A Decision Support System for Multi-Objective Multi-Asset Roadway Asset Management (DSRAM)

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Abstract

The limited available budget along with old aging infrastructure in nation magnifies the role of strategic decision making for maintenance of infrastructure. The challenging objective is to maintain the infrastructure asset systems in a state of good repair and to improve the efficiency and performance of the infrastructure systems while protecting and enhancing the natural environment. Decision makers are in need of a decision support system to consider these multiple objectives and criteria to effectively allocate funding and achieve the highest possible return on investment on their infrastructure. The research proposes and validates a framework for such decisions. The proposed model aims at finding optimal techniques for maintenance of multiple roadway asset items while taking into account time, cost, level of service and environmental impacts. Therefore, the goal is to answer what are the optimal combinations of maintenance techniques for roadway assets while more than one objective is being optimized. In other words, the main objective is to develop a decision support system for selecting and prioritizing necessary actions for MR&R (Maintenance, Repair and Rehabilitation) of multiple asset items in order for a roadway to function within an acceptable level of service, budget, and time while considering environmental impacts. To achieve these desirable outcomes, this model creates a two-stage framework for a sustainable infrastructure asset management. First a multi-objective problem based on the multi colony ant colony optimization is analyzed. The objectives of the problem are: (i) Minimizing maintenance costs, (ii) Minimizing maintenance time, (iii) Minimizing environmental impacts and (iv) Maximizing level of service improvement. In the second stage, the results of the multi objective optimization will be prioritized using a Multi Criteria Decision Making (MCDM) process. The proposed approach will simultaneously optimize four conflicting objectives along with using a multi criteria decision-making technique for ranking the resulted non-dominated solutions of multi objective optimization. The results of implementation of the proposed model on a section of I-64 highway are presented for a sub-set of asset items. Moreover, the proposed model is validated using a scalable test problem as well as comparison with existing examples. Results reveal the capability of the model in generation of optimal solutions for the selection of maintenance strategies. The model optimizes decision making process and benefits decision makers by providing them with solutions for infrastructure asset management while meeting national goals towards sustainability and performance-based approach. In addition, provides a tool to run sensitivity analysis to evaluate annual budget effects and environmental impacts of different resource allocation scenarios. Application of the proposed approach is implemented on roadway asset items but it is not limited to roadways and is applicable to other infrastructure assets.

To the memory of my father, **Mansour Shoghli,**
for inspiring my fascination in science and learning

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Introduction

1.1 Introduction and background

Americans spend 4.2 billion hours a year stuck in traffic at a cost of $78.2 billion a year--$710 per motorist. Roadway conditions are a significant factor in about one-third of traffic fatalities. Poor road conditions cost U.S. motorists $67 billion a year in repairs and operating costs--$333 per motorist; 33% of America's major roads are in poor or mediocre condition and 36% of the nation's major urban highways are congested (Asce, 2009). A recent report by the American Society of Civil Engineers (ASCE), evaluated different civil infrastructure systems in the U.S. and rated the condition of roadways as D- (Asce, 2009). The challenge of maintaining the infrastructures at the best possible condition by investing the minimum amount of money keeps transportation agencies continually searching for innovative approaches to eventually provide optimum benefits to taxpayers (De La Garza et al., 2008). In a developed society satisfactory performance of civil infrastructure can guarantee economic growth and social development. Highway infrastructure as a significant part of the public asset plays a special role to ensure the mobility of citizens and transportation of goods. Therefore, special attention should be placed in maintaining highway assets. Moreover, the limited and constrained available budget along with old aging infrastructure in nation magnifies the role of strategic decision making for maintenance, repair and rehabilitation (MR&R)[1] of highways.

[1] *Maintenance* means any work task that prolongs the life of the facility without increasing its capability, strength or capacity. *Repair* concerns mostly local damages and means to mend and to put into good shape and working order again. *Rehabilitation* concerns mostly the whole section and means to put back in good condition, to re-establish on affirm, sound basis, to bring back to full use.

The decision making used for selecting and prioritizing necessary actions to maintain a facility or a system to function within an acceptable level of service and safety, while considering budget constraints is called infrastructure management. There are many reported successful applications of decision support systems in the construction industry such as bridge management and pavement management decision support systems. They have helped engineers, practitioners and decision makers through improved identification of infrastructure assets information, methodologies developed for needs assessment and analytical tools for the evaluation of possible solutions (Abu Dabous, 2008).

1.2 Path leading to the proposed research

There have been many studies around the world for the management of highway infrastructure. During the last decades various types of individual highway asset items management such as bridge management system (BMS) and pavement management system (PMS) have been developed. Research in these areas is still ongoing with new findings and progress (Aristeidis, 2005) but there remain much room for a research that takes into account all the asset items simultaneously in highway area to develop a comprehensive decision support system considering various asset items. An example list of asset groups and asset items to be maintained by the contractor and any state DOT is shown in table 1. It reveals that there exist different asset items in highways which should be considered in the decision making process.

Table 1 List of asset groups and asset items that make of the highway infrastructure

Asset Group	Asset Item
Shoulders	Shoulders – Hard Surfaced Shoulders – Non-hard Surfaced
Roadside	Grass Landscaping Brush and Tree control Concrete Barrier Sound Barrier Slopes Fence
Drainage	Paved Ditches Unpaved Ditches Pipes Box Culverts Under/Edge Drains Storm Drains/Drop Inlets Curb and Gutter Sidewalks Storm Water Management Ponds
Traffic	Pavement Messages Pavement Striping Pavement Markers Delineators/Object Markers Glare Foils Regulatory Signs Other Signs Luminaries Guardrail Impact Attenuators Truck Ramps Cross Overs Rumble Strips
Pavement	Paved Lanes
Bridges	Deck Superstructure Substructure Slope/Channel Protection

1.3 Research objectives

The main objective of this research is to develop a Decision support system for multi-objective multi-asset Roadway Asset Management. It aims at finding optimal techniques for maintenance, repair and rehabilitation (MR&R) of roadway assets while taking into account time, cost, level of service and Environmental Impacts. In order to accomplish such a decision support system the other objective of the research is to develop a multi-objective optimization model to find a solution for the combinatorial infrastructure asset management problem. In addition, to develop a robust meta-heuristic algorithm as an alternative technique for solving multi-objective optimization problem. Finally to prioritize Pareto optimal solution using a multi-criteria decision making technique.

The goal is to answer:

- What are the optimal combination of maintenance options for roadway assets to maintain four conflicting objectives of time, cost, level of service and Environmental Impact?
- What algorithm is suitable for solving a multi-objective optimization problem?
- What is an appropriate approach for prioritizing Pareto optimal solutions resulted from multi-objective optimization?

2

Literature Review

This chapter provides a literature review of highway asset management: (i) general asset management, (ii) Previously developed highway asset management techniques, (iii) Decision making and optimization for asset management, (iv) Sustainability considerations for asset management.

2.1 Asset Management in General

Asset management "*is defined as a systematic process of operating, maintaining, and upgrading transportation assets cost-effectively. It combines engineering and mathematical analyses with sound business practice and economic theory. The total asset management concept expands the scope of conventional infrastructure management systems by addressing the human element and other support assets as well as the physical plant (e.g., highway, transit systems, airports, etc.). Asset management systems are goal driven and, like the traditional planning process, include components for data collection, strategy evaluation, program development, and feedback. The asset management model explicitly addresses integration of decisions made across all program areas. Its purpose is simple—to maximize benefits of a transportation program to its customers and users, based on well-defined goals and with available resources.*" (FHWA, 1999).

- **Blueprint for Developing and Implementing an Asset Management System**

One of the main objectives of asset management is improving the decision making process for allocating funds among costs of an agency's assets so that the best return on investment is obtained. Asset management is also defined as "a process of resource allocation and utilization" (Aashto, 2002; Krugler, 2007). A well-structured asset management system should be capable of evaluating the effects of investing different levels of funding in each of these various types of assets and the effects of investing more in one type while investing less in another. Moreover, It should be capable of considering both short term and long term impacts of allocating different resources (Krugler, 2007).

American Association of State Highway and Transportation Officials guide entitled "*transportation asset management guide*" (Aashto, 2002) explains asset management concepts and principles within their business processes. It deals with decisions of an agency in resource allocation and utilization in managing its transportation infrastructure system.

Federal Highway Administration's asset management primer (Fhwa, 1999) provides basics of asset management. To address the answers to the questions: What is asset management? Why do we need asset management? Moreover, current practices in asset management are addressed and a vision into future for improving the process is explained.

New analytical tools to support asset management is discussed in National Cooperative Highway Research Program's "Analytical Tools for Asset Management" (Nchrp, 2005). It mainly explains the needed tools in trade-off analysis for resource allocation to assist decision makers.

Best Practices for Linking Strategic Goals to Resource Allocation and Implementation Decisions Using Elements of a Transportation Asset Management Program is a report by Midwest Regional University Transportation Center (Pagano et al., 2004) that tries to link strategic goals to resource allocation using the experiences and best practices in a diverse set of states.

Switzer and Mcneil (2004) developed a road map for transportation asset management that aims at identification of research needs along with providing significant milestones along the way. It is based on the initiatives from a number of professional and government organizations.

Another useful reference that should be addressed is "*a scanning tour to observe asset management experiences, techniques, and processes in four countries; Australia, Canada, England and New Zealand*" (Geiger et al., 2005) that is sponsored by FHWA, AASHTO, and NCHRP. In this study, the U.S. team observed that asset management as an organizational culture and decision-making process is critical to transportation programs facing significant capital renewal and preservation needs and that successful programs require top-level commitment.

2.2 Previously developed highway asset management techniques

There exist a wide range of techniques being developed for the management of various highway asset items. During the last decades various types of asset management systems focusing on individual asset items such as bridge management systems (BMS) and pavement management systems (PMS) have been developed. Research in these areas is still ongoing with new findings and progress (Abu Dabous and Alkass, 2008; Albitres and Martin, 2007; Aristeidis, 2005; De La Garza and Krueger, 2007; Gharaibeh et al., 2006; Gharaibeh et al., 1999; Hastak et al., 2005; Hegazy, 2006; Li and Sinha, 2004).

Abu Dabous et al. (2008) developed a decision support method for multi-criteria selection of bridge rehabilitation strategy. Authors report that the current decision-making approach for bridge management is life cycle cost optimization and a single criterion decision making process which does not consider the indirect impact of MR&R of the bridges on users and society. Sound decision making should take into account indirect cost components such as user delay costs, economical, social and environmental impact costs. They propose a bridge decision managing system considering multiple and conflicting criteria. They eventually developed a comprehensive decision support system for bridges, one individual asset item of highways. Similar studies are reported both for the bridge asset item and also other individual assets (Abu Dabous, 2008).

Selih et al. (2008) developed a high level multiple-criteria decision support system in highway infrastructure management. This research develops a Decision Support System (DSS) to determine the priority ranking of asset rehabilitation projects. They present the results for a selected case study consisting of 27 overpasses for a highway section. They believe the proposed system meets the pre-defined combination of several criteria and therefore yields the maximized overall benefit.

Gharibeh et al. (1999) developed a prototype highway asset management system to integrate network and project level management and evaluate the outcomes of certain scenarios using GIS application. de la Garza et al. (2007) propose a simulation technology to make pavement management decisions and also provide a simulation environment for renewal or maintenance strategies. Abaza et al. (2004) have designed an integrated pavement management system for planning and scheduling of pavement maintenance and rehabilitation work. A discrete-time Markovian model to predict pavement deterioration is applied in their developed system. Ferreira et al. (2002) have developed an optimization model for a network-level pavement management system using genetic-algorithm to solve the model.

Amekudzi et al. (2001) developed a system to analyze investment tradeoffs under uncertainty for competing infrastructure using a Shortfall Analysis to estimate investments for minimum standards of safety, serviceability and preservation quantitative risk-based approach. Moreover, for estimations of marginal utilities of investments in competing facilities the Maarkiwitzi Theory has been used. Authors believe that developed framework is an appropriate approach for simultaneously capturing tradeoffs in expenditure in competing infrastructure facilities along with the major risks associated with these investments. The framework is also a point of departure for discussions on superior investments from the standpoint of managing the maintenance of infrastructure to provide an increasingly higher value to its users. National, state and municipal public works agencies may adopt this framework to merge quasi-independent infrastructure management systems into integrated systems for asset management.

Falls et al. (2006) refer to the problem of integration of asset categories in response to not having a mechanism for producing a single program list that has been developed with cross-optimization techniques. Authors present the concept of Asset Service Index (ASI) as a potential integration mechanism in asset management systems. ASI uses the specific performance model of the asset category and replacement cost to calculate a single index that can be used to develop optimized multi-layer programs for complex assets. This research presents the concept of the ASI as a potential integration mechanism in asset management systems. Currently, integration across asset categories is considered only at the database level; however, true integration should occur at several levels in the asset management framework. By working with the concept that asset value can become a tool for cross optimization, as well as performance measurement and reporting, ASI is presented for consideration.

Zhang et al. (2002) has developed an integrated urban infrastructure management system (UIMS) for managing urban transportation infrastructure. UIMS is a computerized tool which is intended to assist decision makers in managing their infrastructure effectively. The system consists of two subsystems: pavement management and bridge management. UIMS integrates these two separate systems by means of ultimate data sharing and also provides a single evaluation index to compare pavement and bridges simultaneously. UIMS is a tool for network level management. It addresses M & R needs, assigns specific projects for pavement and bridges and makes budget allocations between these projects.

Wu et al. (2008) have tried to solve the problem of resource allocation to regional pavement-preservation using a hybrid multi-objective optimization model. They have utilized goal programming and analytic hierarchy process respectively for dealing with multiple objectives and priority setting under multiple criteria. The model considers two conflicting objectives of maximization of the preservation effectiveness in terms of extended service life and minimization of the total cost of the preservation. Authors further discuss the applicability of the model using a short- term pavement preservation budgeting problem for a state DOT with nine maintenance districts.

Chan and Tan (2003) have proposed a procedure for optimal fund allocation for multidistrict highway agencies. They employ the genetic-algorithm optimization technique to allocate the total funds available to the district or regional agencies in order to best achieve specified goals of agencies subject to operational and resource constraints. It considers both the overall objective of the central agency and a goal specified by each district or regional agency. They have demonstrated the practicality of the solution with a pavement maintenance fund allocation example of a three-region management structure administered with different goals or objectives indicated by the central and regional authorities. Authors believe that the proposed procedure is able to consistently allocate funds to areas where they are most needed, resulting in better overall network pavement conditions.

Fwa and Farhan (2012) developed a multi-dimensional highway asset budget allocation optimization approach. They proposed a two stage approach in solving the multi-asset multi-objective pavement network maintenance optimal budget allocation problem. In the first stage of the approach the individual multi-objective asset systems are analyzed independently to establish a family of optimal Pareto solutions for each of them. Maintenance cost minimization is selected as a common objective for the individual asset systems that serves as a link for interaction with the Stage II analysis. In the second Stage, an optimal algorithm for budget allocation to individual assets by performing cross-asset trade-off to achieve the optimal budget solution for the given overall system level objectives is proposed.

2.3 Decision making and optimization

Efficient allocation of resources plays an important role in successful highway asset management practice. Therefore, many optimization techniques have been widely utilized as a decision-support system in various areas of resource allocation problems (Krugler, 2007). Finding optimal fund allocation has been actively pursued for general project management (Hegazy, 1999), for multidistrict highway agencies (Chan and Tan, 2003), and for infrastructure projects (Gabriel et al., 2006b). In a linear programming model for pavement management Davis and Van Dine (1988) developed a model capable of minimizing user costs subject to budget and production capacity for optimizing maintenance and reconstruction activities.

More recently, computing power paves the way for the optimization methods to solve more realistic and complicated problems. Transportation projects are often being evaluated in accordance with multiple criteria, such as different stakeholders' benefits and drawbacks. Moreover, these projects include a wide range of asset items, such as pavement, bridges, roadside and etc. Although, classic optimization deals with single-objective deterministic systems, many attempts in the literature are reported using multiple objectives. In some cases, multiple objectives are aggregated into a single objective function by assigning weights to the objectives that are often solved using heuristic techniques such as genetic algorithms (Chan and Tan, 2003; Hegazy, 1999)

The fact of optimizing several objectives simultaneously has made the problem solving more complicated in multi-objective optimization. There are many multi-objective real-world problems that are complex and meta-heuristic procedures help to deal with them. This field has been strongly developed in the last years. Some researchers have designed genetic algorithms to deal with multi-objective optimizations in construction such as time-cost trade-off problems, and they have adapted genetic algorithms for optimizing construction bi-objective time and cost (Feng et al., 1997; Li and Love, 1997; Zheng and Ng, 2004). As mentioned, the goal of multi-objective optimization problems is to find the best compromise between multiple and conflicting objectives. Considering all objectives in these problems, there will be more than one solution that optimizes simultaneously all the objectives and there is no distinct superiority between these solutions. Usually there is not a single best solution being better than the remainder with respect to every objective. Therefore, we are faced with a set of solutions which are better than remainder solutions called Pareto Front. Among the feasible solutions, ones belonging to the Pareto front are known as non-dominated solutions, while the remaining solutions are known as dominated.

Since none of the Pareto set solutions are absolutely better than the other non-dominated solutions, all of them are equally acceptable as they satisfy all of the objectives.

The literature review of decision making techniques has resulted in identification of two main categories of decision making techniques: (1) Multi-Objective Decision Making (MODM); (2) Multi-Criteria Decision Making (MCDM). The goal for MODM techniques is to find the best compromise between multiple and conflicting objectives we have in the asset management field. Considering all the objectives in these problems there will be more than one solution that optimizes simultaneously all the objectives, and there is no distinct superiority between these solutions. Usually there is not a single best solution being better than the remainder with respect to every objective. Therefore, we are having a set of solutions which are better than remainder solutions called Pareto front. Another category of decision making techniques is Multi Criteria Decision making (MCDA) which aims at supporting decisions that are faced with numerous and conflicting evaluations. MCDA highlights these conflicts in order to derive a way to come to a compromise in a transparent process.

In both MODM and MCDM categories various techniques along with their application in highway area are reported such as application of Analytic Hierarchy Process (AHP) for highway asset management (Šelih et al., 2008), application of multi objective optimization for time-cost-quality optimization in highways (El-Rayes and Kandil, 2005), and application of a modified AHP technique for bridge management (Abu Dabous and Alkass, 2008). Moreover, these techniques need to be analyzed to identify the most appropriate techniques in modeling the current problem.

One of the reported applications of MODM is for highway time-cost-quality optimization. El-Rayes and Kandil (2005) have utilized a multi objective approach for time-cost-quality trade-off analysis in highway projects. Their model is designed to search for optimal resource utilization plans that minimize construction time and cost while maximizing its quality. In the optimization process, first the model is formulated which incorporates all major decision variables and objectives. Then the quality in the project is quantified in order for the quality objective to be considered in optimization problem. Finally, the model is implemented in which a multi objective Genetic Algorithm (GA) is utilized for highway construction and rehabilitation to enable the simultaneous optimization of time, cost and quality. They analyze an application example to show the capabilities of the model (El-Rayes and Kandil, 2005).

Abu Dabous et al. (2008) have developed an application of MCDM for bridge management. The designed model considers indirect impact of the maintenance, repair and replacement actions. Their method is a modified version of Analytic Hierarchy Process that ranks alternative bridge rehabilitation strategies.

The chronological review of the key literature is summarized in Table 2.

Table 2 Chronological review of key literature for multi objective asset management

Reference	Technique	Area of application
Sinha et al. (1981)	Goal Programing	Fund allocation for Maintenance and perservation of Highway
Ravirala et al. (1996)	Goal Prgramming	Network level bridge managment
Dissanayake et al. (1999)	Weighted Sum Method	Critical Highway Safety needs
Pilson et al. (1999)	Genetic Algorithm for Multi-objective optimization	Pavement Management
Chan and Tan (2003)	Genetic Algorithm	Fund allocation for multi district agencies
Wang et al. (2003)	Weigted sum method	Pavement maintenance and rehabilitation
Li and Sinha (2004)	Multi attribute utility theory	Highway asset management
El-Rayes and Kandil (2005)	Genetic algorithm	Highway resource allocation
Gharaibeh et al. (2006)	Multi attribute utility theory	Fund allocation across assets
Kandil and El-Rayes (2006)	Multi Objective and Multi Attribute Decision Making	Optimal construction resource utilization
Wu et al. (2008)	Goal Programming and AHP	Regional pavement resource allocation
Li and Sinha (2009)	AHP	Relative weights of goals and performance measures
Fwa and Farhan (2012)	Multi objective optimization and Dynamic programming	Multi-asset budget allocation

There had been key studies that developed decision support systems for highway asset management using multi objective and multi criteria decision making techniques. But, there was not sufficient attention on consideration of multiple asset items in roadways. In addition, only a few studies such as Kandil and El-Rayes (2006) have reported the combined application of both multi objective and multi criteria decision making for the purpose of roadway asset management.

2.4 Multi-objective Optimization

2.4.1 An overview of multi –objective techniques

General formulation of governing equations on a multi-objective optimization is explained in order to address the definition and terms in this area

A multi-objective decision making problem wishing to minimize K objectives can be defined as follows (Marler and Arora, 2004):

$x = \{x_1, \dots, x_n\}$, where x is an n-dimensional decision variable vector in the solution space X, x^s Vector is desired that minimizes a given set of K objective functions:

$$z(x^s) = \{z_1(x^s), \dots, z_K(x^s)\} \qquad \textbf{(1)}$$

The solution space X is generally restricted by series of constraints and bounds on the decision variables. For example $g_j(x^s) = b_j$ for $j = 1, \dots, m$.

Most real-world engineering optimization problems are implicitly or explicitly multi-objective, and approaches to find the best feasible solution to be implemented can be quite challenging for the decision-maker. In this kind of problem, the analyst either determines a single solution or identifies a set of non-dominated solutions, often referred to as Pareto-optimal set (Taboada and Coit, 2005).

Determination of a single ultimate solution for multi-objective problems is performed using methods such as the weighted sum method, utility theory, goal programming, etc. In the case of the weighted sum method, the obtained solution can be highly sensitive to the weights used in the scalarization process, while the main difficulty with using utility theory, for many practitioners, is the determination of meaningful utility functions. In such methods, the value of the weights chosen or the utilities used dictates the final solution.

Therefore, these traditional methods require that the decision-maker has broad knowledge about the underlying problem. The other general approach is the determination of a set of non-dominated solutions (Pareto-optimal set). The complexity of solving multi-objective problems involves two types of problem difficulties: i) multiple, conflicting objectives, and ii) a highly complex search space. With multiple objectives, there is generally not one unique solution which is best (global minimum or maximum) with respect to all objectives but a set of solutions which cannot be dominated by any other solutions in the search space. These solutions are known as Pareto optimal solutions or non-dominated solutions.

