generally underestimate the deterioration rates throughout the planning horizon and can result in a significant unexpected backlog.

The ESL-based linear models may significantly underestimate the rate of deterioration, and as a result, distort the efficiency of an optimizer. Under the level of service constrain, the general linear models cause a large percentage of poor and very poor asset; and under a fixed budget, an over optimistic prediction leads to deficit projects. Besides optimization approach, a deterioration model based on local assessment data is another key factor to the quality of condition-based financial planning. The improvements achieved through an optimized solution can be translated into substantial higher level of service to the community as shown by this study. A capital planning tool with optimization capability can maximize the overall performance of a network over a multi-year analysis horizon while satisfying multiple constraints, such as budget limits, levels of service, operational considerations, alignment with other departments, etc., all at the same time. The resulting fund allocation plan represents the best possible course of action in terms of timing and selection of assets and treatment alternatives. Instead of prescribing a fixed budget for each road class, as was done in this comparison, an optimized solution can determine the best ratio for allocating the available budget by imposing specific Level of Service constraints for each road class. The optimization's ability to effectively meet various criteria from all stakeholders can result in a much higher support from the political council and the community during the funding approval and project justification process. This leads to a defendable, practical, and technically robust plan that results in the highest investment efficiency of the taxpayer money.

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