The ultimate goal of a multi-objective optimization algorithm is to identify solutions in the Pareto optimal set. However, identifying the entire Pareto optimal set, for many multi-objective problems, is practically impossible due to its size. In addition, for many problems, especially for combinatorial optimization problems, proof of solution optimality is computationally infeasible. Therefore, a practical approach to multi-objective optimization is to investigate a set of solutions (the best-known Pareto set) that represent the Pareto optimal set as well as possible. With these concerns in mind, a multi-objective optimization approach should achieve the following three conflicting goals (Konak et al., 2006; Zitzler et al., 2000):

1. The best-known Pareto front should be as close as possible to the true Pareto front. Ideally, the best-known Pareto set should be a subset of the Pareto optimal set.

2. Solutions in the best-known Pareto set should be uniformly distributed and diverse over of the Pareto front in order to provide the decision-maker a true picture of trade-offs.

3. The best-known Pareto front should capture the whole spectrum of the Pareto front. This requires investigating solutions at the extreme ends of the objective function space.

For a given computational time limit, the first goal is best served by focusing the search on a particular region of the Pareto front. On the contrary, the second goal demands the search effort to be uniformly distributed over the Pareto front. The third goal aims at extending the Pareto front at both ends, exploring new extreme solutions.

2.4.2 Meta-heuristic multi-objective optimization

Heuristic rules and exact solution methods dominate earlier operational research to support construction and engineering decision making. However they are deficient to deal with large scale problems. Various meta-heuristic algorithms based on biological and animal behavior have become popular lately. Meta-heuristics are general purpose high level search frameworks that can be applied to any optimization problem with the use of appropriate local problem dependent solution procedures. Examples of meta-heuristics include simulated annealing (SA), ant colony optimization (ACO), evolutionary algorithm (EA), genetic algorithm (GA), particle swarm optimization (PSO), and shuffled frog-leaping (SFL). Theoretically, each meta-heuristic can be applied to optimize each project life related topic, though the effectiveness might vary. The reason for focusing on meta-heuristics is their superiority in handling highly nonlinear, multi-modal, constrained, discontinuous, and non-differentiable optimization models often encountered in project management (Liao et al., 2011).

Among the different problems approached by meta-heuristics time–cost optimization as a combinatorial optimization problem has been continuously modeled based on genetic algorithm, ant colony optimization and other meta-heuristics. In principle, the optimal solution for these problems can be found by enumeration. The major construction projects often involve numerous activities, therefore evaluation of all possible combinations within a short period of time and a reasonable cost may not be feasible (Afshar et al., 2009; Ng et al., 2000). As an example, the total number of alternative combinations of time and cost for an assumed MR&R project with 20 deficiencies and 6 MR&R options for each deficiency may exceed 3.66×10^{15} cases. Hence a new search algorithm would then be indispensable for a comprehensive and yet efficient two objective optimization. The existing techniques for these type of optimization problems can be categorized as: (1) heuristic methods; and (2) mathematical programming approaches (Feng et al., 1997; Li and Love, 1997). Although the weaknesses of the heuristics and mathematical methods are widely documented in the literature, the main deficiency with most of the mathematical models is their inability to handle more than one objective (Zheng and Ng, 2004). In addition, they may easily be trapped in local optima. An efficient approach to the problems like time-cost trade-off problem requires a multi-objective optimization algorithm with greater freedom in exploring the solutions space to reduce the likelihood of being trapped in local optima (Zheng and Ng, 2004).

Liao et al. (2011) reviewed meta-heuristic applications for project and construction management. Table 3 represents summarized applications of various meta-heuristic approaches. As discussed earlier, one simple approach to deal with multi-objective optimization problems is converting multiple objectives into one single objective by weighting. However, correctly assigning the weights is a challenge. In Table 3 the numbers in parentheses indicate the number of papers that consider multiple objectives (the alternative approach to the weighting) attempting to find the set of non-dominated solutions.

Table 3 Summary of meta-heuristic usages in construction management (Adapted from Liao et al. (2011))

Topic	SA	TS	ACO	EA/GA	PSO	HS	SFL	Hybrid	More than 1
Engineering Design				5					
Cost Estimation				3					
Planning									
Site preparation	1								
Site/floor layout		1	1	9	1			1[3]	
Site routing				1					
1D stocking cutting				2					
Supply chain/logistics			1	1					
Equipment selection				3(1)					
Scheduling									
Resource unconstrained	2		3	2					1[2]
Resource constrained									
Time-cost tradeoff			3(3)	12(8)		1(1)	1		
Resource allocation			2(1)	8(3)	2(1)				
Resource leveling	1			3					
Integrated models				5(2)					
Monitoring and Control				1					

Note: (1) Numbers in parenthesis indicate number of papers that consider multiple objectives.
(2) This study employs two metaheuristics, i.e., SA and TS.
(3) This is a ant-GA hybrid.

With recent advances in artificial intelligence as a branch of computer science and the fast growth in computer technology, a new breed of optimization techniques has emerged (Dorigo et al., 1996). Researchers have reported the robustness of the Ant Colony Optimization (ACO) algorithm and its capacity to efficiently search for and find a near and/or optimum solution. This is especially true in discrete optimization problems. Several researchers (Feng et al., 1997; Hegazy, 1999; Li and Love, 1997) have adapted genetic algorithms for construction optimization. However, in recent years, multi-objective ant algorithms have been proposed to solve various multi-objective optimization problems.

Gambardella et al. (1999) applied a two colony ACO approach to the vehicle routing problem with time windows. Gravel et al. (2002) proposed an ACO algorithm for a multi- objective problem arising in a real-world scheduling problem for aluminum casting center. Afshar et al. (2007) proposed an ACO approach for solving three objective optimization problem as well as two objective time-cost trade-off problem. Chaharsooghi and Meimand Kermani (2008) proposed a modified ACO to obtain a set of Pareto solutions efficiently for multi-objective resource allocation. Their proposed algorithm was tested with the same example used by Lin and Gen (2008) and found to perform better than hybrid GA developed by Lin and Gen (2008).

Based on the results reported by Garcia-Martinez et al. (2007) on comparison different ACO and GA approaches and considering successful reported applications of ant colony optimization in discrete domains. A modified multi colony ant colony optimization is proposed for four-objective optimization problem of the current research. The steps of proposed algorithm are discussed in detail in section 3.1.3.

2.5 Mutli-criteria decision making

2.5.1 An overview of MCDM techniques

Multi-criteria decision-making (MCDM) problem is concerned with the identification of the levels of preference of decision alternatives (DAs), based on the judgments made over a number of criteria. An analysis of MCDM must accommodate the situation of decision-maker (DM) offering diverse preference judgments on the DAs over the different criteria. There is an active area of research when the MCDM problem compounded with a group decision-making (GDM) environment. In which the judgments from each member of the group are then aggregated together to allow a final group decision to be made(Beynon, 2005).

One of the earliest applications of multi criteria analysis is the one proposed by Benjamin Franklin to Joseph Priestley. The weighting and scoring procedure used falls a little short of what may be required in decision making of larger problems. But, like many multi criteria analysis procedures, it has the effect of encouraging the decision maker (DM) to think carefully about identifying key criteria. More recently than Franklin, a number of researchers have developed the linear multi attribute model and ways of applying it that are helpful in various circumstances. Two important perspectives in this respect derive, respectively, from Keeney and Raiffa (1993) and Edwards (1971). Keeney and Raiffa developed a set of procedures, consistent with the earlier normative foundations, which would allow decision makers to evaluate multi-criteria options in practice. Edwards used to research on a work in which psychologically-oriented decision researchers had been trying to build models to reflect how expert decision makers make decisions. He came to develop a technique named SMART (Simple Multi-Attribute Rating Technique).

The Simple Multi-Attribute Rating Technique (SMART) proposed by Edwards (1971) is a Multi-Criteria Decision Analysis (MCDA) method in which a finite number of decision alternatives under a finite number of performance criteria are evaluated. The purpose of the analysis is to rank the alternatives in a subjective order of preference and, if possible to tact the overall performance of the alternatives via the proper assignment of numerical grades.

Prior to elucidation of two approaches, in order to address the MCDM techniques clearly and for future reference in comparison of different techniques, a standard decision table along with parametric structure of multi-criteria decision making techniques is represented. Here, a general multi-attribute decision making problem with m criteria and n alternatives is considered. Let $C_1, \dots, C_m$ and $A_1, \dots, A_n$ respectively stand for the criteria and alternatives. In the Table 4, that represents features of the multi-attribute decision making methodology, each row represents a criterion and each column shows the performance of an alternative. The score a_{ij} describes the performance of alternative A_j against criterion C_i. Here, it is assumed that a higher score value corresponds to a better performance. It should be noted that any goal of minimization can be easily transformed into a goal of maximization. As shown in decision table, weights $w_1, \dots, w_m$ are assigned to the criteria. Weight w_i reflects the relative importance of criteria C_i to the decision, and is assumed to be positive. They represent the view of a decision maker or combine the opinions of a group of experts using a group decision technique.

Table 4 Decision Table

		x_1	.	.	x_n
		$\mathbf{A}_1$	.	.	$\mathbf{A}_n$
w_1	$\mathbf{C}_1$	a_{11}	.	.	a_{m1}
.	.	.	.	.	.
.	.	.	.	.	.
w_m	$\mathbf{C}_m$	a_{m1}	.	.	a_{mn}

2.5.1.1 Simple Multi-Attribute Rating Technique (SMART)

SMART is one of the simple and effective methods in this area. The ranking value x_j of alternative A_j is obtained simply as the weighted algebraic mean of the values associated with it as follows:

$$x_j = \frac{\sum_{i=1}^{m} w_i a_{ij}}{\sum_{i=1}^{m} w_i}, j = 1, \dots, n. \quad (2)$$

Edwards (1977) proposed another simple technique to assess weights for each of the criteria in SMART to reflect its relative importance to the decision. In this method, the criteria are ranked in order of importance and the least important criterion will have a 10 points. Then, the next least-important criterion is chosen, more points are assigned to it, and so on, to reflect their relative importance. The final weights are calculated by normalizing the sum of the points to one. Edwards and Barron (1994) proposed a variant of the SMART technique that uses Swings in this technique and is named SMARTS. This variant of SMART considers the amplitude of the values in the course of the comparison of the importance of the criteria.

2.5.1.2 Analytic Hierarchy Process (AHP)

The AHP technique proposed by Saaty (1980) is based on the basic idea of transforming subjective assessments of relative importance to a set of overall scores or weights. AHP is one of the most widely applied multi attribute decision making methods. The methodology of AHP uses pairwise comparisons of the criteria. For example, how important is criterion C_i relative to criterion C_j? This process is used to establish the weights for criteria and similar questions are to be answered to assess the performance scores for alternatives on the subjective criteria. The first step is structuring the decision hierarchy from the top with the goal of the decision, then the objectives from a broad perspective, through the intermediate levels (criteria on which subsequent elements depend) to the lowest level (which usually is a set of the alternatives). Consider how to derive the weights of the criteria. Assume first that the m criteria are not arranged in a tree-structure. For each pair of criteria, a pairwise comparison question asking the relative importance of the two is asked. The responses can use a scale expressing the intensity of the preference for one criterion versus another (Saaty, 2008). The following nine-point scale is an example of such scale:

1= Equal importance or preference.

3= Moderate importance or preference of one over another.

5= Strong or essential importance or preference.

7= Very strong or demonstrated importance or preference.

9= Extreme importance or preference.

If the judgment is that criterion Cj is more important than criterion Ci, then the reciprocal of the relevant index value is assigned.

Let Cij denote the value obtained by comparing criterion Ci relative to criterion Cj. Because the decision maker is assumed to be consistent in making judgments about any one pair of criteria and since all criteria will always rank equally when compared to themselves, we have $Cij = 1/Cji$ and $Cii = 1$. The entries C_{ij}, $i, j = 1, \dots, m$ can be arranged in a pairwise comparison matrix C of size $m \times m$.

Then a set of weights that are most consistent with the relativities expressed in the comparison matrix is estimated. While there is complete consistency in the judgments made about any one pair, consistency of judgments between pairs, i.e. $CijCkj = Cik$ for all i, j, k, is not guaranteed. Therefore, an m-vector of the weights should be searched such that the mxm matrix W of entries wi/wj will provide the best fit to the judgments recorded in the pairwise comparison matrix C(Saaty, 2003).

In the practice the criteria are often arranged in a tree-structure. Then, AHP performs a series of pairwise comparisons within smaller segments of tree and then between sections at a higher level in the tree-structure.

Similar to calculation of the weights for the criteria, AHP also uses a technique based on pairwise comparisons to determine the relative performance scores of the decision table for each of the alternatives on each subjective (judgmental) criterion. Now, the pairwise questions to be answered ask about the relative importance of the performances of pairs of alternatives relating the considered criterion. Responses use the same set of nine index assessments as before, and the same techniques can be used as at computing the weights of criteria.

2.5.1.3 Weighted Sum Method (WSM)

The weighted sum model (WSM) is one of the most commonly used techniques, particularly in single dimensional problems. If there are M alternatives and N criteria then, the best alternative is the one that satisfies (in the maximization case) the following expression (Triantaphyllou and Mann, 1989):

$$A^{*}_{WSM} = \max_{i} \sum_{j=1}^{N} a_{ij} w_j, \text{ for } i = 1,2,3, \dots, M \tag{3}$$

Where A (WSM score)= the WSM score of the best alternative, N= the number of criteria, a_{ij}= the actual value of the *i*th alternative in terms of jth criterion, w_j=the weight of importance of the *j*th criterion.

Application of the current technique for multi-dimensional decision-making problems results in difficulty of combining different dimensions, and consequently different units and the result is equivalent to adding apples and oranges.

2.5.1.4 Weighted Product Method (WPM)

The weighted product model (WPM) is very similar to the WSM with a difference that in the model instead of addition there is multiplication. Each alternative is compared with the others by multiplying a number of ratios, one for each criterion. Each ratio is raised to the power equivalent of the relative weight of the corresponding criterion. In general, in order to compare the alternatives $A_K$and A_L the following product (Triantaphyllou and Mann, 1989) has to be calculated:

$$R\left(\frac{A_K}{A_L}\right) = \prod_{j=1}^{N}(\frac{a_{Kj}}{a_{Lj}})^{w_j} \qquad (4)$$

Where N= the number of criteria, a_{ij}= the actual value of the ith alternative in terms of the jth criterion, w_j=the weight of importance of the jth criterion.

If the term $\mathrm{R}\left(\frac{\mathrm{A_K}}{\mathrm{A_L}}\right)$ is greater than or equal to one, then it indicates that alternative A_K is more desirable than alternative A_L (in the maximum case). Therefore, the best alternative is the one which is better than or equal to all other alternatives.

2.5.1.5 Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE)

This method uses the outranking principle to rank the alternatives, combined with the ease of use and decreased complexity. It performs a pair-wise comparison of alternatives in order to rank them with respect to a number of criteria. The method uses preference function $P_j(a,b)$ which is a function of the difference d_j between two alternatives for any criterion $j, i.e. d_j = f(a,j) - f(b,j)$, where $f(a,j)$ and $f(b,j)$ are values of two alternatives a and b for criterion j. The indifference and preference thresholds q' and p' are also defined depending upon the type of criterion function. Two alternatives are indifferent for criterion j as long as d_j does not exceed the indifference threshold q'. If d_j becomes greater than p', there is a strict preference. Multi-criteria preference index, $\pi(a,b)$ a weighted average of the preference functions $P_j(a,b)$ for all the criteria is defined as(Pohekar and Ramachandran, 2004):

$$\pi(a,b) = \frac{\sum_{j=1}^{J} w_j P_j(a,b)}{\sum_{j=1}^{J} w_j} \tag{5}$$

$$\emptyset^{+}(a) = \sum_{A} \pi(a,b) \tag{6}$$

$$\emptyset^{-}(a) = \sum_{A} \pi(b,a) \tag{7}$$

$$\emptyset(\boldsymbol{a}) = \emptyset^{+}(a) - \emptyset^{-}(a) \tag{8}$$

where w_j is the weight assigned tothe criterion j; $\emptyset^{+}(a)$ is the outranking index of a in the alternative set A; $\emptyset^{-}(a)$ is the outranked index of a in the alternative set A; $\emptyset(\boldsymbol{a})$ is the net ranking of a in the alternative set A. The value having maximum $\emptyset(\boldsymbol{a})$ is considered as the best. a outranks b iff $\emptyset(a) > \emptyset(b)$, a is indifferent to b iff $\emptyset(a) > \emptyset(b)$

2.5.1.6 The Elimination and Choice Translating Reality (ELECTRE)

This method is capable of handling discrete criteria of both quantitative and qualitative in nature and provides complete ordering of the alternatives. The problem is to be so formulated that it chooses alternatives that are preferred over most of the criteria and that do not cause an unacceptable level of discontent for any of the criteria. The concordance, discordance indices and threshold values are used in this technique. Based on these indices, graphs for strong and weak relationships are developed. These graphs are used in an iterative procedure to obtain the ranking of alternatives (Pohekar and Ramachandran, 2004). This index is defined in the range (0–1), provides a judgment on degree of credibility of each outranking relation and represents a test to verify the performance of each alternative. The index of global concordance C_{ik} represents the amount of evidence to support the concordance among all criteria, under the hypothesis that A_i outranks A_k. It is defined as follows:

$$C_{ik} = \frac{\sum_{j=1}^{m} W_j c_j(A_i A_k)}{\sum_{j=1}^{m} W_j} \tag{9}$$

where W_j is the weight associated with j^{th} criteria. Finally, the ELECTRE method yields a whole system of binary outranking relations between the alternatives.

2.5.2 Comparative study of MCDM techniques

SMART and AHP, apply to the subjective weighting of a finite number of alternatives $A_1, \ldots, A_n$ under a finite number of conflicting performance criteria $C_1, \ldots, C_m$. But in the pairwise comparison step of the AHP two alternatives are presented to the decision maker to judge them under a particular criterion and to express his/her indifference between them. In SMART, however, the decision maker is asked to rank the alternatives under a particular criterion and to refine his/her judgments by the assignments of grades to them. In other words, in the applications of AHP, decision makers classify the alternatives in a smaller number of groups on a vaguely defined range of desirability, where after they judge them in pairs via inspection of the classification. In SMART the direct rating procedure is followed, where one judges the performance of an alternative by choosing an appropriate value between a predetermined lower limit for the worst alternative and a predetermined upper limit for the best alternative.

In applications of AHP firstly decision problem is decomposed into a hierarchy of more easily comprehended sub-problems, each of which can be analyzed independently. The classic hierarchy structure that comes with AHP is another difference with SMART.

There exist number of concerns about AHP reported in literature, including (a) the potential internal comparison inconsistency as a result of inconsistent pairwise comparisons by decision makers, (b) the questionable theoretical foundation of the rigid 1-9 scale, (c) Rank reversals that possibly arises when a new alternative is introduced or removed, (d) Large number of comparisons where there are either a large number of attributes and/or alternatives to be evaluated. It is why there been several attempts to modify AHP by avoiding some of the criticisms (It is comprehensively discussed in (Triantaphyllou, 2000)).

Furthermore, the AHP has strengths in terms of focusing the attention of the decision maker on developing a structure to consider all the key factors that differentiate a good choice of an option from a poor one. Pairwise comparisons are generally accepted in practice as a means of establishing information about the relative importance of criteria and the relative performance of options. Pairwise comparison matrix provides some redundant information about relative values allows some cross-checking to be done. The resulting weights or scores are probably more consistent compared to the case of performing a narrower set of judgments (Dodgson et al., 2009).

The main attraction of SMART is its simplicity that can be easily taught to and used by a decision maker. The advantage of the SMART model is that it is independent of the alternatives. Since the ratings of alternatives are not relative, changing the number of alternatives considered will not in itself change the decision scores of the original alternatives. This characteristic is particularly useful when new alternatives or features are added to the existing comparison. Any further evaluations necessary need not begin right from the start but the process can continue from the previous scores obtained. Moreover, it is less demanding in its information input requirements from the decision maker compared to AHP.

The main weakness of SMART is the judgmental location measures as judges may be reluctant to approach the extremes closely, especially the lower extreme. Moreover, purely judgmental location measures are difficult to score. Another weakness is that a given question in SMART is asked only once, while the AHP asks a question in a number of ways using pairwise comparisons. Thus SMART does not benefit from the smoothing process that the AHP enjoys.

Salminen et al. (1998) discuss the characteristics of SMART, ELECTRE III and PROMETHEE comparatively: In SMART all differences in criteria values are taken into account while in PROMETHEE differences in criteria values are not taken into account totally; it does not matter, how much the preference threshold is exceeded. In ELECTRE III is also it does not matter how much a value of a criterion is better than of another criterion. Uncertainty is dealt with probability distributions in SMART, with constant thresholds in PROMTHEE and with constant or proportional thresholds.

There have been many studies in the literature comparing multi criteria decision making. As applicability and performance of these techniques depend on the number of criteria and alternatives it is not easy to conclude a general rule for applying these techniques. Zanakis et al (1998) compared five of the techniques for different numbers of criteria and alternatives. They have selected: (1) Simple Additive Weighting (SAW), (2) Multiplicative Exponent Weighting (MEW), (3) Analytic Hierarchy Process (AHP), (4) ELECTRE and (5) TOPSIS (Technique for preference by similarity to the ideal solution). The rational for selecting these techniques has been popularity of them (Zanakis, 1998).

There have been also other studies comparing MCDM techniques including above methods. Karni et al. (1990) studied on ELECTRE, AHP and SAW and concluded that rankings did not differ significantly in the real life case studies of using these techniques. Lootsma (1990) compared AHP and ELECTRE as representing American and French schools in MCDA thought found to be unexpectedly close to each other. Hobbs et al. (2000) and Goicoechea et al. (1992) had an study on water supply planning in which had graduate students and U.S. Army Corps Engineers evaluate AHP, ELECTRE, SAW and other methods. Their results were contradictory, the first found perceived differences across methods and users, while the later study did not. Finally, Gomes (1989) compared ELECTRE to his method TODIM (a combination of direct rating, AHP weighting and dominance ordering rules) on a transportation problem and concluded that both methods produced essentially the same ranking of alternatives.

The challenging issue of comparing different techniques is the effect of number of alternatives and criteria in the performance of techniques. The result of simulation experiment based on different number of criteria and alternatives by Zanakis et al.(1998) revealed that in general as the number of alternatives increases, the methods tend to produce similar final weights, but dissimilar rankings, and more rank reversals (fewer top rank reversals for ELECTRE). The number of criteria had little effect on AHPs, MEW and ELECTRE. TOPSIS rankings differ from those of SAW more for large number of criteria. ELECTRE produces more rank reversals in problems with many criteria. All AHP variations are more similar and closer to SAW than the other methods. ELECTRE is the least similar to SAW, followed by MEW method. TOPSIS behaves closer to AHP and differently from ELECTRE and MEW, except for problems with few criteria. In terms of rank reversals, the four AHP versions were uniformly worse than TOPSIS, but more robust than ELECTRE.

Moreover, Pohekar et al. (2004) reviewed more than 90 published papers to analyze the applicability of various MCDM methods for energy planning. It is observed that AHP is the most popular technique followed by PROMETHEE and ELECTRE. Salminen et al. (1998) studied three widely used techniques; ELECTRE III, PROMETHEE I,II, and SMART in the context of four different real applications to environmental problems. They conclude that no remarkable differences in the solutions of SMART and PROMETHEE are evident when SMART is used with linear value functions. Also, the difference from ELECTRE III solutions to PROMETHEE and SMART solutions is not great. They recommend ELECTRE III when one has to choose only one of the methods since other methods have no superior features when compared to it.

Applications

MCDM techniques have been widely reported as decision-aids in numerous publications. To mentions a few in the field of current research and also out of this field respectively, AHP has been used by Abu Dabous and Alkass (2008) for multi-criteria selection of bridge rehabilitation strategy. Selih et al. used a modified version of AHP for highway infrastructure management (2008). There are numerous more reported applications of AHP such as: Cooper and Qui (2006), Gabriel et al.(2006a), Levary (2008), Park and Rothrock (2007).

ELECTRE has been applied in urban transportation energy conservation by Tzeng and Shiau (1987). Siskos and Assimakoppoulos (1989) applied ELECTRE for highway planning, Salminen et al. (1998) used a version of ELECTRE in the context of environmental problem. There are also lots of other reported applications for this technique such as Becali et al. (2003), Haralambopoulos et al. (2003), Hokkanen et al.(1997), Papadopoulos et al. (2008).

PROMETHEE applications include, Zheng et al. (2007) who applied it for evaluation of social and economic environment of highway construction, Balali et al. (2010) applied the technique for selecting appropriate building system. More applications include Duvivier et al. (2007), Jugovic et al. (2006), Beynon et al. (2008). There exist also numerous applications of other technique reported by: Ulvila (1980), Corner et al. (1991), Behzadian et al. (2010), Salminen et al. (1998), Pohekar et al. (2004).

2.5.3 Group decision making

Group decision-making is aggregating different individual preferences on a given set of alternatives to a single collective preference. A group decision situation may involve multiple decision-makers (DMs), with probable different skills, experience and knowledge of the problem.

Similar to what was done to introduce SMART and AHP in order to address the group decision-making clearly parametric structure of problem is represented. Consider a decision problem with l decision makers $D1, \dots, Dl$, n alternatives $A1, .., An$ and m criteria $C1, \dots, Cm$. Denote the result of the evaluation of decision maker Dk for alternative Aj on the criterion C_i by $\mathrm{a}_{\mathrm{ij}}^{\mathrm{k}}$. Moreover, the individual preferences on the criteria are expressed as weights: let the weights of importance $w_i^k \geq 0$ be assigned at criterion C_i by decision-maker D_k, $i = 1, \dots, m; k = 1, \dots, l$.

In the process of group decision making, voting powers are used as an indicator of different knowledge and priority of the group members.

Let $V(w)_i^k$ denote the voting power assigned to D_k for weighing on criterion C_i, and $V(q)_i^k$ the voting power assigned to D_k for qualifying (scoring) on criterion $C_i, i = 1, \ldots, m;\ k = 1, \ldots, l$.

The method of calculating the group utility (group ranking value) of alternative A_j is as follows:

For each criterion C_i, the individual weights of importance of the criteria will be aggregated into the group weights W_i:

$$W_i = \frac{\sum_{k=1}^{l} V(w)_i^k w_i^k}{\sum_{k=1}^{l} V(w)_i^k}, i = 1, \ldots, m \quad (10)$$

The group qualification Q_{ij} of alternative A_j against criterion C_i is:

$$Q_{ij} = \frac{\sum_{k=1}^{l} V(q)_i^k a_{ij}^k}{\sum_{k=1}^{l} V(q)_i^k}, i = 1, \ldots, m, j = 1, \ldots, n. \quad (11)$$

The group utility U_j of A_j is determined as the weighted algebraic mean of the aggregated qualification values with the aggregated weights:

$$U_j = \frac{\sum_{i=1}^{m} W_i \quad Q_{ij}}{\sum_{i=1}^{m} W_i}, i = 1, \ldots, n \quad (12)$$

Above aggregation is the weighted algebraic mean. However, there are also other techniques offered.

The approach of the AHP can also be extended to group decision support (Dyer and Forman (1992)), Since the AHP is based on pairwise comparison matrices, Aczel and Saaty (1983) showed that by reasonable assumptions the only synthesizing function is the geometric mean. Another approach was proposed by Gass and Rapcsak (1998) for generating group decisions in AHP. It involves the aggregation of the individual weight vectors determined by singular value decomposition, taking the voting powers of the group members also into account. Of course, the extensions of the outranking methods for group decision support have also been developed. Macharis et al. (1998) presents a PROMETHEE procedure for group decision support. Another method, based on ELECTRE methodology, was proposed by Leyva-López and Fernandez-Gonzalez (2003) for group decision support.

The application of various aggregation methods are model based and it depends on the number of decision makers, number of criteria and the MCDM techniques that has been applied. For the purpose of current research the geometric mean technique is applied.

More communication between decision makers to help them better understand the decision problem will help them identify their preferences more correctly. Feedback of group preferences will provide them the opportunity to assess where they stand with respect to other members of the group and give them the option to revise their preferences.

2.6 Roadways and Sustainability

This section covers the previous attempts in the field of sustainable roadway/highway construction and maintenance. While a significant number of measures for environmental impact analysis concerning industrial products have appeared over the past years, these measures for road construction and maintenance are almost new. Recently, there are research projects under progress to evaluate the environmental impact of roadway construction, maintenance, and rehabilitation as well as impact of utilization of various technologies, processes and materials. In order to support these efforts, there is a need to measure and explain different aspects of sustainability related to roadway asset items in terms of Green House Gas (GHG) emission and energy consumption (Giustozzi et al., 2012a).

Mukherjee and Cass (2012) addressed the challenges of global climate change by developing and implementing a project based life cycle assessment framework to utilize it for the estimation of GHG emissions of the processes and materials utilized in highway construction and repair. The proposed approach considers life cycle emissions to calculate the GHG for typical highway construction and maintenance work items. It also accounts for emissions due to use of equipment during the service life of the pavements. The proposed framework based in life cycle assessment aims at developing project emission inventories for highway construction, rehabilitation and maintenance as well as analyzing the inventories to calculate the metrics for construction emission estimation. They used 14 highway construction and rehabilitation projects in the State of Michigan for implementation of their method and to validate the analysis approach (Mukherjee and Cass, 2012).

Cass and Mukherjee (2011) developed and illustrated a method that can be utilized for quantification of the life-cycle emissions of various pavement designs. The research gives emphasizes to the construction and the resulting method can be used to develop and analyze construction phase life-cycle inventories. Instead of using the approaches that use traditional LCA for alternative pavement comparisons, researchers propose a shift to context sensitive process-based approach to use the actual observed construction data for calculation of GHG using hybrid LCA.

The International Road Federation has designed a methodology for the calculation and modelling of greenhouse gas emissions (GHG) from road construction projects (Zammataro, 2010). The ultimate purpose of the developed tool is to facilitate a detailed environmental analysis of road projects, provide a basis for comparative analysis of various road construction techniques and materials, find optimal road construction site supply considering material providers and to support detailed estimation of GHG emissions. The resulting calculations are given in the unit of CO2 equivalent and consideration of a range of different scenarios and construction methods.

3

Methodology

To achieve research objectives a multi-objective decision making approach is developed based on the mutli-colony ant colony optimization. The algorithm is modified to meet the characteristic of the research problem. In this chapter first the proposed algorithm is introduced. Then, the algorithm is validated using two techniques.

3.1 Proposed research approach

3.1.1 Mathematical formulation

First, a general formulation of governing equations on the multi-objective decision making applied to the research is explained. Then, mathematical formulation of the present research is presented.

A multi-objective decision making problem wishing to minimize[2] K objectives can be defined as follows:

$\mathbf{x} = \{x_1, \ldots, x_n\}$, where x is an n-dimensional decision variable vector in the solution space X, $\mathbf{x}^s$ Vector is desired that minimizes a given set of K objective functions:

$$\boldsymbol{z}(\boldsymbol{x}^s) = \{\boldsymbol{z}_1(\mathbf{x}^s), \ldots, \boldsymbol{z}_K(\mathbf{x}^s)\} \tag{13}$$

[2] Modeling of the research problem deals with both maximization and minimization of objectives that can be easily converted to all minimization if comparing with this general rule is desired.

The solution space X is generally restricted by series of constraints and bounds on the decision variables. For example $g_j(\mathbf{x}^s) = b_j \; for \; j = 1, \dots, m$.

The proposed research model is a multi-objective problem which consists of four main objectives. The objectives of the problems are defined as follows: (1) Minimization of MR&R cost, (2) Maximization of MR&R Level of Service, (3) Minimization of MR&R Time, (4) Minimization of Environmental Impact.

$$\boldsymbol{z}(\boldsymbol{x}^s) = \{\boldsymbol{T}(\mathbf{x}^s), \boldsymbol{C}(\mathbf{x}^s), \boldsymbol{LoS}(\mathbf{x}^s), \boldsymbol{EII}(\mathbf{x}^s)\} \tag{14}$$

T= Time

C= Cost

LoS=Level of service

EII= *Environmental Impact Index*

In the proposed model of decision making for sustainable roadway asset management (DSRAM) different locations in the roadway in need of maintenance actions are identified. There exist various maintenance, repair and rehabilitation (MR&R) options for improving the condition of roadway. Each deficiency has a set of possible MR&R options and the goal is finding the optimal/near optimal ways of project completion in the search space of whole possible combination of these MR&R actions utilization to deficiencies.

Decision variable vector as defined earlier is: $\mathbf{x} = \{x_1, \dots, x_n\}$ in the solution space X. In the current problem n is the number of deficiencies in the selected project and x is a set of feasible MR&R solutions for the project. $\boldsymbol{x}^s$ is the desired set of solutions among the feasible solutions that optimizes all objectives z.

Decision variable are function of various parameters that form the time, cost, level of service and Environmental Impact Index. Those parameters are the origin of decision variables.

3.1.1.1 Formulation of the four objective functions and their brief explanation and equation of the relevant constraints

I. Project completion time

Project completion time is equal to duration of critical path. "T" is defined to find the longest path among various possible paths in precedence network diagram of MR&R actions.

$$T = \max_{L_k \in L} \left\{ \sum_{i \in L_k} t_i^{(k)} x_i^{(k)} \right\} \tag{15}$$

Where $t_i^{(k)}$ represents the duration of MR&R of deficiency i when performing the $(k)th$ MR&R action; and $x_i^{(k)}$stands for the index variable of activity i when performing the (k)th option. If $x_i^{(k)} = 1$ then the activity i perform the $(k)th$ option, while $x_i^{(k)} = 0$ means not. The sum of index variables of all options should be equal to 1. L_k means the activity sequence on the kth path, and $i1_k, i2_k, i3_k, \dots, in_k$ where ij_k represents the sequence number of activity j on the Kth path. L stands for the set of all paths of a network, and $L = \{L_k \mid k = 1, 2, \dots, m\}$, where m symbolizes the number of all paths of a network.

II. Project completion cost

The total cost of a project consists of the sum of the cost of all MR&R actions within a project network. Subsequently, equation 2 can be forwarded to compute the total cost of a project. The MR&R action might have different natures. Their cost might be a function of length, area or other characteristics of the deficiency. Given the rate of the maintenance techniques the cost will be calculated as follows:

$$C = \sum_{i \in A} (c_i^{(k)} \, x_i^{(k)}) \tag{16}$$

Where $c_i^{(k)}$ cost of maintenance of activity i under the kth option, that equals to the quantities of the MR&R actions multiplied by its price;

III. Project Level of Service (LoS) Improvement

The Level of service (LoS) Improvement investigates how well the roadway is maintained. Level of service is defined based on evaluation of asset items condition in the roadway that is a physical level of service. For instance, evaluation elements and details of level of service for VDOT-VMS contract is shown in Table 6.

$$LOS(t) = \sum_{i \in A} w_i \times L_{i(t)}^{(k)} \tag{17}$$

Where $L_i^{(k)}$= level of service of individual asset item i in time scope of (t) after MR&R with (k)th option; w_i is weighting factor of asset item, an example of assets' weighting factor used in VDOT's contracts is shown in Table 5. For instance, evaluation elements and details of level of service for VDOT-VMS contract is shown in Table 6.

Table 5 An example of weighting factors used in the VMS contracts of VDOT

Asset Group	Sub-Asset Group	Asset Item	2001 VMS	2007 VMS
Pavement	Paved Shoulders	Surface Defects	5.33	5.33
		Drop Off	5.83	5.83
		Separation	5.66	5.66
		Drainage	5.50	5.50
		Sub-total Paved Shoulders	**7.17**	**7.17**
	Unpaved Shoulders	Drop Off	5.83	5.83
		Drainage	5.50	5.50
		Sub-total Unpaved Shoulders	1.00	1.00
		Total Pavement Group	**0.1560**	**0.1560**
Roadside		Vegetation	5.67	5.67
		Debris and Road Kill	8.50	8.50
		Litter	4.67	4.67
		Landscaping	4.83	4.83
		Brush and Tree Control	5.33	5.33
		Concrete Barrier	8.17	8.17
		Sound Barrier	4.83	4.83
		Slopes	5.83	5.83
		Fences	5.00	5.00
		Total Roadside	**0.2350**	**0.2350**
Drainage		Cross Pipes	8.50	8.50
		Box Culverts(≤ 36 SF)	8.00	8.00
		Paved Ditches	6.67	6.67
		Unpaved Ditches	6.33	6.33
		Under/Edge Drains	8.33	8.33
		Storm Drains/Drop Inlets	8.67	8.67
		Curb and Gutter	4.00	4.00
		Sidewalks	3.17	3.17
		Storm Water Management Pond	5.33	5.33
		Total Drainage Group	**0.2370**	**0.2370**
Traffic		Signals	9.17	9.17
		Signs Regulatory	8.00	8.00
		Signs Other	8.00	8.00
		Lighting	6.50	6.50
		Guardrail	8.50	8.50
		Impact Attenuators	9.33	9.33
		Object Markers/ Delineators	4.83	4.83
		Glare Foils	5.50	5.50
		Pavement Message	6.33	6.33
		Pavement Markings	8.67	8.67
		Pavement Markers	8.00	8.00
		Truck Ramps	6.00	6.00
		Cross Over	5.00	5.00
		Rumble Strip	-	**5.00**
		Total Traffic	**0.3720**	**0.3720**

Table 6 Level of service evaluation elements and details

Level-of-Service Element	Sub-elements	Evaluation Method	Range (from Worst Condition to Best Condition)
Fence to Fence Asset Groups	- Shoulders - Roadside Asset Items - Drainage Asset Items - Traffic Asset Items	Grading on a Percentage Scale	0%-100%
Paved Lanes		Load-Related Distress Index (LDR)	0-100
		Non Load-Related Distress Index (NDR)	0-100
		Critical Composite Index (CCI)	0-100
		International Roughness Index (IRI)	No Theoretical Limit for the Worst Condition-0
Bridges	- Deck - Superstructure - Substructure - Slope/Channel Protection	Grading on a Number Scale	0-9

IV. Environmental Impact Index (EII)

Environmental impacts are usually measured through the computation of greenhouse gases (GHG) emitted to the atmosphere and energy consumption during life cycle of a product. Lower amounts of GHG and energy consumption means more sustainable the material, process, or strategy. There are several steps involved in road construction, maintenance, repair and rehabilitation that contribute to the production and release of GHG emissions and use of energy. The environmental impacts for each project can be calculated based on equipment used, local conditions, and standard construction and maintenance practices. Techniques utilized for Maintenance, repair and rehabilitation of highways may correspond to different amounts of GHG emission and energy consumption. Considering environmental impacts in Multi-objective optimization means making more informed decision for sustainable roadway MR&R. Moreover, it can help to identify areas sensitive to GHG emissions and energy consumption, and present various mitigation options that take cost, time and level of service implications into account. Decision makers in the highway sector can easily compare various construction alternatives and optimize their practices to both minimize environmental impacts, time, cost and maximize level of service.

$$EII = \sum_{i \in A} (w_G GHG_i^{(k)} + w_E E_i^{(k)}) \tag{18}$$

Where $GHG_i^{(k)}$= Normalized emission level of asset item i undergone MR&R with (k)th option; $w_E E_i^{(k)}$= Normalized energy consumption level of asset item i undergone MR&R with (k)th option; w_G is weighting factor of Greenhouse Gas emission while w_E is weighting factor of energy consumption.

In a multi-objective decision making the solution space is generally restricted by a series of constraints and there are bounds on decision variables. In the present research bounds on decision variables are those that limit them to decent input data. Such as input Quality numbers in the 0-100 range for quality scoring of some asset items or descent cost data, duration for MR&R of deficiency and similar data which will be matched to conform the standard input format. Moreover, the decision variable vector should be:

$$\begin{gathered} \mathbf{x} = \{\boldsymbol{x_1}, \dots, \boldsymbol{x_n}\} \\ \mathbf{0} < \boldsymbol{x_i} \leq \boldsymbol{k_i}, \boldsymbol{i} = \mathbf{1}, \dots, \boldsymbol{n} \end{gathered} \tag{19}$$

Where n is the number of deficiencies in the selected project and k is the corresponding constrains for the deficiency.

3.1.2 Implementation of the proposed model

The proposed model is a two stage approach. In the first stage, a multi-objective problem which consists of four main objectives is analyzed. The objectives of the problems are defined as follows: (1) Minimization of MR&R costs, (2) Maximization of MR&R Level of Service Improvement, (3) Minimization of MR&R Time, (4) Minimization of Environmental Impact Index (EII). In the second stage, the results of the multi objective optimization will be further processed based on a Multi Criteria Decision Making (MCDM) process.

The methodology that is developed in this research aims at finding an optimal set of solutions to optimize the four above mentioned objectives. As a result, appropriate MR&R actions for asset items in need of remedy will be selected. The developed methodology as shown in Figure 1 flowchart:

1) Start

2) Inspection/Data collection: Similar to other asset management systems, in the first step, assets should be inspected and their condition data be collected.

3) Immediate MR&R: In case the asset item does not meet minimum requirements of a functioning asset item, then necessary rehabilitation actions should be taken.

4) There are various possible deficiencies threatening identified asset items. In order for decision makers to improve the condition of asset items they may utilize one of the MR&R options. These options, corresponding to various asset items, are populated in a MR&R vs Deficiencies matrix as a database for decision making process.

5) Utilizing various options of MR&R will result in different time, cost, level of service and environmental impact of delivered MR&R projects. In this step

for all of the identified MR&R techniques corresponding time, cost, level of service and environmental impact will be organized in a matrix named TCLI.

6) Having the identified distresses of asset items, possible MR&R actions and corresponding time, cost, level of service and environmental impact of those asset items, the proposed model will use a multi objective optimization technique to find a set of non-dominated solutions.

7) Finally, resulted solution of multi objective optimization will be narrowed down using a multi criteria decision making (MCDM)

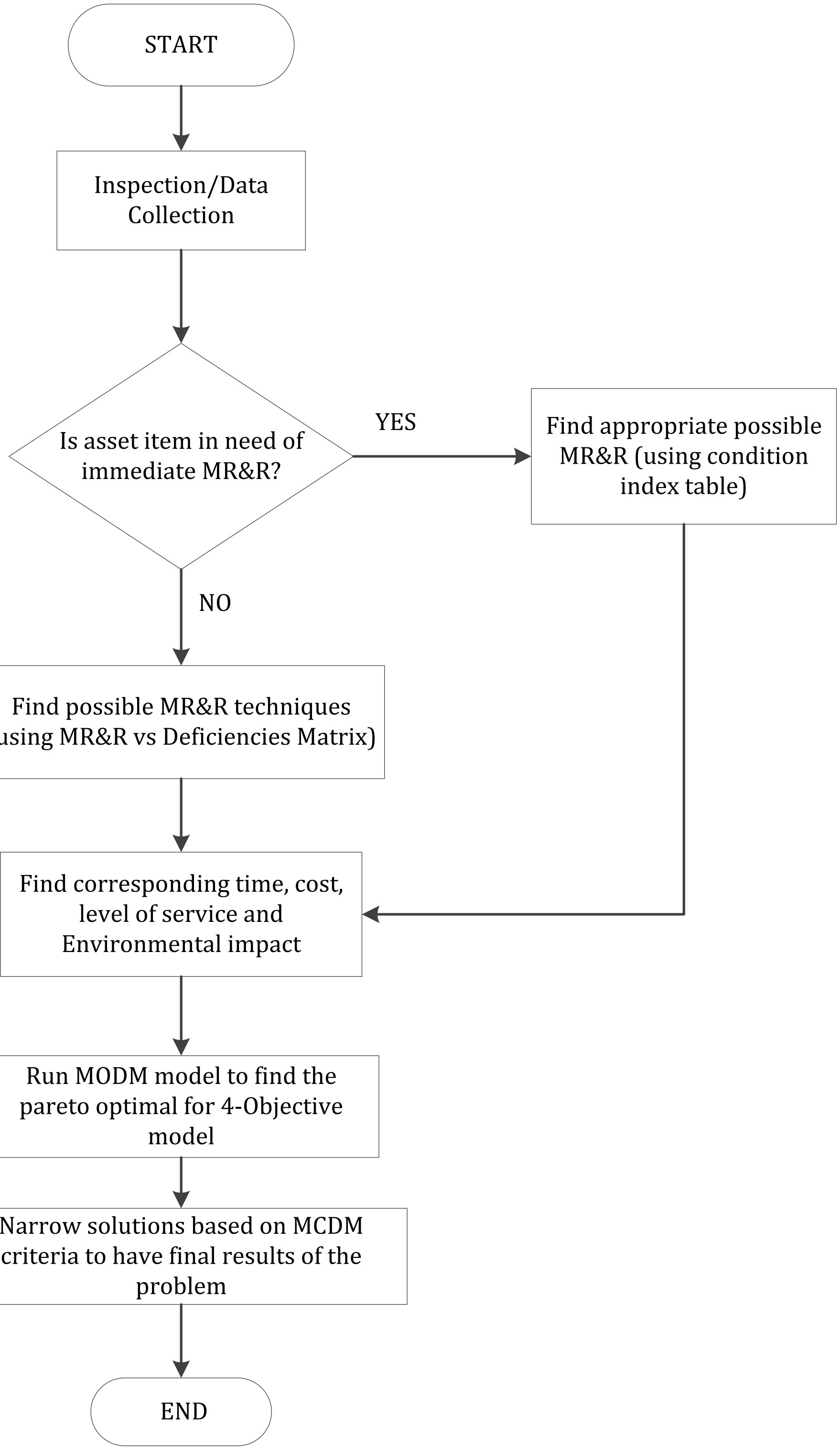


Figure 1 The flow diagram of the proposed approach of DSRAM

3.1.3 Proposed algorithm for multi objective optimization

3.1.3.1 Multi objective Ant Colony Optimization

In recent years, evolutionary and meta-heuristic algorithms have been extensively used as search optimization tools in various domains. Ease of use and wide range of application may be considered as the primary reasons for their success. The source of inspiration for Ant Colony Optimization (ACO) algorithms is the ability of ants in finding the shortest route between their nest and a food source, even though they are blind (Dorigo et al., 1996). Researchers have reported the strength of ACO algorithms and their capability to efficiently search for an optimum/near optimum particularly in discrete optimization problems.

In general, ACO algorithms employ a finite size of artificial ants with defined characteristics which cooperatively search for high quality solutions to the problem. Starting from an initial state each ant builds a solution which is similar to a chromosome in a genetic algorithm. While building its own solution, each ant behaves based on the collected information on its own performance and uses this information to modify the representation of the problem, as seen by the other ants. The ants' internal states store information about the ants' past behavior, which can be employed to compute the fitness of the generated solution. Artificial ants are programmed to release and update pheromone while developing a solution. The amount of pheromone deposited is made proportional to the fitness value of the solution that an artificial ant has developed. Evaporation feature of the algorithm provides a tool to avoid rapid drift of all the ants towards the same part of the search. In order to simulate the pheromone evaporation, the pheromone persistence coefficient (ρ) is defined that enables greater exploration of the search space and minimizes the chance of premature convergence to sub-optimal solutions. A probabilistic decision policy is also used by the ants to direct their search towards the most interesting regions of the search space. The level of stochasticity in the policy and the strength of the updates in the pheromone trail determine the balance between the exploration of new points in the state space and the exploitation of accumulated knowledge (Afshar et al., 2007; Dorigo et al., 1996).

Let $\tau_{ij}(t)$ be the total pheromone deposited on path *ij* at time t, and $\eta_{ij}(t)$ be the heuristic value of path *ij* at time t according to the measure of the objective function. Transition probability from node *i* to node *j* at time period t may be defined as (Dorigo et al., 1996):

$$P_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum_{l \in allowed}[\tau_{il}(t)]^{\alpha}[\eta_{il}(t)]^{\beta}} & \text{if } j \in \text{allowed} \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

Where α and β are parameters that control the relative importance of the pheromone trail versus a heuristic value. Let q be a random variable uniformly distributed over [0, 1], and q0∈ [0, 1] be a tunable parameter. The next node j that ant k chooses to go is (Dorigo et al., 1996):

$$j = \begin{cases} \arg \max_{l \in allowed_k} \left\{[\tau_{il}(t)]^{\alpha}[\eta_{il}(t)]^{\beta}\right\} & if \;\; q \le q_0 \\ J & otherwise \end{cases} \tag{21}$$

Where J = a random variable selected according to the probability distribution of $\rho_{ij}(t)$. The pheromone trail is changed globally. Upon completion of a tour by all ants in the colony, the global trail updating is done as follows (Dorigo et al., 1996):

$$\tau_{ij}(t+1) \xleftarrow{iteration} \rho.\tau_{ij}(t) + \Delta\tau_{ij} \tag{22}$$

Where 0 ≤ ρ ≤ 1; ρ = evaporation (i.e., loss) rate, the symbol ← is used to show the next iteration and Δτij represents the updating value of

$$\Delta\tau_{ij} = \begin{cases} \frac{Q}{f(k)} & \text{if edge(i, j) is traversed by the } k_{th} \text{ ant} \\ 0 & \text{otherwise} \end{cases} \tag{23}$$

Where Q is a constant, representing the amount of pheromone an ant put on the path after an exploitation, and f(k) is the value of objective in each iteration.

In the present problem each activity has some options for MR&R (options for utilization of resources) and the objective is to find the optimal/near optimal ways of project delivery in the search space of whole possible combinations of MR&R options for the remedy of deficiencies. In general, in order to apply ACO algorithm to a specific problem, the problem should be represented in a graph structure easily covered by ants, as shown in Figure 2. In which a project with N activities (deficiencies) and K MR&R options is characterized. The horizontal axis represents the activity (deficiency) number and the vertical axis the numbers of MR&R options. The path of arrows represents a typical solution which may be selected by ants (see Figure 2).

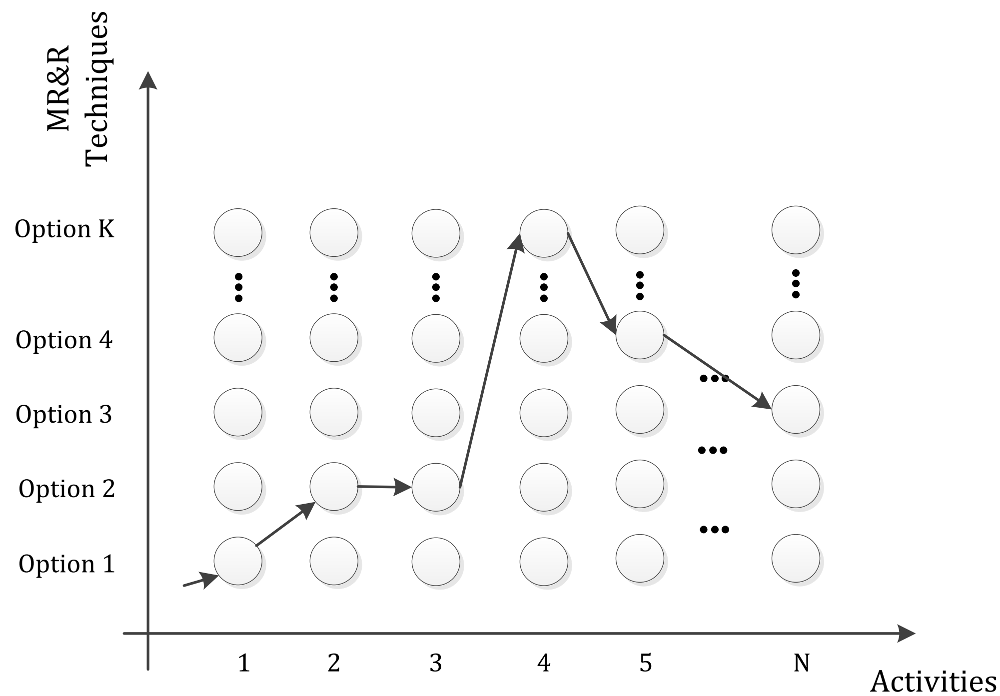


Figure 2 Graph representation of problem for a project with N activities and K resources utilization option

For more clarification of the solution and future reference a solution vector is defined that demonstrates the options of resource utilization for all of the deficiencies respectively. For example mentioned vector for the route identified in Figure 2 will be V= [1, 2, 2, k, 4, …, 3].

The proposed algorithm is a non-dominated archiving algorithm consisting four colonies of ant each corresponding to the problem objectives. All the colonies have the same number of ants and the effort of these set of ants in each colony is to find an optimal/near optimal solution for the objective of the colony. The process of pheromone update and next cycle solution generation will be based on the fitness value and pheromones of the colony. In the next step, algorithm will generate new solutions using transition probabilities and this time solutions are not evaluated in the corresponding colony. Another colony will be selected and the produced solutions are transferred to the next colony to be evaluated according to the assigned objective and the global trail of that colony is updated. This process of solution exchange will be continued to cover all the colonies of the problem.

The whole process of finding set of solutions in the first colony and having the following colonies respectively use these generated solutions continues up to a predefined iteration called cycle iteration. In this step, the values of the objectives are calculated according to the generated solutions of forth colony and the non-dominated ones are moved to the external set called Archive. After the completion of a cycle, the global pheromone trails of all colonies are set to the initial value of τ_0. In the next step, the second cycle is started and at the end of the cycle, derived non-dominated solutions are moved to the same Archive. The dominated solutions of Archive are moved out and another pheromone updating is done for all colonies according to the existing solutions in Archive. The whole process is repeated until all the non-dominated solutions (Pareto set) of Archive satisfying all the constraints or a predetermined number of iterations is met. The solutions of Archive are the final Pareto answers of the multi-objective optimization problem. In the next sections the process of implementation of the proposed algorithm is explained using a flow diagram as well as a high level pseudo code.

3.1.3.2 The Procedure of proposed algorithm

The flow diagram shown in Figure 3 represents the proposed algorithm's procedure. The steps of implementation of Multi-Colony Ant Colony Optimization on the four objectives of Time-Cost-Level of Service-Environmental Impact Index are is as follows:

i) Read the project data and heuristic parameters of ACO algorithm and generate a set of ants as well as initial pheromone for all four colonies of ants as indicated in ”1”.

ii) Generate random solutions as shown in ”2”. These solutions are a set of possible maintenance options for the problem that are randomly selected for the initiation of the problem. As previously discussed, ants select their paths based on the amount of pheromone and the pheromone is set to be the same for all paths in the previous step. Therefore first set of solutions are randomly generated.

iii) Calculate the project duration for the generated solutions. This step happens in the Time colony. The critical path for the initial solutions generated in the previous step is calculated using the formulation presented in ”3”. The objective of the time colony is to minimize the total project time.

iv) Update the pheromone for the Time colony based on the fitness value, which is project duration as shown in ”4”. The more amount of pheromone will be assigned to the paths that have a better project completion time or in another word their T is smaller. This amount is proportional to the amount of their time compared with other solutions.

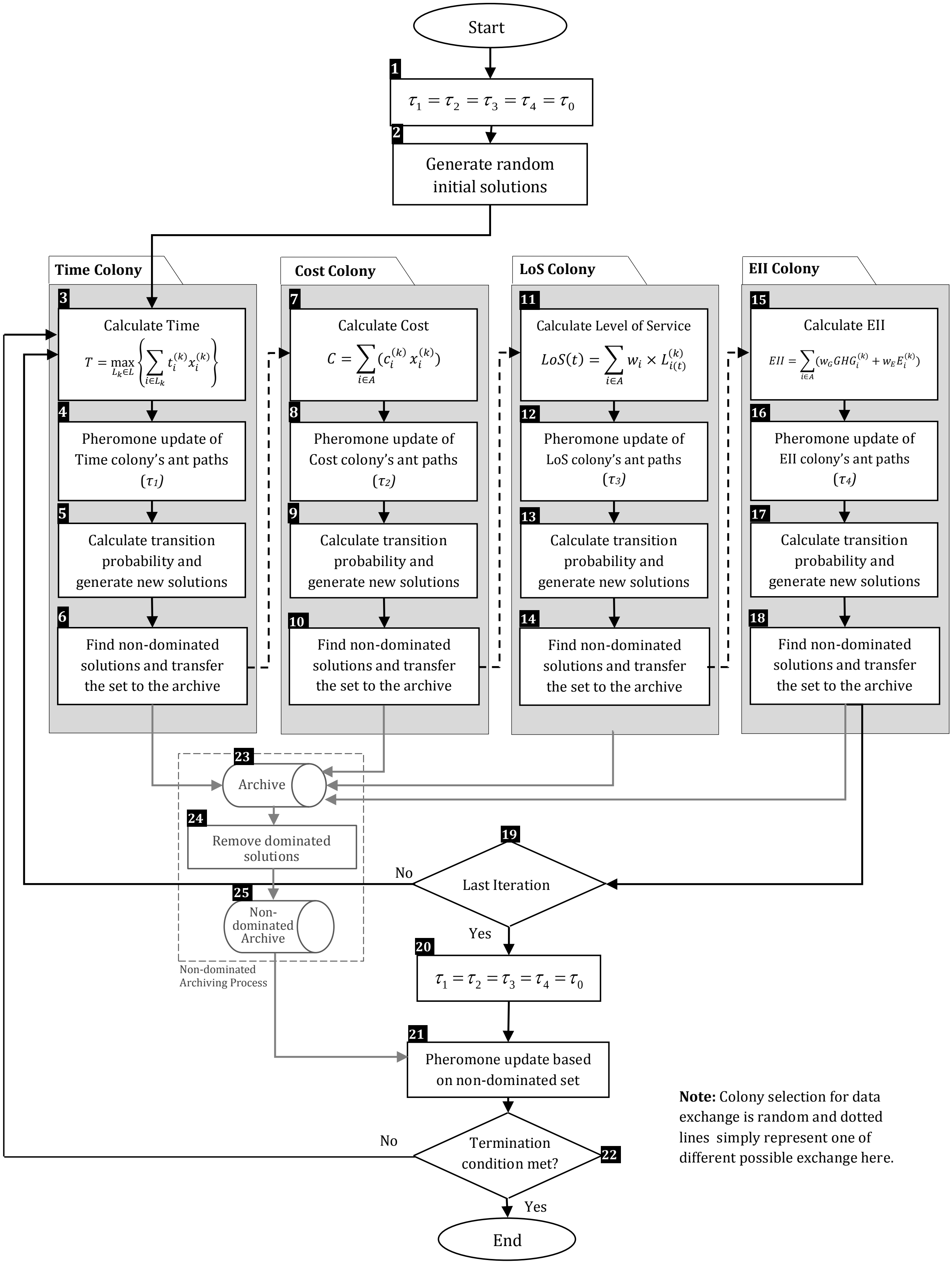
v) Calculate transition probability and generate new solutions as in ”5”. Based on the current pheromone amount the probability of path selection in each node is calculated using equation (20). Then, a new set of ants generate new solutions. As noted, ants’ decisions for selecting paths are based on the transition probability. Therefore, ants will tend to select the paths with more amount of pheromone.

vi) Find non-dominated solutions and transfer the Pareto set to the non-dominated archive ”6”. The generated solutions are screened to keep only the non-dominated solutions. These solutions are archived in a set named non-dominated archive ”23”.

vii) The non-dominated solutions of the time colony are now transferred to the Cost colony. The total cost the solutions are calculated using the formulation in ”7”. The pheromones of the cost colony are then updated based on the cost fitness of the solutions. Then, a new set of solutions will be generated based on the calculated transition probability and similar to time colony non-dominated solutions is found and transferred to the non-dominated archive.

viii) The similar procedure is followed for LoS and EII colonies in the steps from ”11” to ”18”.

ix) The process of optimization in colonies and solution transfer is repeated for a specified number of iterations. Thereafter, the pheromone of the paths is reset to an equal initial amount and the pheromones are updated based on the global non-dominated solutions archive in ”25”. The termination condition in ”22” is a user defined condition that indicates number of time that this loop is desired to be carried out. Then, the whole processes of optimization of colonies are implemented similar to previous loop. The difference is that in each global iteration the initial solutions are generated based on the most updated non-dominated archive. The final solutions to the problem are the solutions in the last global iteration in the non-dominated archive.



Note: Colony selection for data exchange is random and dotted lines simply represent one of different possible exchange here.

Figure 3 Flow diagram of the proposed multi-objective multi colony ant colony optimization

3.1.3.3 Framework of the proposed four objective optimization algorithm

There are different options in configuration of a multi-objective ant colony optimization. One of the important design decisions when applying an ACO algorithm is the definition of the pheromone information. In the present model multiple pheromone matrices are constructed for pheromone information (τ). Therefore, four Pheromone matrices each corresponding to one of the four colonies are constructed. The pheromone information will be utilized for pheromone update and path selections. Another component of the proposed algorithm is the pheromone update approach. The *PheromoneUpdate* component determines which solutions update the pheromone information. As previously discussed in the present model two approaches of pheromone updates is constructed. In each cycle based on the best solutions of the corresponding colony and in the global iterations based on the non-dominated solutions in the archive. The proposed algorithm is having a multi colony structure in which each colony represents an objective. Figure 4 elaborates the framework of the proposed algorithm:

```
InitializePheromoneInformation()
W_c= MultiColonyWeights()
A^bf := 0
iter := 0
while not stopping criteria met do
    A^iter := 0
    for c cycles do
        for each ant k do
            s:= ConstructSolution(τ,η)
            T = DUR (s)
            τ_1 = τ (T)
            s:= ConstructSolution(τ_1, η)
            A^iter := RemoveDominated(A^iter ∪ {s})
        end for
        for each ant k do
            C = COST(s)
            τ_2 = τ (C)
            s:= ConstructSolution(τ_2, η)
            A^iter := RemoveDominated(A^iter ∪ {s})
        end for
        for each ant k do
            L = LoS(s)
            τ_3 = τ (L)
            s:= ConstructSolution(τ_3, η)
            A^iter := RemoveDominated(A^iter ∪ {s})
        end for
        for each ant k do
            I = EII(s)
            τ_4 = τ (I)
            s:= ConstructSolution(τ_4, η)
            A^iter := RemoveDominated(A^iter ∪ {s})
        end for
    end for
    A^bf := RemoveDominated(A^bf ∪ A^iter)
    PheromoneUpdate(A^bf)
    iter := iter + 1
end while
Output: A^bf
```

Figure 4 A high level representation of the proposed multi objective ant colony optimization

First, the algorithm initializes the pheromone information (function InitializePheromoneInformation, line 1) and the set of weights of each colony (function MultiColonyWeights, line 2) will be assigned to each colony where W_c is weight of colony c. A^{bf} is the archive of all non-dominated solutions ever found (best-so-far archive). The new solution is added to the archive of the current iteration shared by all colonies A^{iter} (line 6). Once all ants from all colonies have finished constructing solutions, the best-so-far archive A^{bf} is updated with the non-dominated solutions found in the current iteration A^{iter} (function RemoveDominated, line 34). The update of the pheromones consists of calculation of the objective of each colony and calculation of pheromone based on this objective. After each iteration the pheromone is updated based on the best so far solutions in the archive of solutions (line 35). The functions for calculation of objectives (lines 10, 16, 22, 28) of colonies corresponds to the mathematical formulations previously discussed in equations 15, 16, 17 and 18. ConstructSolution function works based on the equations 20, 21 and 22previously explained which elaborate the process for transition probability and pheromone update. The code for this research is programmed in VBA and the computation time for first case study of four-objective optimization is 42 minutes (This time depends on the processor under which the code is run).

3.1.4 Proposed algorithm for multi-criteria decision making

In the second stage of model the resulted non-dominated solutions should be narrowed down based on the preferences of decision makers. Different approaches were reviewed in Section 2.5. As large number of non-dominated solutions is predicted for the four-objective optimization the popular AHP technique seems not to be suitable technique for this purpose. In addition, application of AHP will result in a large number of comparisons and internal comparison inconsistency will increase. However, SMART is independent of alternatives. The ratings of alternatives are not relative and changing the number of alternatives also will not change the decision scores of the original alternatives.

For the purpose of implementation of SMART on the problem two approaches is considered; (1) Time, Cost, Level of Service and Environmental Impact Index to be considered as the attributes of the SMART technique. (2) A new set of criteria to be developed based on the preferences of decision maker that might include the four objectives of the problem. The second approach needs interaction with decision makers to reflect their preferences.

3.2 Model Verification and Validation

One of the important elements of the research is validation of methodology and results. The technical correctness of results of a model refers to verification that is being done by checking all components to identify and eliminate errors. One could state that verification is concerned with "doing things right," and validation is "doing the right thing" (Lucko and Rojas, 2010). Verification and validation process needs to be done for the developed multi objective optimization model. In the first step the developed model should be verified to ensure that the procedures of algorithm as well as process of coding the algorithm are correct.

For validation purpose the results of the proposed model is being compared with existing problems in the literature. An 18-activity network configuration that was originally introduced by Feng et al. (1997) to illustrate construction time-cost trade-off analysis is selected as a means of comparison. It had been a two objective optimization problem. Later on, El-Rayes and Kandil (2005) used the same problem for their multi objective time-cost-quality optimization in highway construction. The results of the proposed model will be compared with the results of the three objective optimization problems to measure the capability of the proposed model in generating better or same results. As Different optimization techniques and heuristic information are utilized in this comparison, it should be noted that this comparison alone cannot prove the robustness of an algorithm. The sound comparison can be performed with the knowledge of exact parameters of algorithms. If the proposed algorithm generates the same or better results compared to existing problems, it could be only inferred that the proposed algorithm is going in the right direction. To validate the robustness of the proposed algorithm another validation process which is comparison with standard test problems is utilized.

Moreover, to validate the efficiency of the multi objective optimization model in handling the four objective optimization problems, standard test problems with previous knowledge of the shape and the location of the resulting Pareto-optimal front, will be solved with the proposed approach. Abraham and Jain (2005) suggested three different approaches for systematically designing test problems for this purpose. The simplicity of construction, scalability to any number of design variables and objectives, and introduction of controlled difficulties in both converging to the true Pareto-optimal front and maintaining a widely distributed set of solutions are the main features of the suggested test problems (Abraham and Jain, 2005). The following is a generic Sphere Problem having M objectives as an instance of these test problems is presented here (Deb et al., 2005).

$$
\begin{array}{ll}
\text{Minimize} & f_1(\mathbf{x}) = (1+g(\mathbf{x}_M))\cos(x_1\pi/2)\cos(x_2\pi/2)\cdots\cos(x_{M-2}\pi/2)\cos(x_{M-1}\pi/2),\\
\text{Minimize} & f_2(\mathbf{x}) = (1+g(\mathbf{x}_M))\cos(x_1\pi/2)\cos(x_2\pi/2)\cdots\cos(x_{M-2}\pi/2)\sin(x_{M-1}\pi/2),\\
\text{Minimize} & f_3(\mathbf{x}) = (1+g(\mathbf{x}_M))\cos(x_1\pi/2)\cos(x_2\pi/2)\cdots\sin(x_{M-2}\pi/2),\\
\vdots & \vdots\\
\text{Minimize} & f_{M-1}(\mathbf{x}) = (1+g(\mathbf{x}_M))\cos(x_1\pi/2)\sin(x_2\pi/2),\\
\text{Minimize} & f_M(\mathbf{x}) = (1+g(\mathbf{x}_M))\sin(x_1\pi/2),\\
 & 0 \le x_i \le 1, \quad \text{for } i = 1,2,\ldots,n,\\
\text{where} & g(\mathbf{x}_M) = \sum_{x_i\in\mathbf{x}_M}(x_i-0.5)^2.
\end{array}
\tag{24}
$$

The Pareto-optimal solutions corresponds to x_M^* =0.5 and k = $|x_M|$ = 10 as suggested by Deb et al. (2005). The total number of variables is n =M+k−1.

DTLZ2 developed by Deb et al. (2005) is a test problem identical to above generic problem. In this test problem Pareto-optimal front takes non-negative values and the front is the first quadrant of a sphere of radius one. Any two points on such a surface are non-dominated to each other. Figure 5 and Figure 6 show this surface along with the population of two popular algorithms test results on problem. Figure 5 represents Non-dominated Sorting Genetic Algorithm II (NSGA-II) population on this test problem. The NSGA is a Multi Objective Optimization algorithm base on Genetic Algorithm (GA). The objective of the NSGA algorithm is to improve the adaptive fit of a population of candidate solutions to a Pareto front constrained by a set of objective functions. NSGA-II is the updated version of the NSGA which is popular in solving multi-objective optimization (Deb et al., 2002). Figure 6 represents SPEA2 population on test problem DTLZ2. Strength Pareto Evolutionary Algorithm (SPEA) is another evolutionary technique for finding or approximating Pareto-optimal set for multi-objective optimization problems. SPEA2 is an improved SPEA which incorporates a fine-grained fitness assignment strategy, a density estimation technique, and an enhanced archive truncation method (Zitzler et al., 2001). Figure 5 and Figure 6 reveals that these algorithms find Pareto-optimal solutions very close to the true Pareto-optimal front.

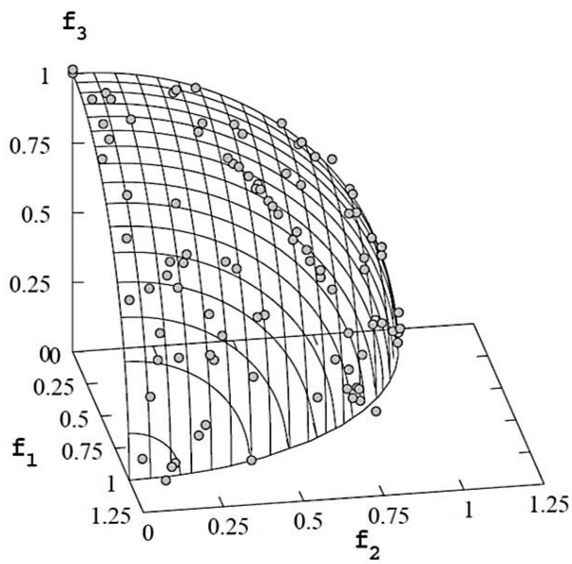


Figure 5 The NSGA-II population on test problem DTLZ2

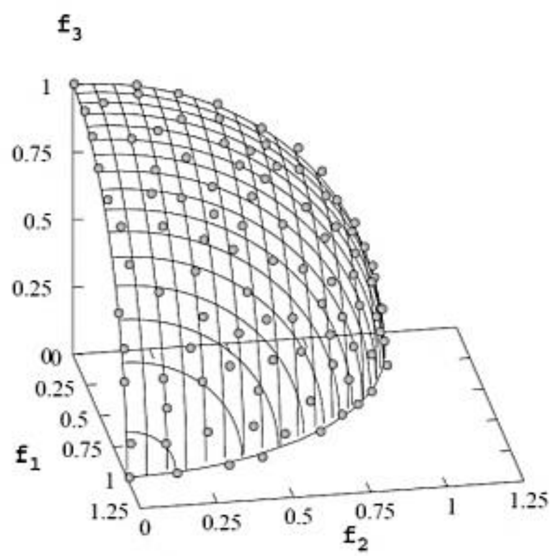


Figure 6 The SPEA2 population on test problem DTLZ2

3.2.1 Implementation of the proposed model on DTLZ2 test problem

The proposed Multi-Colony Ant Colony Optimization (MCACO) was fed with decision variables and objective functions of DTLZ2 that was introduced in previous section. The formulation for this three objectives optimization based on DTLZ2 is as follows:

$$Minimize\ f_1(\mathrm{x}) = \left(1 + g(\mathrm{x}_3)\right) \cos\left(\frac{x_1 \pi}{2}\right) \cos\left(\frac{x_2 \pi}{2}\right)$$

$$Minimize\ f_2(\mathrm{x}) = \left(1 + g(\mathrm{x}_3)\right) \cos\left(\frac{x_1 \pi}{2}\right) \sin\left(\frac{x_2 \pi}{2}\right)$$

$$Minimize\ f_3(\mathrm{x}) = \left(1 + g(\mathrm{x}_3)\right) \sin\left(\frac{x_1 \pi}{2}\right) \qquad (25)$$

$$0 \le x_i \le 1, for\ i = 1,2, \dots, n,$$

$$where\ g(\mathrm{x}_3) = \sum_{x_i \epsilon \mathrm{x}_M} (x_i - 0.5)^2$$

The Non-dominated results of running MCACO on DTLZ2 is shown Figure 7. The results prove the ability of the proposed algorithm in generating Pareto front that is very close to the optimal front of the test problem. MCACO generates 143 non-dominated solutions of which 83 are on the true-optimal surface. In other words 58% of the generated solutions are true optimal and remaining solutions are near optimal. Deb et al. (2005) report that for larger dimensions problems average distance of solutions from the true-optimal surface can be used to analyze the capability of the model. In the current problem the average distance of the points are 0.02 and all the near optimal solutions are in %5 proximity of the true-optimal surface.

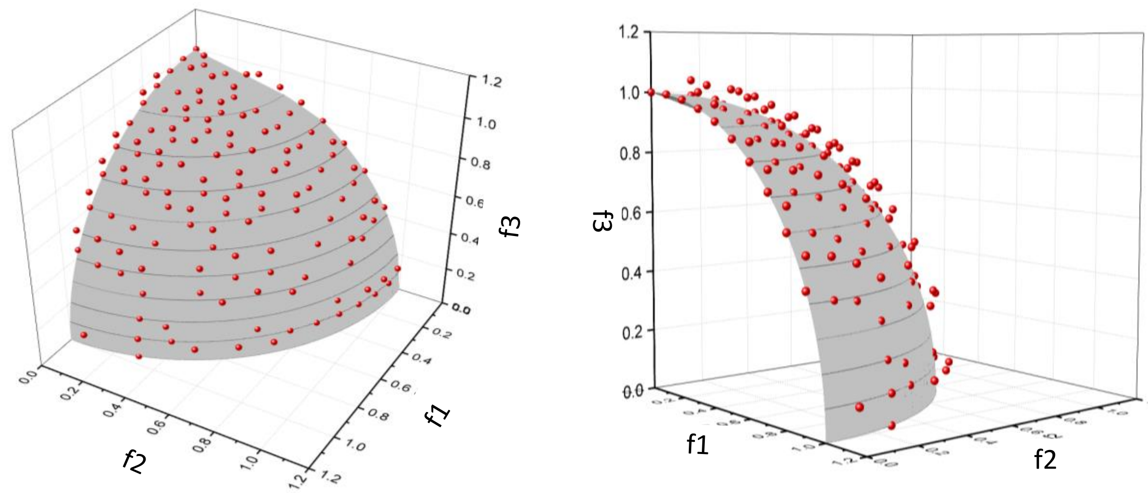


Figure 7 Proposed model's set of non-dominated solution on test problem

3.2.2 Comparison with existing problems

El-Rayes and Kandil (2005) utilized a classic problem for their multi objective time-cost-quality optimization in highway construction. Results of the current proposed model will be compared with the results of the three objective optimization problem of El-Rayes et al. to measure the capability of the proposed model in generating the same or better solutions. It should be noted that the techniques used for solving the problem are from different nature using different meta-heuristic algorithms and this type of comparison does not necessarily prove the robustness of the proposed algorithm. 18-activity network configuration is used in the case study shown in Table 8. The example was originally introduced by Feng et al. 1997 to illustrate construction time–cost trade-off analysis. There is an average of 3.4 units of resource utilization options to construct each of the 18 activities, which produces more than 3.6 billion i.e., 3.418 possible combinations for delivering the entire project (El-Rayes and Kandil 2005). Each of these possible combinations leads to a unique impact on project performance, and the main challenge here is to search this large solution space to find a solution that establishes an optimal and delicate balance among construction time, cost and Quality.

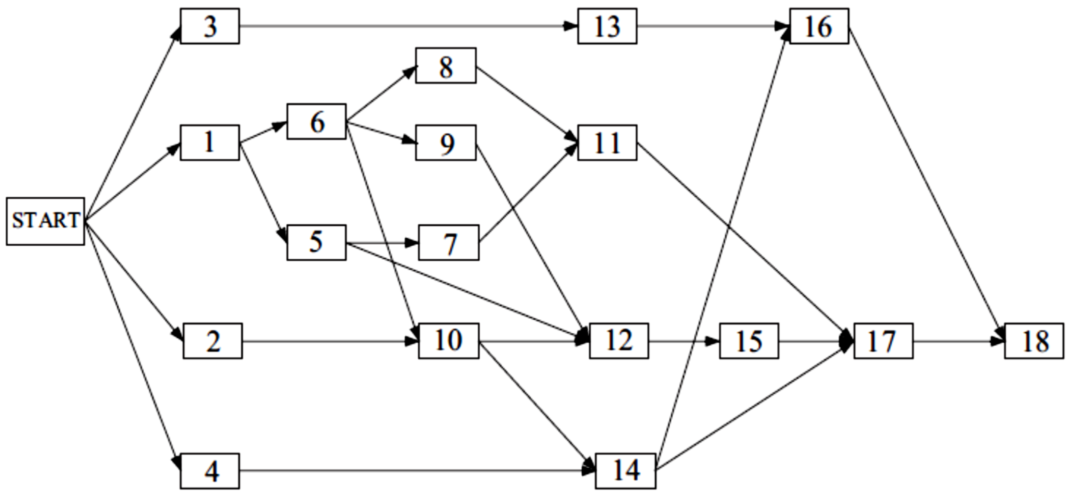


Figure 8 Network diagram of 18 activity used in El-Rayes example problem

Characteristics of the project in term of activities duration, resource utilization options and corresponding cost and quality of such utilizations are shown in Table 7. These data are fed to the proposed algorithm base on Multi-Colony Ant Colony Optimization.

Table 7 Time, Cost and weighted quality of possible resource utilization options

Activity	Resource utilization option	Time (days)	Cost ($)	Activity Weight	Weighted Quality (%)
1	1	14	2,400	3	2.94
	2	15	2,150		2.67
	3	16	1,900		2.46
	4	21	1,500		2.19
	5	24	1,200		1.86
2	1	15	3,000	5	4.8
	2	18	2,400		4.55
	3	20	1,800		4.3
	4	23	1,500		3.65
	5	25	1,000		3.1
3	1	15	4,500	8	7.92
	2	22	4,000		6.4
	3	33	3,200		4.88
4	1	12	45,000	11	7.92
	2	16	35,000		6.4
	3	20	30,000		4.88
5	1	22	20,000	10	9.9
	2	24	17,500		9.1
	3	28	15,000		7.4
	4	30	10,000		6.1
6	1	14	40,000	11	10.56
	2	18	32,000		8.36
	3	24	18,000		6.82
7	1	9	30,000	10	9.6
	2	15	24,000		7.1
	3	18	22,000		6.3
7	1	14	220	1	0.95
	2	15	215		0.83
	3	16	200		0.75
	4	21	208		0.68
	5	24	120		0.61
9	1	15	300	1	0.99
	2	18	240		0.94
	3	20	180		0.84
	4	23	150		0.73
	5	25	100		0.63

Table 7 (Continued)

Activity	Resource utilization option	Time (days)	Cost ($)	Activity Weight	Weighted Quality (%)
10	1	15	450	1	0.95
	2	22	400		0.8
	3	33	320		0.65
11	1	12	450	2	1.9
	2	16	350		1.44
	3	20	300		1.24
12	1	22	2,000	3	2.94
	2	24	1,750		2.61
	3	28	1,500		2.13
	4	30	1,000		1.83
13	1	14	4,000	7	6.79
	2	18	3,200		5.04
	3	24	1,800		4.27
14	1	9	3,000	6	5.94
	2	15	2,400		4.74
	3	18	2,200		3.78
15	1	16	3,500	7	6.23
16	1	20	3,000	3	2.91
	2	22	2,000		2.61
	3	24	1,750		2.37
	4	28	1,500		2.19
	5	30	1,000		1.86
17	1	14	4,000	6	5.82
	2	18	3,200		4.38
	3	24	1,800		3.72
18	1	9	3,000	5	4.85
	2	15	2,400		3.7
	3	18	2,200		3.25

The proposed optimization model was robust enough to generate 349 Pareto optimal solutions. Each of these solutions corresponds to one resource utilization option for the project. In order to visually represent the results a fitted surface in three dimensional time-cost-quality space is represented in Figure 9.

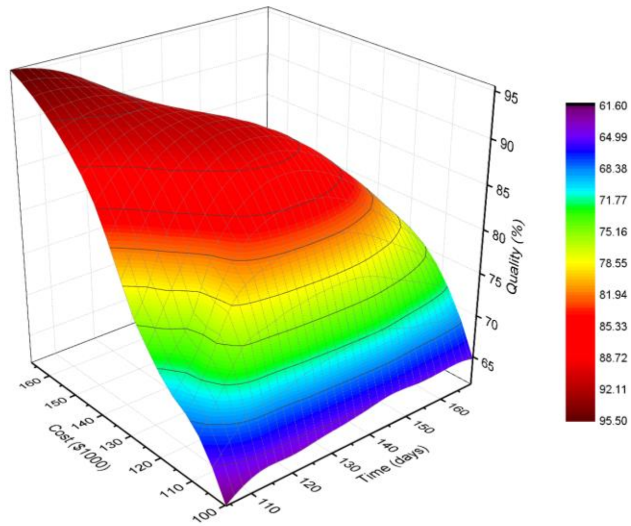


Figure 9 3D representation of fitted surface to the non-dominated results

To compare the 349 non-dominated solutions of the present model (DSRAM) with 305 solutions of El-Rayes et al. (2005) a 3 dimensional comparison chart of the solutions is represented in Figure 10. As shown these algorithms generate 41 equal solutions and other solutions are very close. It is concluded that DSRAM is a robust algorithm capable of generating valid solutions. In addition, DSRAM generates solutions that outperform the ELR's solutions. The comparison will be discussed using a performance metric function.

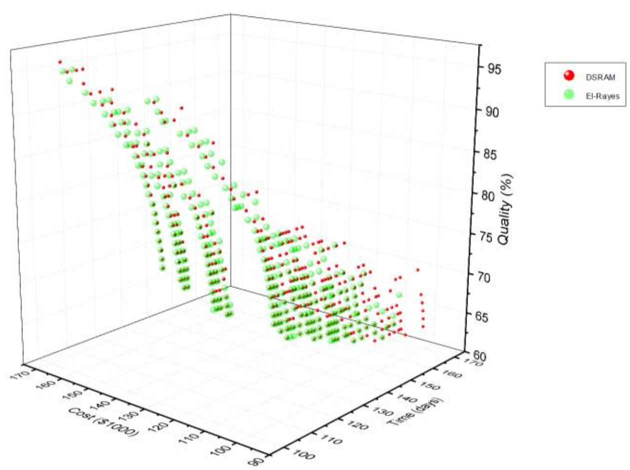


Figure 10 Comparison of 349 results of DSRAM with 305 Results of El-Rayes on the same example

To further discuss the validity of the present DSRAM model the results are compared base on a function that determines the ability of the generated non-dominated set to dominate the set that it is being compared with. In the multi-objective optimization the definition of algorithm performance is substantially more complex than for single-objective optimization problems, because the optimization goal itself consists of multiple objectives: (i) The distance of the resulting non-dominated set to the Pareto-optimal front should be minimized. (ii) A good distribution of the solutions found is desirable. The assessment of this criterion might be based on a certain distance metric. (iii)The extent of the obtained non-dominated front should be maximized, i.e., for each objective, a wide range of values should be covered by the non-dominated solutions.(Zitzler et al., 2000).

Here, the C function based on the following definition proposed by (Zitzler et al., 2000) is used to compare the non-dominated sets.

Definition: Let $X', X" \subseteq X$ be two sets of decision vectors. The function C maps the ordered pair $(X', X")$ to the interval [0,1]:

$$C(X', X") := \frac{|\{a \in X" : \exists\ a' \in X' : a \leq a'\}|}{|X"|}$$

The value $C(X', X") = 1$ means that all solutions in $X"$ are dominated by or equal to solution in X'. The opposite, $C(X', X") = 0$, represents the situation when none of the solutions in $X"$ are covered by the set X'. Note that both $C(X', X")$ and $C(X", X')$ have to be considered, since $C(X', X")$ is not necessarily equal to 1- $C(X", X')$.

The results of comparison of these sets (ELR=El-Rayes et al., DSRAM=present model) of non-dominated solutions is summarized in the Table 8.

Table 8 Performance metrics of the comparison of two sets

Comparison Performance Metrics	**Values**
Number of solutions in DSRAM	349
Number of solutions in ELR	305
C (DSRAM, ELR)	0.87
C (ELR, DSRAM)	0.17
Dominated solutions of DSRAM	15
Dominated solutions of ELR	239
Equal solutions	41
Equal and dominated solutions of DSRAM	56
Equal and dominated solutions of ELR	280

Results of comparison can improve the robustness of the present model in generating Pareto front. DSRAM results partially covers about 87% of the ELR results. However, these results can prove the validity of the proposed algorithm, because of the complexity of the meta-heuristic multi objective techniques it cannot easily be inferred the present model is more robust and further comparisons needs to be carried out when the met-heuristic data of the both techniques are available. In summary, the comparison fully proves the validity of the current technique in generating non-dominated solutions for similar examples.

4

Case Analysis

4.1 An overview of the characteristics of the case studies

Three cases are discussed in this chapter. First, in section 4.2 a 3-Objective Cost-LoS-EII case is presented to illustrate the MODM meta-heuristic algorithm. Second, in section 4.3 a 4-Objective Time-Cost-LoS-EII case is presented to show the application of MCDM to the set of non-dominated optimal solutions. Third, in section 4.5 a 3-Objective Time-Cost-LoS case is presented to illustrate the meta-heuristic algorithm on multi-asset items. The purpose of the second case study is to find the optimal maintenance solutions among the various possible pavement maintenance techniques to implement the maintenance program with minimum possible time, cost and GHG while maximizing the level of service improvement. In the following subsections, a description of the data needed is presented.

4.1.1 Pavement maintenance techniques

The pavement maintenance techniques are presented in Table 9 and a brief description of these pavement maintenance techniques is discussed in Appendix A.

Table 9 Maintenance Techniques (Adapted from Cerea (2010))

	Treatments
1	Crack Seal
2	H.I.R.
3	Micro-surfacing
4	Mill & Resurfacing
5	Novachip
6	Overlay
7	Slurry Seal

4.1.2 Inspection and evaluation of maintenance needs

In the first step, a two lane pavement inspection between mile marker 2 and 140 has been carried out. Highway pavement area is categorized as sections with similar maintenance needs and the sections with no need of maintenance. Results of this inspection are summarized in Table 10. The possibility of utilizing different techniques for the maintenance of these 23 section is based on the initial condition of the section and the after inspection evaluation.

Table 10 Characteristics of the case study, possible maintenance actions and pavement maintenance needs

Section	Range	Lane width (m)	Maintenance Area (m^2)	Maintenance (Y/N)	Possible Actions
1	MM 2-10	3.7	95,273	Y	1,7
2	MM 10-15	3.7	59,546	Y	2,5,8
3	MM 15-18	3.7	35,727	Y	1,7
4	MM 18-21	3.7	35,727	Y	1,7
5	MM 21-26	3.7	59,546	Y	3,4,6
6	MM 26-30	3.7	47,637	Y	3,4,6
7	MM 30-35	3.7	59,546	Y	2,3,4,6
8	MM 35-42	3.7	83,364	Y	1,7
9	MM 42-50	3.7	95,273	N	N/A
10	MM 50-56	3.7	71,455	Y	1
11	MM 56-73	4	90,123	N	N/A
12	MM 73-81	4	102,998	Y	1,7
13	MM 81-89	4	102,998	N	N/A
14	MM 89-95	4	77,248	Y	2,5,8
15	MM 95-102	4	90,123	Y	3,4,6
16	MM 102-108	4	77,248	Y	3,4,6,7
17	MM 108-114	4	77,248	Y	1,7
18	MM 114-119	4	64,374	Y	2,5,8
19	MM 119-123	4	51,499	N	N/A
20	MM 123-127	4	51,499	Y	1,7
21	MM 127-131	4	51,499	N	N/A
22	MM 131-135	4	51,499	Y	2,5,8
23	MM 135-140	4	64,374	Y	1,7

4.1.3 Scheduling of maintenance activities

In order to calculate the duration of maintenance project the duration of pavement maintenance using each of the techniques is needed. In addition the precedence relation between activities is required. Application of these techniques for maintenance purpose of each section will need a unique time. The amount of time depends on the production rate of the treatment, amount of work and other project specific parameters.

Figure 11 is a schematic bar chart representing the scheduling of the maintenance activities for the case study. Durations in the figure are simple assumptions for illustration purpose only and these durations will vary based on the maintenance options utilization. However, the amount of time needed for application of each of these activities is shown in Table 14. The present model will calculate the project duration based on Critical Path Method (CPM) technique for various combinations of the treatment option utilizations.

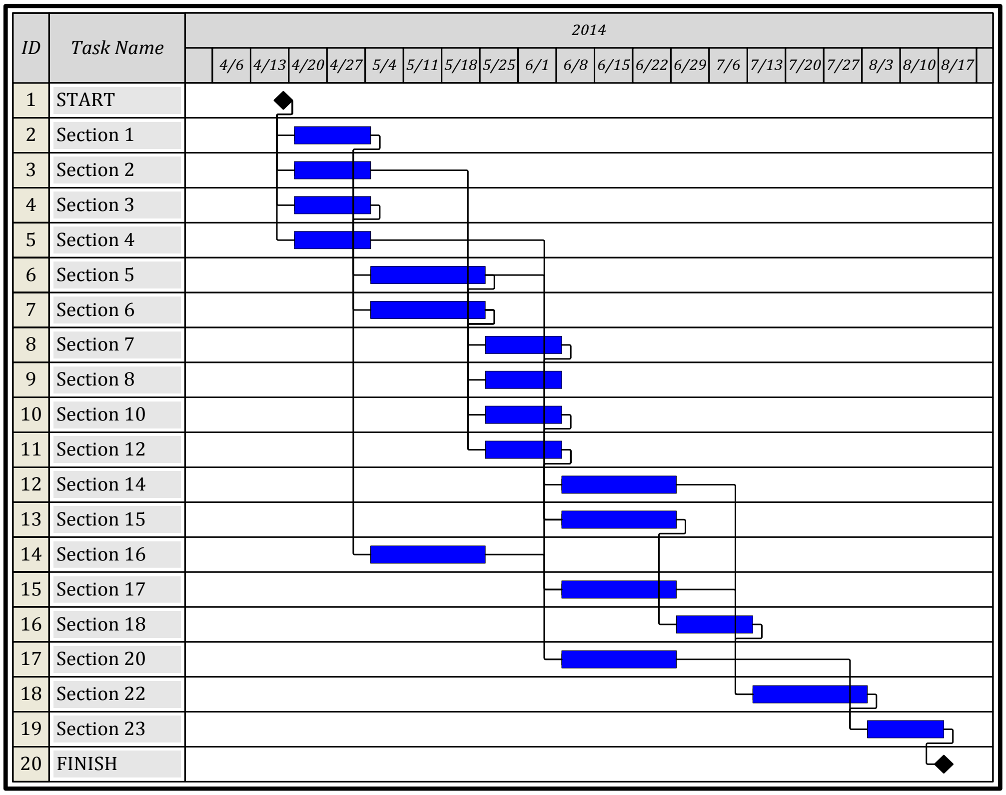


Figure 11 Schematic schedule of pavement maintenance project

4.1.4 Project cost

As discussed earlier, total time, cost, level of service and environmental impacts of the project depends on the combination of selected treatment options. Therefore, cost of these techniques is needed. These data are adapted from Cerea (2010) and the average prices of these techniques are presented in Table 11.

Table 11 Average Price of treatment options (adapted from Cerea (2010))

	Treatment	**Price** [$/m2]
1	Crack Seal	0.947
2	H.I.R.	4.516
3	Microsurfacing	2.166
4	Mill & Resurf.	3.102
5	Novachip	5.185
6	Overlay	2.379
7	Slurry Seal	1.113

4.1.5 Environmental Impact of the project

One of the important aspects of project is the environmental impact of the project. AS presented earlier the environmental impact here is defined with Environmental Impact Index (EII) that considers both energy consumption and GHG emissions. These data on energy consumptions and CO_2 emission is shown in Table 12. calculations are adapted from adapted from Cerea (2010) and details of such calculation is presented in Appendix B. In the present case study the amounts of energy consumption and emissions are first normalized to 10-100 scale and equal weighting factors is assigned to these factors. It means both factors have the same contribution in environmental impact index.

Table 12 Energy consumption and CO2 emission of treatment options (Adapted from Cerea (2010))

Treatment	Variations	Energy (MJ/m^2)	CO_2 (kg/ m^2)
Crack Seal	-	3.83	0.27
H.I.R.	-	35.93	2.61
Microsurfacing	-	34.53	1.84
Mill & Resurf.	HMA	53.40	3.95
	WMA	41.92	3.57
Novachip	-	35.12	2.76
Overlay	HMA	42.60	3.14
	WMA	39.69	3.04
Slurry Seal	-	26.31	3.34

4.1.6 Level of Service Improvement

The computation of the benefit of the application of different maintenance techniques on level of service requires knowledge of the anticipated performance of the pavement. There are several techniques for such prediction. However, in this case study the improvement in the performance of the project is calculated based on the data adapted from Giustozzi et al. (2012b) that is shown in Figure 12 and Figure 13. These graphs represent the improvement effect of the pavement maintenance techniques in form of Performance Jump (PJ) and Present Serviceability Index (PSI).

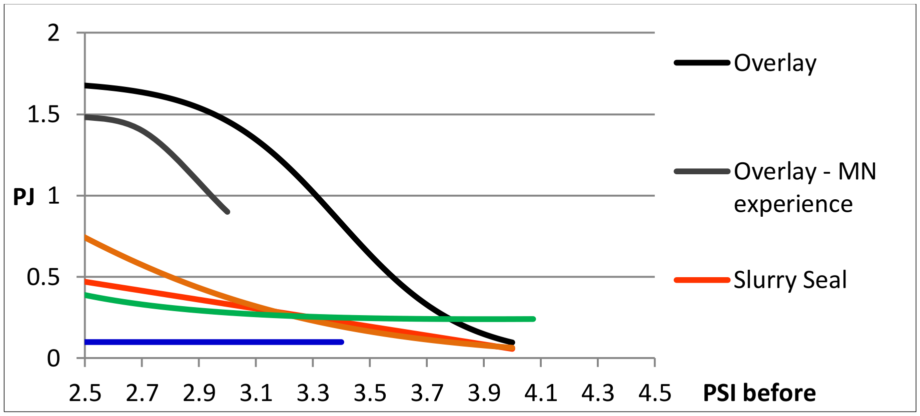


Figure 12 Performance Jump trends with previous PSI for different treatments (adapted from Cerea (2010))

Weight factors of LoS improvement for the sections are a function of the maintenance length of section which is covered by the treatment and the PSI is assumed to be 3 for Novachip and Overlay and 2.5 for all other techniques.

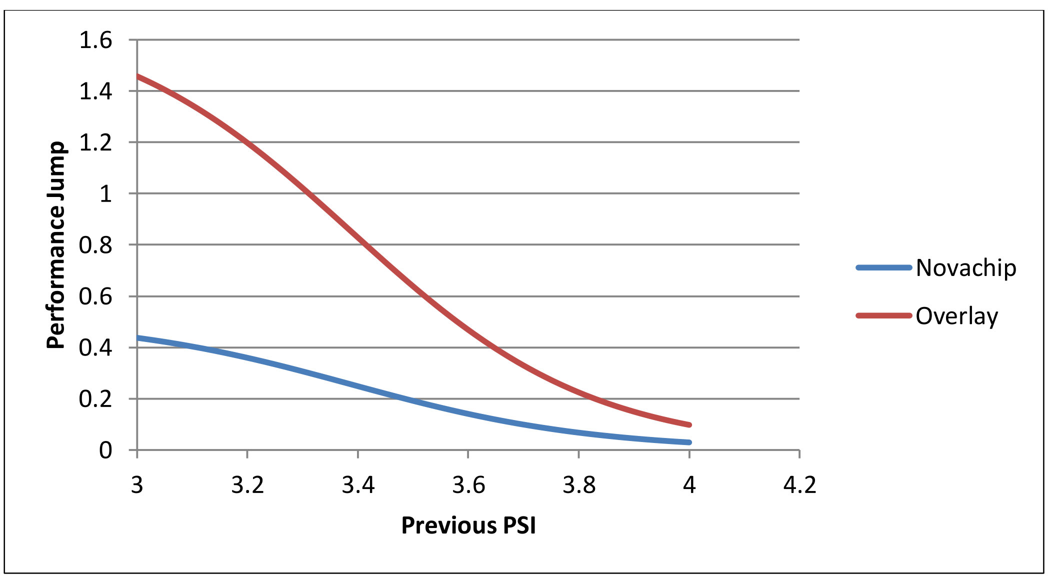


Figure 13 Performance jump curve for the Novachip maintenance (adapted from Cerea (2010))

For example the calculation process of level of service improvement as a result of utilizing maintenance option 1 (crack seal) for section 1 is as follows:

$$w_1 = \frac{L_1}{L} = \frac{8}{128} = 0.063$$

Where w_1 is the weight factor of the section 1. The performance jump values extracted from Figure 12 and Figure 13 are normalized into the scale of 10 to 100 as shown in Table 13 .

The normalized Los for section 1 is calculated as below:

Section 1: $LoS_N = 10 + \frac{(PJ_1 - PJ_{Min})}{PJ_{Max} - PJ_{Min}} \times 90 = 10$

Table 13 Normalization LoS improvements using performance jump curves

	Maintenance Option	Performance Jump (PSI=2.5)	Normalized Level of Sevice Improvement (LoS_N)
1	Crack Seal	0.1	10
2	H.I.R.	2.7	100
3	Microsurfacing	0.4	20
4	Mill & Resurf.	2	76
5	Novachip	0.5	24
6	Overlay	1.7	65
7	Slurry Seal	0.8	34
	Min	**0.1**	
	Max - Min	**2.6**	

Then the weight factor is applied. Therefore, the total sum of the LoS improvements in the sections will be a value in the scale of 10-100.

$$LoS_1 = w_1 \times LoS_N$$

$$LoS_1 = 0.063 \times 10 = 0.63$$

Where LoS_1 is the weighted level of service improvement for section 1, w_1 is the weight factor of section 1 and LoS_N is the normalized level of service improvement by maintenance option 1 (crack seal). The total level of service imrpovemt for the entire project is as follows:

$$LoS_T = \sum_{i=1}^{23} LoS_i$$

Where LoS_T is the total level of service improvement and i is the section number.

The data corresponding to the time, cost, level of service improvement and environmental impacts of various maintenance options are summarized in Table 14.

Table 14 Available Maintenance Actions and Their Characteristics

Section	Range	Section Length (Mile)	Lane Width (m)	Mainten-ance Area (m^2)	Mainte-nance Need (Y/N)	Possible Mainten-ance Actions	Time (days)	Cost ($1000)	LoS improve ment	Environmental Impact Index (E.I.I.)
1	MM 2-10	8	3.7	95,273	Y	1	38	90	0.63	12
						7	13	106	2.13	54
2	MM 10-15	5	3.7	59,546	Y	2	10	269	3.91	32
						5	10	309	0.94	31
3	MM 15-18	3	3.7	35,727	Y	1	14	34	0.23	10
						7	5	40	0.80	26
4	MM 18-21	3	3.7	35,727	Y	1	14	34	0.23	10
						7	5	40	0.80	26
5	MM 21-26	5	3.7	59,546	Y	3	7	129	0.78	30
						4	15	185	2.97	43
						6	12	142	2.54	36
6	MM 26-30	4	3.7	47,637	Y	3	6	103	0.63	26
						4	12	148	2.38	36
						6	10	113	2.03	31
7	MM 30-35	5	3.7	59,546	Y	2	10	269	3.91	32
						3	7	129	0.78	30
						4	15	185	2.97	43
						6	12	142	2.54	36
8	MM 35-42	7	3.7	83,364	Y	1	33	79	0.55	12
						7	11	93	1.86	48
9	MM 42-50	8	3.7	95,273	N	N/A	N/A	N/A	N/A	N/A
10	MM 50-56	6	3.7	71,455	Y	1	29	68	0.47	11
11	MM 56-73	7	4	90,123	N	N/A	N/A	N/A	N/A	N/A
12	MM 73-81	8	4	102,998	Y	1	41	98	0.63	13
						7	14	115	2.13	57
13	MM 81-89	8	4	102,998	N	N/A	N/A	N/A	N/A	N/A
14	MM 89-95	6	4	77,248	Y	2	13	349	4.69	39
						5	13	401	1.13	38
15	MM 95-102	7	4	90,123	Y	3	11	195	1.09	41
						4	23	280	4.16	61
						6	18	214	3.55	50
16	MM 102-108	6	4	77,248	Y	3	10	167	0.94	37
						4	19	240	3.56	53
						6	15	184	3.05	44
						7	10	86	1.59	45

Table 14 (Continued)

Section	Range	Section Length (Mile)	Lane Width (m)	Mainten-ance Area (m^2)	Mainte-nance Need (Y/N)	Possible Mainten-ance Actions	Time (days)	Cost ($1000)	LoS improve ment (%)	Environmental Impact Index (E.I.I.) (%)
17	MM 108-114	6	4	77,248	Y	1	31	73	0.47	12
						7	10	86	1.59	45
18	MM 114-119	5	4	64,374	Y	2	11	291	3.91	34
						5	11	334	0.94	33
19	MM 119-123	4	4	51,499	N	N/A	N/A	N/A	N/A	N/A
20	MM 123-127	4	4	51,499	Y	1	21	49	0.31	11
						7	7	57	1.06	33
21	MM 127-131	4	4	51,499	N	N/A	N/A	N/A	N/A	N/A
22	MM 131-135	4	4	51,499	Y	2	9	233	3.13	29
						5	9	267	0.75	28
23	MM 135-140	5	4	64,374	Y	1	26	61	0.39	11
						7	9	72	1.33	39

4.2 Implementation of the proposed model for three objective Cost-LoS-EII Trade-off

The proposed model is implemented on the case study with consideration of three objectives: minimization of cost, minimization of environmental impacts and maximization of the level of service improvement. Here, we assumed that time is not a limitation for the project and other three objectives are the driving goals. However, in the next section the model will be implemented on the case study considering all four objectives. The input data for cost, level of service and environmental impact of this case study is presented in Table 14. It should be noted that the data for time is not used in this case study.

In this application the proposed model generated 186 non-dominated solutions. Each of these solutions corresponds to a unique way to deliver the pavement maintenance project. These non-dominated solutions are shown in Figure 14.

Each point corresponds to a solution for multi-objective Cost-EII-LoS pavement management optimization. The total project cost of the non-dominated solutions changes from $2,370,000 to $2,941,000 while total Level of Service Improvement ranges from 12 to 45 and total Environmental Impact Index ranges from 396 to 698.

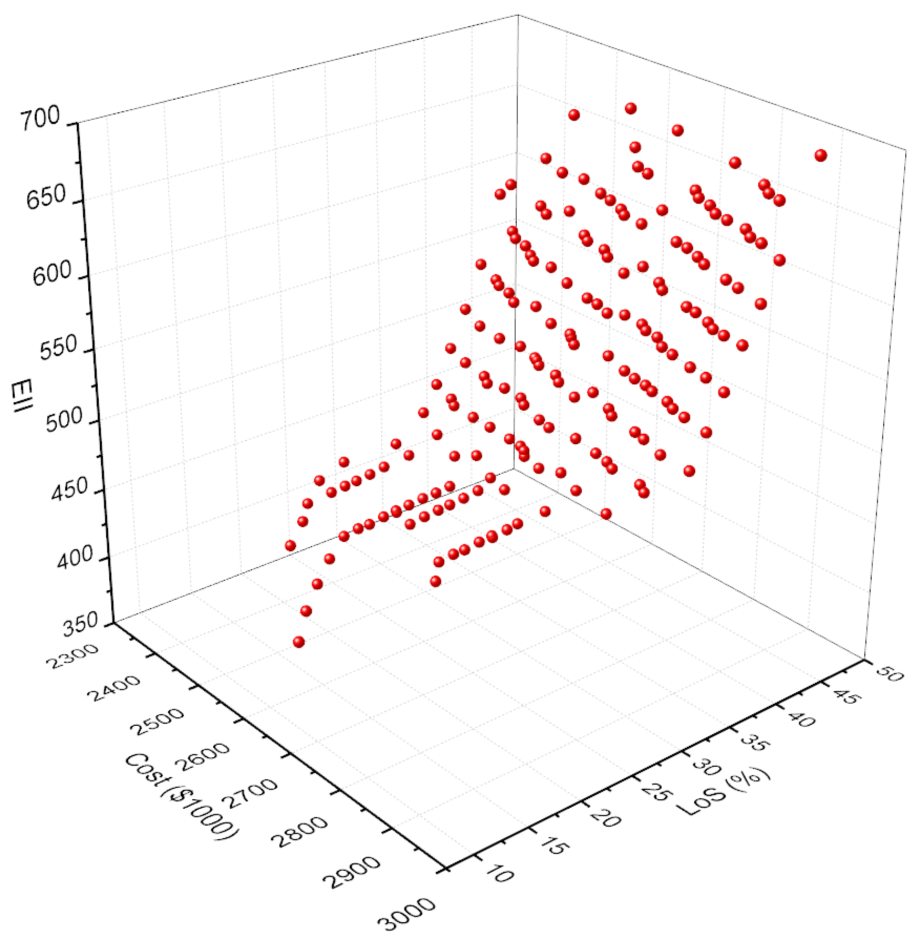


Figure 14 Non-dominated solutions of three objective Cost-LoS-EII pavement maintenance optimization

To illustrate the trend of the Pareto front a surface is fitted to the results in the three dimensional objectives space as shown in Figure 15.

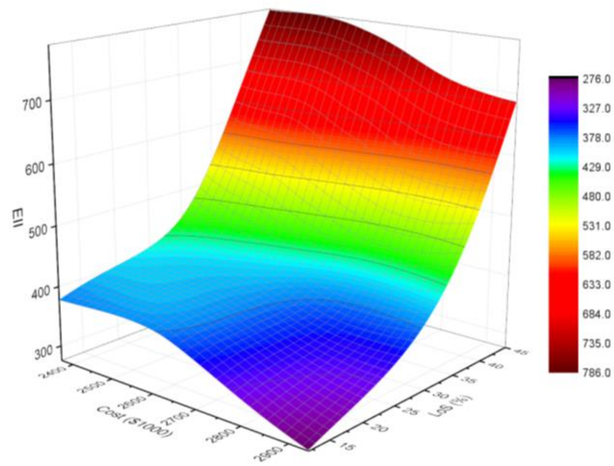


Figure 15 Visual presentation of a fitted surface to the solutions of Cost-LoS-EII optimization

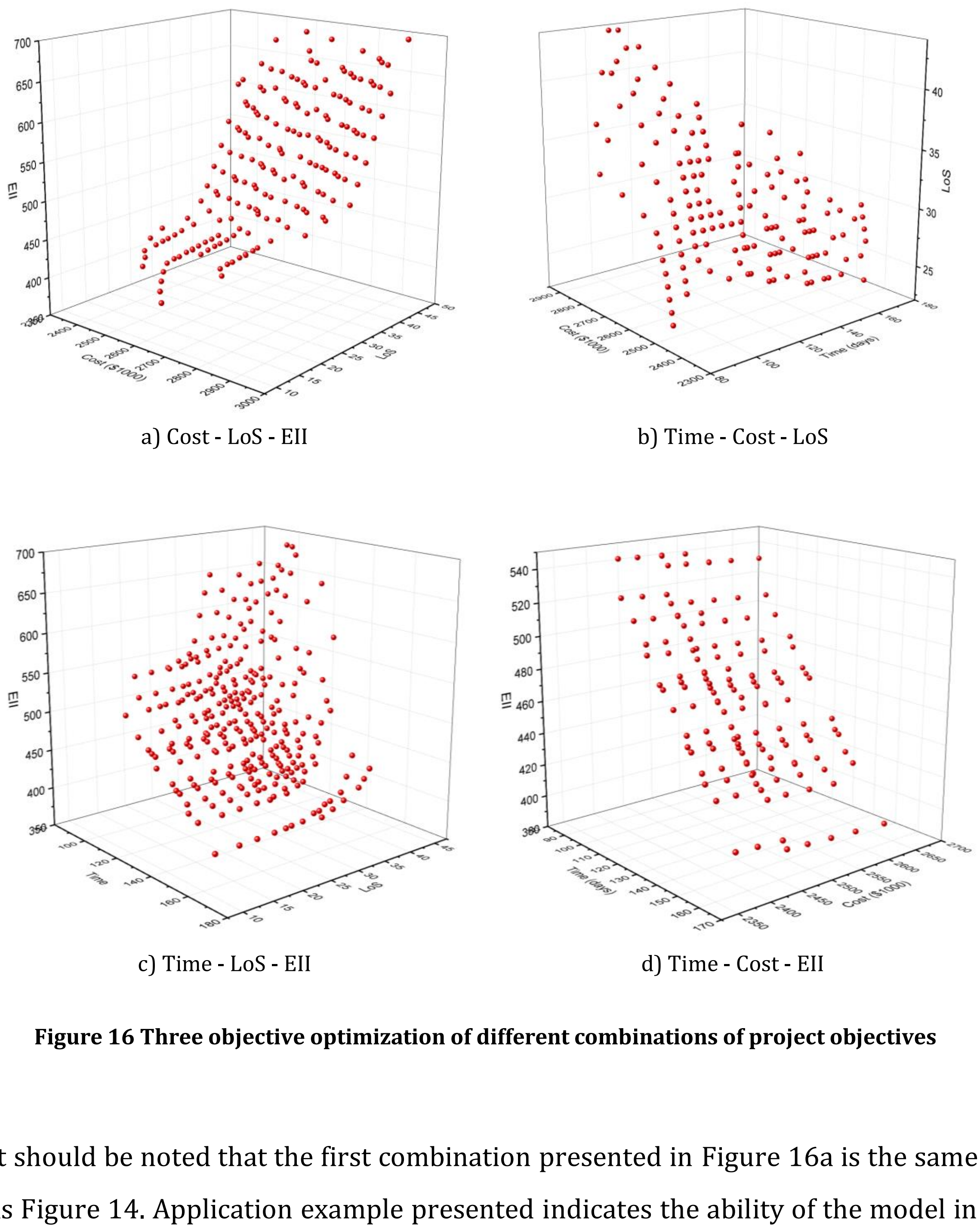
4.3 Implementation of the model for four objective Time-Cost-LoS-EII Trade-off

The proposed model is implemented on the case study to optimize four objectives: minimization of time, cost, environmental impacts and maximization of the level of service improvement. The input data for this case study is presented in Table 14. The model generated 1003 non-dominated solutions. A sample set of these solutions is presented in Table 15.

Table 15 A sample set of 15 solutions of 4 objective optimization

ID	Time	Cost	LoS	EII	Selected maintenance options for the Sections																	
					1	2	3	4	5	6	7	8	10	12	14	15	16	17	18	20	22	23
1	142	2,422	31	467	2	1	1	1	3	3	4	1	1	1	1	1	4	1	1	1	1	1
2	127	2,426	31	487	2	1	1	1	3	1	2	1	1	1	1	3	4	1	1	2	1	1
3	142	2,415	30	464	2	1	1	1	1	3	2	1	1	1	1	3	4	1	1	1	1	1
4	135	2,477	33	486	1	1	1	1	2	1	4	1	1	1	1	3	4	1	1	2	1	2
5	146	2,432	32	473	1	1	1	2	3	1	4	1	1	1	1	3	4	1	1	1	1	2
6	146	2,413	30	451	1	1	1	1	1	1	4	1	1	1	1	3	4	1	1	1	1	2
7	121	2,442	33	499	2	1	1	1	3	1	4	1	1	1	1	3	4	1	1	1	1	2
8	146	2,426	31	457	1	1	1	1	3	1	4	1	1	1	1	3	4	1	1	1	1	2
9	135	2,434	32	479	1	1	1	1	3	1	4	1	1	1	1	3	4	1	1	2	1	2
10	138	2,424	31	481	2	1	1	2	1	1	4	1	1	1	1	3	4	1	1	1	1	1
11	135	2,415	30	470	1	1	1	1	3	1	4	1	1	1	1	1	4	1	1	2	1	2
12	131	2,430	32	489	2	1	1	1	3	3	4	1	1	1	1	1	4	1	1	2	1	1
13	134	2,426	31	484	1	1	1	1	1	1	4	1	1	1	1	3	4	2	1	1	1	2
14	123	2,421	30	491	1	1	1	1	1	3	4	1	1	2	1	1	4	1	1	1	1	2
15	138	2,418	30	465	2	1	1	1	3	1	2	1	1	1	1	3	4	1	1	1	1	1

To illustrate trade-off among objectives of the problem Figure 16 represents different combinations of project objectives for three-objective optimization.



a) Cost - LoS - EII

b) Time - Cost - LoS

c) Time - LoS - EII

d) Time - Cost - EII

Figure 16 Three objective optimization of different combinations of project objectives

It should be noted that the first combination presented in Figure 16a is the same as Figure 14. Application example presented indicates the ability of the model in generation of optimal solutions for the case study. It answers to the research question of: what are the optimal combinations of maintenance options for roadway asset maintenance while maintaining conflicting objectives of the problem. Here, both three-objective and four-objective optimization is implemented and presented.

4.4 Implementation of SMART Multi-Criteria decision making for prioritization of solutions

The Simple Multi-Attribute Rating Technique (SMART) proposed by Edwards (1971) is a Multi-Criteria Decision Analysis (MCDA) method in which a finite number of decision alternatives under a finite number of performance criteria are evaluated. This technique is discussed in section 2.5.1.1. The purpose of the analysis is to rank the alternatives in a subjective order of preference and, if possible to tact the overall performance of the alternatives via the proper assignment of numerical grades. The ranking value x_j of alternative A_j is obtained simply as the weighted algebraic mean of the values associated with it as follows:

$$x_j = \frac{\sum_{i=1}^{m} w_i a_{ij}}{\sum_{i=1}^{m} w_i}, j = 1, \dots, n. \tag{26}$$

A numerical score to measure the attractiveness of the course of actions facing decision makers will be derived. If no element of risk and uncertainty is involved in the decision this will referred as the value of the course of action. If risk and uncertainty is involved it is referred as the utility of the course of action.

4.4.1 Decision makers

In this example we assume only one decision maker is responsible for the prioritization of the maintenance strategy. However, group decision making based on the explained approach in chapter 2 can also be utilized for this purpose.

4.4.2 Alternatives

The alternative courses of action in this problem are the 1003 non-dominated solutions of the first stage of multi objective optimization. These are all alternatives for delivering the maintenance project. Here, based on the budget constraints, time limitations, target level of service improvement and environmental impact constrains the alternatives will be narrowed down and then the remaining solutions are the actual alternatives for Multi-Criteria Decision making technique. Constraints and limitations of the agency for the existing case study are summarized in Table 16.

Table 16 Constraints and limitations of the solutions

Objectives	Value Range	Lower limit	Upper limit
Time (days)	88 - 169	-	150
Cost ($1000)	2,370 - 2,941	-	2500
Level of Service Improvement	12 - 45	30	
Environmental Impacts Index (EII)	396 - 698	-	500

The solutions of the 4 objective optimization are narrowed down based on the constraints of Table 16. Applying these constraints to the pool of 1003 non-dominated results led to 30 solutions. These solutions are the alternatives of SMART decision making process. Table 17 represents the resulted answers along with their corresponding maintenance strategy for the road sections.

Table 17 Set of feasible answers after applying the constraints

ID	Time	Cost	LoS	EII	Selected maintenance options for the Sections																	
					1	2	3	4	5	6	7	8	10	12	14	15	16	17	18	20	22	23
1	**142**	**2,422**	**31**	**467**	2	1	1	1	3	3	4	1	1	1	1	1	4	1	1	1	1	1
2	**127**	**2,426**	**31**	**487**	2	1	1	1	3	1	2	1	1	1	1	3	4	1	1	2	1	1
3	**142**	**2,415**	**30**	**464**	2	1	1	1	1	3	2	1	1	1	1	3	4	1	1	1	1	1
4	**135**	**2,477**	**33**	**486**	1	1	1	1	2	1	4	1	1	1	1	3	4	1	1	2	1	2
5	**146**	**2,432**	**32**	**473**	1	1	1	2	3	1	4	1	1	1	1	3	4	1	1	1	1	2
6	**146**	**2,413**	**30**	**451**	1	1	1	1	1	1	4	1	1	1	1	3	4	1	1	1	1	2
7	**121**	**2,442**	**33**	**499**	2	1	1	1	3	1	4	1	1	1	1	3	4	1	1	1	1	2
8	**146**	**2,426**	**31**	**457**	1	1	1	1	3	1	4	1	1	1	1	3	4	1	1	1	1	2
9	**135**	**2,434**	**32**	**479**	1	1	1	1	3	1	4	1	1	1	1	3	4	1	1	2	1	2
10	**138**	**2,424**	**31**	**481**	2	1	1	2	1	1	4	1	1	1	1	3	4	1	1	1	1	1
11	**135**	**2,415**	**30**	**470**	1	1	1	1	3	1	4	1	1	1	1	1	4	1	1	2	1	2
12	**131**	**2,430**	**32**	**489**	2	1	1	1	3	3	4	1	1	1	1	1	4	1	1	2	1	1
13	**134**	**2,426**	**31**	**484**	1	1	1	1	1	1	4	1	1	1	1	3	4	2	1	1	1	2
14	**123**	**2,421**	**30**	**491**	1	1	1	1	1	3	4	1	1	2	1	1	4	1	1	1	1	2
15	**138**	**2,418**	**30**	**465**	2	1	1	1	3	1	2	1	1	1	1	3	4	1	1	1	1	1
16	**138**	**2,461**	**31**	**472**	2	1	1	1	2	1	2	1	1	1	1	3	4	1	1	1	1	1
17	**125**	**2,426**	**31**	**492**	2	1	1	1	1	3	2	1	1	1	1	3	4	1	1	1	1	2
18	**121**	**2,429**	**31**	**493**	2	1	1	1	3	1	2	1	1	1	1	3	4	1	1	1	1	2
19	**131**	**2,417**	**30**	**480**	1	1	1	1	1	3	4	1	1	1	1	1	4	2	1	1	1	2
20	**126**	**2,418**	**30**	**492**	2	1	1	1	1	1	2	1	1	1	1	3	4	2	1	1	1	1
21	**119**	**2,425**	**31**	**495**	2	1	1	1	3	1	4	1	1	1	1	1	4	2	1	1	1	1
22	**134**	**2,482**	**33**	**497**	1	1	1	1	2	1	4	1	1	1	1	3	4	2	1	1	1	2
23	**119**	**2,424**	**30**	**492**	1	1	1	1	3	1	4	1	1	2	1	1	4	1	1	1	1	2
24	**121**	**2,423**	**30**	**490**	2	1	1	1	3	1	4	1	1	1	1	1	4	1	1	1	1	2
25	**146**	**2,469**	**32**	**464**	1	1	1	1	2	1	4	1	1	1	1	3	4	1	1	1	1	2
26	**127**	**2,420**	**30**	**484**	2	1	1	1	3	1	4	1	1	1	1	1	4	1	1	2	1	1
27	**125**	**2,420**	**30**	**489**	2	1	1	1	3	3	2	1	1	1	1	1	4	1	1	1	1	2
28	**131**	**2,430**	**31**	**486**	1	1	1	1	3	3	4	1	1	1	1	1	4	2	1	1	1	2
29	**125**	**2,433**	**32**	**495**	2	1	1	1	3	3	4	1	1	1	1	1	4	1	1	1	1	2
30	**123**	**2,434**	**32**	**497**	1	1	1	1	3	3	4	1	1	2	1	1	4	1	1	1	1	2

4.4.3 Attributes

Attributes are used to measure the performance in relation to objectives. In this case study Time, Cost, LoS Improvement and Environmental Impact Index are considered as attributes. For each attribute a value or utility should be assigned. In this problem, it is assumed that no uncertainty is involved and therefore values are assigned to the attributes. In the next step, it is desired to find out how well the different alternatives perform on each of the attributes. Determining the time, cost, LoS and EII for the current problem is easy as they are given as a result of multi-objective optimization process. It is assumed that there is a linear relationship between the values and amounts of attributes in this problem. It means that for example a decrease in time from 121 days to 119 days has the same attractiveness for decision maker as decreases from 123 days to 121 days.

4.4.4 Weights of attributes

In the SMART technique, one approach for weighting is that attributes are ranked in order of importance and a minimum point is assigned to the least important criterion. Then, the next-least-important criterion is chosen, more points are assigned to it, and so on, to reflect their relative importance. The final weights are obtained by normalizing the sum of the points to one. Table 18 shows the original weights out of 100 for the criteria of the problem. These original weights are results of decision maker's judgment on the importance level of the problem attributes. It is indicated that for the current problem it is assumed that for example the LoS is 75% as important as the Cost. The normalized weights assigned for time, cost, LoS and EII are respectively as 10, 40, 30 and 20.

Table 18 Original and Normalized weights of attributes

Attribute	Original Weights	Normalized weights
Cost	100	40
LoS	75	30
EII	50	20
Time	25	10

After assigning the above values to the problem the score of each alternative will be calculated. Alternatives will be ranked based on the total score as shown in Table 19. It should be noted that all objective except LoS are minimized. Score of LoS is inverted to represent a minimization. Therefore, the alternatives with smaller scores are in higher priority. For example the total score of the alternative 22 (Alt. ID 22) which is ranked as the last option is as follows:

$$Score = \frac{\sum_{i=1}^{m} w_i a_{ij}}{\sum_{i=1}^{m} w_i}$$

Normalized value for time:

$$Time_N = 1 + \frac{(T_{22} \ - T_{Min})}{T_{Max} - T_{Min}} \times 9 = 6$$

Likewise normalized cost, level of service and EII are all equal to 10.

$$Score = \frac{(0.1 \times 6) + (0.4 \times 10) + \left(0.3 \times \frac{1}{10}\right) + (0.2 \times 10)}{0.1 + 0.4 + 0.3 + 0.2}$$

$Score = 6.56.$

The results of prioritization of the solutions in the non-dominated set presented in this section completely answer to the research question of how to appropriately prioritize the Pareto optimal solutions. First the constraints were applied to the solutions and SMART technique was utilized to rank the solutions in the short list.

Table 19 Ranking of maintenance alternatives

Rank	Alt. ID	Weights	Time	Normalized Time	Cost	Normalized Cost	LoS	Normalized LoS	EII	Normalized EII	Score
			0.1		0.4		0.3		0.2		
1	6		146	10	2,413	1	30	1	451	1	1.90
2	11		135	6	2,415	1	30	1	470	5	2.35
3	3		142	9	2,415	1	30	1	464	3	2.36
4	15		138	7	2,418	2	30	1	465	4	2.42
5	8		146	10	2,426	3	31	4	457	2	2.58
6	1		142	9	2,422	2	31	4	467	4	2.61
7	19		131	5	2,417	2	30	1	480	6	2.70
8	26		127	4	2,420	2	30	1	484	7	2.87
9	27		125	3	2,420	2	30	1	489	8	2.99
10	20		126	3	2,418	2	30	1	492	9	3.03
11	14		123	2	2,421	2	30	1	491	9	3.05
12	24		121	2	2,423	2	30	1	490	8	3.05
13	21		119	1	2,425	3	31	4	495	9	3.05
14	2		127	4	2,426	3	31	4	487	8	3.07
15	10		138	7	2,424	2	31	4	481	7	3.11
16	23		119	1	2,424	2	30	1	492	9	3.11
17	17		125	3	2,426	3	31	4	492	9	3.19
18	13		134	6	2,426	3	31	4	484	7	3.19
19	18		121	2	2,429	3	31	4	493	9	3.25
20	28		131	5	2,430	3	31	4	486	8	3.37
21	9		135	6	2,434	4	32	7	479	6	3.42
22	12		131	5	2,430	3	32	7	489	8	3.45
23	5		146	10	2,432	3	32	7	473	5	3.46
24	29		125	3	2,433	4	32	7	495	9	3.64
25	30		123	2	2,434	4	32	7	497	10	3.70
26	7		121	2	2,442	5	33	10	499	10	4.11
27	16		138	7	2,461	7	31	4	472	5	4.70
28	25		146	10	2,469	8	32	7	464	3	5.05
29	4		135	6	2,477	9	33	10	486	8	5.91
30	22		134	6	2,482	10	33	10	497	10	6.56

Table 20 illustrates the final prioritized results and the maintenance strategy corresponding to these alternatives.

Table 20 Prioritized alternatives and corresponding maintenance strategies

Priority	Alt. ID	SCORE	SECTIONS																	
			1	2	3	4	5	6	7	8	10	12	14	15	16	17	18	20	22	23
1	6	1.90	1	1	1	1	1	1	4	1	1	1	1	3	4	1	1	1	1	2
2	11	2.35	1	1	1	1	3	1	4	1	1	1	1	1	4	1	1	2	1	2
3	3	2.36	2	1	1	1	1	3	2	1	1	1	1	3	4	1	1	1	1	1
4	15	2.42	2	1	1	1	3	1	2	1	1	1	1	3	4	1	1	1	1	1
5	8	2.58	1	1	1	1	3	1	4	1	1	1	1	3	4	1	1	1	1	2
6	1	2.61	2	1	1	1	3	3	4	1	1	1	1	1	4	1	1	1	1	1
7	19	2.70	1	1	1	1	1	3	4	1	1	1	1	1	4	2	1	1	1	2
8	26	2.87	2	1	1	1	3	1	4	1	1	1	1	1	4	1	1	2	1	1
9	27	2.99	2	1	1	1	3	3	2	1	1	1	1	1	4	1	1	1	1	2
10	20	3.03	2	1	1	1	1	1	2	1	1	1	1	3	4	2	1	1	1	1
11	14	3.05	1	1	1	1	1	3	4	1	1	2	1	1	4	1	1	1	1	2
12	24	3.05	2	1	1	1	3	1	4	1	1	1	1	1	4	1	1	1	1	2
13	21	3.05	2	1	1	1	3	1	4	1	1	1	1	1	4	2	1	1	1	1
14	2	3.07	2	1	1	1	3	1	2	1	1	1	1	3	4	1	1	2	1	1
15	10	3.11	2	1	1	2	1	1	4	1	1	1	1	3	4	1	1	1	1	1
16	23	3.11	1	1	1	1	3	1	4	1	1	2	1	1	4	1	1	1	1	2
17	17	3.19	2	1	1	1	1	3	2	1	1	1	1	3	4	1	1	1	1	2
18	13	3.19	1	1	1	1	1	1	4	1	1	1	1	3	4	2	1	1	1	2
19	18	3.25	2	1	1	1	3	1	2	1	1	1	1	3	4	1	1	1	1	2
20	28	3.37	1	1	1	1	3	3	4	1	1	1	1	1	4	2	1	1	1	2
21	9	3.42	1	1	1	1	3	1	4	1	1	1	1	3	4	1	1	2	1	2
22	12	3.45	2	1	1	1	3	3	4	1	1	1	1	1	4	1	1	2	1	1
23	5	3.46	1	1	1	2	3	1	4	1	1	1	1	3	4	1	1	1	1	2
24	29	3.64	2	1	1	1	3	3	4	1	1	1	1	1	4	1	1	1	1	2
25	30	3.70	1	1	1	1	3	3	4	1	1	2	1	1	4	1	1	1	1	2
26	7	4.11	2	1	1	1	3	1	4	1	1	1	1	3	4	1	1	1	1	2
27	16	4.70	2	1	1	1	2	1	2	1	1	1	1	3	4	1	1	1	1	1
28	25	5.05	1	1	1	1	2	1	4	1	1	1	1	3	4	1	1	1	1	2
29	4	5.91	1	1	1	1	2	1	4	1	1	1	1	3	4	1	1	2	1	2
30	22	6.56	1	1	1	1	2	1	4	1	1	1	1	3	4	2	1	1	1	2

The solutions listed in Table 20 each corresponds to a unique project delivery option. For example the solution in the 4th priority (Alt. ID=15) is having the maintenance allocation strategy of [2,1,1,1,3,1,2,1,1,1,1,3,4,1,1,1,1,1] which means for the section 1 of the project, option 2 of pavement maintenance, H.I.R, should be utilized, for the section 2, option 1, crack seal, should be utilized. The codes in the solutions are translated using Table 9 where treatment options are numbered. Table 21 shows how the entire solution translates to maintenance options allocation in the project. Similarly other solutions are translated to the maintenance options for the project.

Table 21 Translation of a solution to maintenance options for Alt ID=15

Sections	Maintenace Options
1	2 H.I.R.
2	1 Crack Seal
3	1 Crack Seal
4	1 Crack Seal
5	3 Micro-surfacing
6	1 Crack Seal
7	2 H.I.R.
8	1 Crack Seal
10	1 Crack Seal
12	1 Crack Seal
14	1 Crack Seal
15	3 Micro-surfacing
16	4 Mill & Resurfacing
17	1 Crack Seal
18	1 Crack Seal
20	1 Crack Seal
22	1 Crack Seal
23	1 Crack Seal

4.5 Three objective case study optimization

This case study is developed with the purpose of considering multi asset items. A sample of I-64 data from mile marker 0 to 57 is utilized for selected asset items. Possible MR&R actions and their corresponding Time, Cost, and Level of Service estimated. The process of model implementation for the example problem is summarized in following steps:

4.5.1 Asset Selection

A subset of assets from those listed in Table 1 have been selected to be used in the development of a 3-objective prototype. Table 22 presents the selected asset items:

Table 22 Selected asset items for prototype problem

Asset Group	Asset Item
Roadside	Concrete Barriers Fence
Drainage	Paved Ditches Pipes
Traffic	Guardrail Rumble Strips

4.5.2 Identification of possible deficiencies

Identification of corresponding distress codes of each asset item. Table 23 shows the asset items and distress codes:

Table 23 Asset items and corresponding distress codes

Asset Group	Asset Item	Distress Codes	
Roadside	Concrte Barriers	217	Vegetation Present
		219	Joint material damaged or missing 10% or greater
	Fence	227	Material Damage 10% or greater
		228	Opening that allows access
		229	Vegetation present 10% or greater
Drainage	Paved Ditches	319	2 inch or greater settlement, damaged joints/ not intact
		320	Undermining or undercutting
		321	Obstructions impeding flow of water
		345	Spalling 25% or greater
		346	Cracking 10% or greater and greater than 1/4" wide
		322	Damaged missing section (includes energy dissipaters)
	Pipes	311	Diameter Closed
		313	Joint Material missing, join seperated
		315	Erosion at ends 1 foot or greater
		316	End Protection damaged or loose
Traffic	Guardrail	411	Damage, rust affecting structural integrity
		426	Loose or missing parts
		415	Cables loose, improperly secured

4.5.3 Identification of possible MR&R actions

Identification of possible MR&R actions corresponding tor defected asset items. These techniques are shown in Table 24.

Table 24 Possible MR&R Actions

Asset Group	Asset Item	Distress Codes		MR&R	MR&R	MR&R
Roadside	Concrte Barrie	217	Vegetation Present	Cut Vegention		
		219	Joint material damaged or missing 10% or greater	Fill with mortar and plaster	Pointing	
	Fence	227	Material Damage 10% or greater	Repair	Removal and Replacement	
		228	Opening that allows access	Repair		
		229	Vegetation present 10% or greater	Cut vegetation		
Drainage	Paved Ditches	319	2 inch or greater settlement, damaged joints/ not intact	Fill and finsih with mortar and plaster	Removal and Replacement	
		320	Undermining or undercutting	Maintenance	Repair	Removal and Replacement
		321	Obstructions impeding flow of water	Obstruction Removal		
		345	Spalling 25% or greater	Fill with mortar and plaster and finish		Removal and Replacement
		346	Cracking 10% or greater and greater than 1/4" wide	Mortar and Resin Spray	Pointing	
		322	Damaged missing section (includes energy dissipaters)	Patch Repair	Fill and Finish with mortar	
	Pipes	311	Diameter Closed	High velocity cleaners	Mechanical cleaning	Removal and Replacement
		313	Joint Material missing, join seperated	Injection in joints or cracks	Patch Repair	Removal and Replacement
		315	Erosion at ends 1 foot or greater	Fill with mortar and plaster	Short -Liners	Mortar Spray
		316	End Protection damaged or loose	Fill with mortar and plaster	Removal and Replacement	
Traffic	Guardrail	411	Damage, rust affecting structural integrity	Rust Removal	Patch Repair	Removal and Replacement
		426	Loose or missing parts	Maintnecne	Patch Repair	Removal and Replacement
		415	Cables loose, improperly secured	Maintenance	Removal and Replacement	
	Rumble Strips			Repair		

4.5.4 Defining project characteristics – Precedence network diagram

Prior to describing the network diagram of project extent of project and its characteristics should be defined.

Table 25 contains the general characteristics of the example project which is result of condition assessment.

Table 25 general characteristics of project

Row	Segment	Direction	Ramps	Begins	Ends	Failing Asset	Item Category	Number Failed	Failure Code
1	7052	E		0.2	0.3	Pipes & Box Culvert <=36sqft	Count	1	311
2						Paved Ditches	Count	3	321
3	7053	E		0.3	0.4	Pipes & Box Culvert <=36sqft	Count	1	311
4	7054	E		0.4	0.5	Paved Ditches	Count	1	321
5						Guardrail	Count	1	411
6						Paved Ditches	Count	4	319
7	7056	E		0.6	0.7	Paved Ditches	Count	2	321
8	7060	E		1	1.1	Paved Ditches	Count	3	319
9	7064	E		1.4	1.5	Fence	Count	1	228
10	7066	E		1.6	1.7	Fence	Count	1	227
11	7077	E		2.7	2.8	Fence	Count	1	228
12						Paved Ditches	Count	4	320
13	7084	E		3.4	3.5	Paved Ditches	Count	2	319
14	7091	E		4.1	4.2	Guardrail	Count	1	426
15	7121	E		7.1	7.2	Fence	Count	1	229
16						Pipes & Box Culvert <=36sqft	Count	1	315
17						Guardrail	Count	1	415
18						Paved Ditches	Count	1	320

Figure 17 and Figure 18 present the applied network diagrams for the 18 activities of

Table 25. Two different network diagrams are considered: (1) one is for verifying the model by comparing to similar network diagram used by El-Rayes et al. (2005) as shown in Figure 17. (2) Another one is based on the characteristics of activities of the current case study as shown in Figure 18.

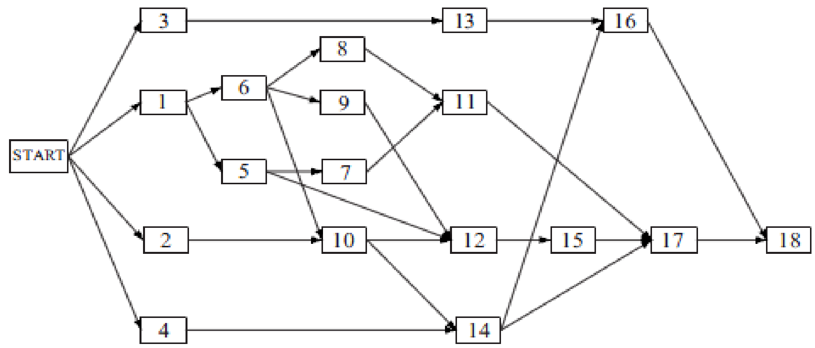


Figure 17 Network diagram of first example problem (Kandil and El Rayes, 2005)

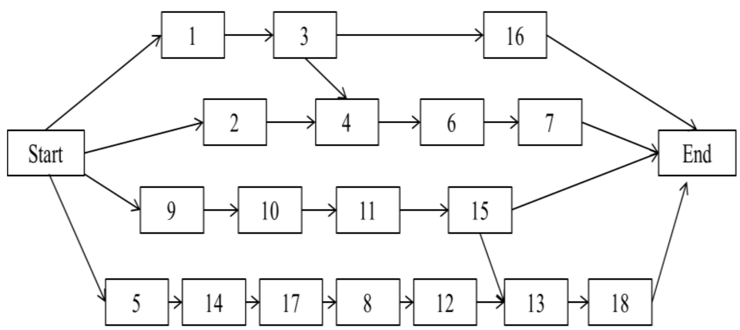


Figure 18 second Network diagram of the problem

4.5.5 Defining project characteristics – Time, Cost, and Level of Service of actions

Time, cost, and Level of Service of selected MR&R actions are presented Table 26. These data set are the input for extracting various delivery options of project in term of time, cost, and Level of Service (the data for Time, Cost and Level of Service is synthetic).

Table 26 Time, cost and Level of Service of selected MR&R actions

Asset Group	Asset Item	Distress Codes		MR&R	Cost	Time	LoS	MR&R	Cost	Time	LoS	MR&R	Cost	Time	LoS
Roadside	Concrte Barrie	217	Vegetation Present	Cut Vegention	-										
		219	Joint material damaged or missing 10% or greater	Fill with mortar and plaster	-			Pointing							
	Fence	227	Material Damage 10% or greater	Repair	3500	2	75	Removal and Replacement	6700	4	90				
		228	Opening that allows access	Repair	2500	2	80								
		229	Vegetation present 10% or greater	Cut vegetation	500	1	90								
Drainage	Paved Ditches	319	2 inch or greater settlement, damaged joints/ not intact	Fill and finsih with mortar and plaster	1900	2	80	Removal and Replacement	3800	4	90				
		320	Undermining or undercutting	Maintenance	500	3	65	Repair	1700	3	75	Removal and Replacement	4500	5	90
		321	Obstructions impeding flow of water	Obstruction Removal	200	1	80								
		345	Spalling 25% or greater	Fill with mortar and plaster and finish	2500	2	75					Removal and Replacement	4200	4	90
		346	Cracking 10% or greater and greater than 1/4" wide	Mortar and Resin Spray	1400	1	75	Pointing	1200	1	85				
		322	Damaged missing section (includes energy dissipaters)	Patch Repair	3200	1		Fill and Finish with mortar	1400	1					
	Pipes	311	Diameter Closed	High velocity cleaners	2200	2	85	Mechanical cleaning	1900	2	80	Removal and Replacement	8000	3	90
		313	Joint Material missing, join seperated	Injection in joints or cracks	1100	2	75	Patch Repair	1500	2	80	Removal and Replacement	3700	3	90
		315	Erosion at ends 1 foot or greater	Fill with mortar and plaster	1100	2	75	Short -Liners	1600	3	80	Mortar Spray	2200	2	85
		316	End Protection damaged or loose	Fill with mortar and plaster	1100	2	75	Removal and Replacement	3700	4	90				
Traffic	Guardrail	411	Damage, rust affecting structural integrity	Rust Removal	700	1	80	Patch Repair	1900	2	85	Removal and Replacement	3500	4	90
		426	Loose or missing parts	Maintnecne	900	1	80	Patch Repair	2500	2	85	Removal and Replacement	3500	3	90
		415	Cables loose, improperly secured	Maintenance	780	1	80	Removal and Replacement	3500	3	90				
	Rumble Strips			Repair											

4.5.6 Results – First Example Problem

Running the model using the example problem has been resulted in 80 non-dominated solutions for the first example project that is based on network diagram of Figure 17. The Pareto set is tabulated in Table 27.

Table 27 Non-dominated solutions of the example project 1

(Based on network diagram of Figure 17)

Total Time	Total Cost	LoS	MR&R 1	MR&R 2	MR&R 3	MR&R 4	MR&R 5	MR&R 6	MR&R 7	MR&R 8	MR&R 9	MR&R 10	MR&R 11	MR&R 12	MR&R 13	MR&R 14	MR&R 15	MR&R 16	MR&R 17	MR&R 18	MR&R 19	MR&R 20
14	29580	81.11	1	1	1	1	1	1	1	1	2	1	1	1	2	1	1	1	3	1	2	1
20	44080	85.00	1	1	1	1	1	2	1	1	2	1	2	1	3	2	3	1	3	1	3	1
14	30780	81.39	1	1	1	1	1	2	1	1	2	1	1	1	2	1	1	1	3	1	2	1
18	35180	82.78	1	1	1	1	1	1	1	1	2	1	1	1	3	1	1	1	3	1	3	1
16	34280	82.50	1	1	1	1	1	1	1	1	2	1	1	1	2	2	1	1	3	1	3	1
20	41480	84.44	1	1	1	1	1	2	1	1	2	1	2	1	3	2	1	1	3	1	3	1
16	36880	83.06	1	1	1	1	1	1	1	1	2	1	1	1	2	2	3	1	3	1	3	1
14	28380	80.56	1	1	1	1	1	1	1	1	1	1	1	1	2	2	1	1	3	1	1	1
14	32680	81.94	1	1	1	1	1	2	1	1	2	1	1	1	2	2	1	1	3	1	2	1
18	39680	83.89	1	1	1	1	1	1	1	1	2	1	1	1	3	2	3	1	3	1	3	1
18	38280	83.61	1	1	1	1	1	2	1	1	2	1	1	1	3	2	1	1	3	1	3	1
13	25700	75.56	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	2	1	1
18	36180	83.06	1	1	1	1	1	1	2	1	2	1	1	1	2	2	1	1	3	1	3	1
14	31480	81.67	1	1	1	1	1	1	1	1	2	1	1	1	2	2	1	1	3	1	2	1
18	40880	84.17	1	1	1	1	1	2	1	1	2	1	1	1	3	2	3	1	3	1	3	1
16	39680	83.61	1	1	1	1	1	3	1	1	2	1	1	1	2	2	3	1	3	1	3	1
14	42680	83.06	1	1	1	3	1	3	1	1	2	1	1	1	2	2	3	1	3	1	2	1
20	45680	85.28	1	1	1	1	1	3	1	1	2	1	2	1	3	2	3	1	3	1	3	1
14	36880	82.78	1	1	1	1	1	3	1	1	2	1	1	1	2	2	3	1	3	1	2	1
13	30700	77.22	1	1	1	1	1	1	1	1	2	1	1	1	2	2	1	1	3	2	2	1
13	29500	76.67	1	1	1	1	1	1	1	1	2	1	1	1	2	2	1	1	3	2	1	1
16	33580	82.22	1	1	1	1	1	2	1	1	1	1	1	1	2	2	1	1	3	1	3	1
18	42480	84.44	1	1	1	1	1	3	1	1	2	1	1	1	3	2	3	1	3	1	3	1
18	48280	84.72	1	1	1	3	1	3	1	1	2	1	1	1	3	2	3	1	3	1	3	1
13	24500	75.00	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	2	1	1
14	27080	80.28	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	1	2	1
13	26300	75.83	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	2	2	1
13	28100	76.39	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1	3	2	2	1
13	27600	76.11	1	1	1	1	1	1	1	1	2	1	1	1	2	1	1	1	3	2	1	1
13	25100	75.28	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	2	1	1
14	26480	80.00	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	1	1	1
13	23900	74.72	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	1	1
14	25880	79.72	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	1	1	1
13	26900	76.11	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	2	2	1
14	25280	79.44	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	1
14	28880	80.83	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1	3	1	2	1
13	23100	74.17	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1
13	23400	74.44	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1
14	24680	79.17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1
22	45980	85.56	1	1	1	1	1	2	2	1	2	1	2	1	3	2	3	1	3	1	3	1
16	45480	83.89	1	1	1	3	1	3	1	1	2	1	1	1	2	2	3	1	3	1	3	1
20	42780	84.72	1	1	1	1	1	2	2	1	2	1	1	1	3	2	3	1	3	1	3	1
13	22800	73.89	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1
14	24180	78.89	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	23580	78.33	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	23880	78.61	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	51480	85.56	1	1	1	3	1	3	1	1	2	1	2	1	3	2	3	1	3	1	3	1
22	44780	85.28	1	1	1	1	1	1	2	1	2	1	2	1	3	2	3	1	3	1	3	1
22	47580	85.83	1	1	1	1	1	3	2	1	2	1	2	1	3	2	3	1	3	1	3	1
22	53380	86.11	1	1	1	3	1	3	2	1	2	1	2	1	3	2	3	1	3	1	3	1
20	40180	84.17	1	1	1	1	1	2	2	1	2	1	1	1	3	2	1	1	3	1	3	1
23	59180	86.39	1	3	1	3	1	3	2	1	2	1	2	1	3	2	3	1	3	1	3	1
18	37080	83.33	1	1	1	1	1	1	1	1	2	1	1	1	3	2	1	1	3	1	3	1
20	50180	85.28	1	1	1	3	1	3	2	1	2	1	1	1	3	2	3	1	3	1	3	1
21	57280	85.83	1	3	1	3	1	3	1	1	2	1	2	1	3	2	3	1	3	1	3	1
21	55980	85.56	1	3	1	3	1	3	2	1	2	1	1	1	3	2	3	1	3	1	3	1
16	35480	82.78	1	1	1	1	1	2	1	1	2	1	1	1	2	2	1	1	3	1	3	1
14	27680	80.56	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	1	2	1
16	32380	81.94	1	1	1	1	1	1	1	1	2	1	1	1	2	1	1	1	3	1	3	1
14	30280	81.11	1	1	1	1	1	1	1	1	2	1	1	1	2	2	1	1	3	1	1	1
14	34080	82.22	1	1	1	1	1	1	1	1	2	1	1	1	2	2	3	1	3	1	2	1
14	35280	82.50	1	1	1	1	1	2	1	1	2	1	1	1	2	2	3	1	3	1	2	1
13	30000	76.94	1	1	1	1	1	2	1	1	1	1	1	1	2	2	1	1	3	2	2	1
16	30480	81.39	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	1	3	1
13	28800	76.67	1	1	1	1	1	1	1	1	2	1	1	1	2	1	1	1	3	2	2	1
16	38080	83.33	1	1	1	1	1	2	1	1	2	1	1	1	2	2	3	1	3	1	3	1
22	42180	84.72	1	1	1	1	1	1	2	1	2	1	2	1	3	2	1	1	3	1	3	1
13	31900	77.50	1	1	1	1	1	2	1	1	2	1	1	1	2	2	1	1	3	2	2	1
13	33500	77.78	1	1	1	1	1	2	1	1	2	1	1	1	2	2	2	1	3	2	2	1
18	33280	82.22	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	1	3	1	3	1
13	35100	78.06	1	1	1	1	1	3	1	1	2	1	1	1	2	2	2	1	3	2	2	1
20	38980	83.89	1	1	1	1	1	1	2	1	2	1	1	1	3	2	1	1	3	1	3	1
17	51280	84.17	1	3	1	3	1	3	1	1	2	1	1	1	2	2	3	1	3	1	3	1
22	43380	85.00	1	1	1	1	1	2	2	1	2	1	2	1	3	2	1	1	3	1	3	1
13	40900	78.33	1	1	1	3	1	3	1	1	2	1	1	1	2	2	2	1	3	2	2	1
16	33380	82.22	1	1	1	1	1	1	2	1	2	1	1	1	2	2	1	1	3	1	2	1
16	44480	83.61	1	1	1	3	1	3	1	1	2	1	1	1	2	2	2	1	3	1	3	1
19	54080	85.00	1	3	1	3	1	3	1	1	2	1	1	1	3	2	3	1	3	1	3	1
18	47380	84.44	1	1	1	3	1	3	2	1	2	1	1	1	2	2	3	1	3	1	3	1
14	41680	82.78	1	1	1	3	1	3	1	1	2	1	1	1	2	2	2	1	3	1	2	1

Figure 19 is the graphic equivalent of non-dominated solutions of first example problem. They graphically represent the solutions in three dimensional space.

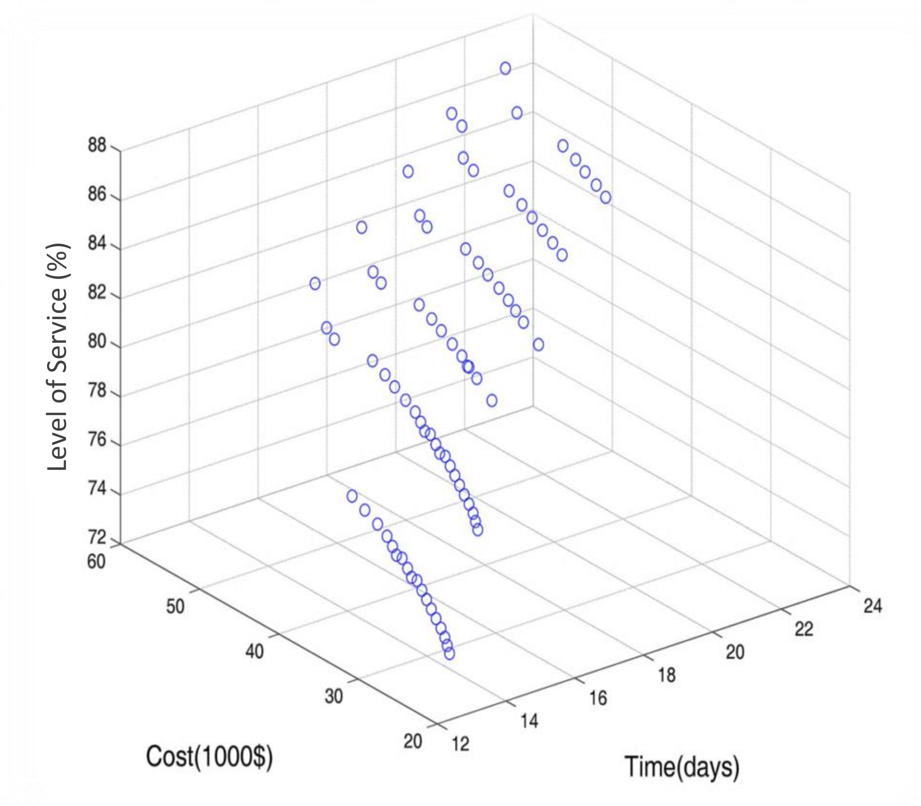


Figure 19 Pareto front of Multi Objective optimization of Time-Cost-Level of Service of example 1

4.5.7 Results – Second Example Problem

Running the model using the example problem has resulted in 139 non-dominated solutions for the second example project (based on network diagram of Figure 17) that a selected number of solutions is shown in Table 28.

Table 28 Selected non-dominated solutions of the example project 2 (Based on network diagram of Figure 18)

Total Time	Total Cost	LoS	MR&R 1	MR&R 2	MR&R 3	MR&R 4	MR&R 5	MR&R 6	MR&R 7	MR&R 8	MR&R 9	MR&R 10	MR&R 11	MR&R 12	MR&R 13	MR&R 14	MR&R 15	MR&R 16	MR&R 17	MR&R 18	MR&R 19	MR&R 20
13	29280	80.83	1	2	1	1	1	1	2	1	1	1	1	1	2	1	1	1	3	1	2	1
17	34280	82.50	1	1	1	1	1	1	2	1	1	1	1	1	2	2	1	1	3	1	3	1
14	32780	81.94	1	1	1	1	1	1	2	1	1	1	2	1	2	1	1	1	3	1	2	1
21	42180	84.72	1	1	1	1	1	1	2	1	2	1	2	1	3	2	1	1	3	1	3	1
15	34680	82.50	1	1	1	1	1	1	2	1	2	1	2	1	2	1	1	1	3	1	2	1
17	44180	83.89	1	3	1	1	1	1	2	1	1	1	2	1	3	1	1	1	3	1	3	1
17	38380	83.61	1	1	1	1	1	1	2	1	1	1	2	1	3	1	1	1	3	1	3	1
15	31480	81.67	1	1	1	1	1	1	2	1	2	1	1	1	2	1	1	1	3	1	2	1
13	27680	80.56	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	1	2	1
15	29580	81.11	1	1	1	1	1	1	1	1	2	1	1	1	2	1	1	1	3	1	2	1
19	36180	83.06	1	1	1	1	1	1	2	1	2	1	1	1	2	2	1	1	3	1	3	1
13	29580	81.11	1	1	1	1	1	1	2	1	1	1	1	1	2	1	1	1	3	1	2	1
15	32380	81.94	1	1	1	1	1	1	2	1	1	1	1	1	2	1	1	1	3	1	3	1
12	26900	76.11	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	2	2	1
17	36480	83.06	1	1	1	1	1	1	1	1	1	1	2	1	3	1	1	1	3	1	3	1
19	39380	83.89	1	1	1	1	1	1	2	1	2	1	2	1	2	2	1	1	3	1	3	1
14	32080	81.67	1	1	1	1	1	2	1	1	1	1	2	1	2	1	1	1	3	1	2	1
12	28800	76.67	1	1	1	1	1	1	2	1	1	1	1	1	2	1	1	1	3	2	2	1
23	50580	85.56	1	3	1	1	1	1	2	1	2	1	2	1	3	2	3	1	3	1	3	1
16	36780	83.06	1	1	1	1	1	2	2	1	1	1	2	1	2	1	1	1	3	1	3	1
12	25700	75.56	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	2	1	1
17	35180	82.78	1	1	1	1	1	1	2	1	1	1	1	1	3	1	1	1	3	1	3	1
19	40280	84.17	1	1	1	1	1	1	2	1	1	1	2	1	3	2	1	1	3	1	3	1
13	26480	80.00	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	1	1	1
21	47780	84.72	1	1	1	3	1	1	2	1	2	1	2	1	2	2	3	1	3	1	3	1
16	42580	83.33	1	3	1	1	1	2	2	1	1	1	2	1	2	1	1	1	3	1	3	1
20	52180	84.72	1	3	1	3	1	2	2	1	2	1	2	1	2	2	1	1	3	1	3	1
24	44080	85.00	1	1	1	1	1	2	1	1	2	1	2	1	3	2	3	1	3	1	3	1
22	49180	85.28	1	1	1	3	1	2	2	1	2	1	2	1	3	2	1	1	3	1	3	1
18	35480	82.78	1	1	1	1	1	2	2	1	2	1	1	1	2	1	1	1	3	1	3	1
20	38280	83.61	1	1	1	1	1	2	2	1	1	1	1	1	3	2	1	1	3	1	3	1
20	46380	84.44	1	1	1	3	1	2	2	1	2	1	2	1	2	2	1	1	3	1	3	1
20	53080	85.00	1	3	1	3	1	2	2	1	1	1	2	1	3	2	1	1	3	1	3	1
23	44780	85.28	1	1	1	1	1	1	2	1	2	1	2	1	3	2	3	1	3	1	3	1
21	47980	85.00	1	3	1	1	1	1	2	1	2	1	2	1	3	2	1	1	3	1	3	1
22	43380	85.00	1	1	1	1	1	2	2	1	2	1	2	1	3	2	1	1	3	1	3	1
18	50280	84.17	1	3	1	3	1	2	2	1	1	1	2	1	2	2	1	1	3	1	3	1
24	51780	85.83	1	1	1	3	1	2	2	1	2	1	2	1	3	2	3	1	3	1	3	1
26	53380	86.11	1	3	1	1	1	3	2	1	2	1	2	1	3	2	3	1	3	1	3	1
19	50980	84.44	1	3	1	3	1	1	2	1	2	1	2	1	2	2	1	1	3	1	3	1
12	34600	76.94	1	3	1	1	1	1	2	1	1	1	1	1	2	1	1	1	3	2	2	1
12	26300	75.83	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	2	2	1
12	25100	75.28	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	2	1	1
13	27080	80.28	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	1	2	1
12	24500	75.00	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	2	1	1
12	23100	74.17	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1
12	40400	77.22	1	3	1	3	1	1	2	1	1	1	1	1	2	1	1	1	3	2	2	1
13	24680	79.17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1
12	28200	76.39	1	1	1	1	1	1	2	1	1	1	1	1	2	1	1	1	2	2	2	1
12	28500	76.39	1	1	1	2	1	1	2	1	1	1	1	1	2	1	1	1	3	2	2	1
24	57580	86.11	1	3	1	3	1	2	2	1	2	1	2	1	3	2	3	1	3	1	3	1
23	56380	85.83	1	3	1	3	1	1	2	1	2	1	2	1	3	2	3	1	3	1	3	1
26	47580	85.83	1	1	1	1	1	3	2	1	2	1	2	1	3	2	3	1	3	1	3	1
24	45980	85.56	1	1	1	1	1	2	2	1	2	1	2	1	3	2	3	1	3	1	3	1
21	53780	85.28	1	3	1	3	1	1	2	1	2	1	2	1	3	2	1	1	3	1	3	1
26	59180	86.39	1	3	1	3	1	3	2	1	2	1	2	1	3	2	3	1	3	1	3	1
20	40580	84.17	1	1	1	1	1	2	2	1	2	1	2	1	2	2	1	1	3	1	3	1
23	44480	85.00	1	2	1	1	1	1	2	1	2	1	2	1	3	2	3	1	3	1	3	1
24	42780	84.72	1	1	1	1	1	2	2	1	2	1	1	1	3	2	3	1	3	1	3	1
21	41880	84.44	1	2	1	1	1	1	2	1	2	1	2	1	3	2	1	1	3	1	3	1
12	23900	74.72	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	1	1
15	30480	81.39	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	3	1	3	1
13	25280	79.44	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	1
12	23400	74.44	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1
13	23880	78.61	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
13	25880	79.72	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	1	1	1
12	22800	73.89	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1

Figure 20 is the graphic equivalent of non-dominated solutions of first example problem. They graphically represent the solutions in three dimensional space.

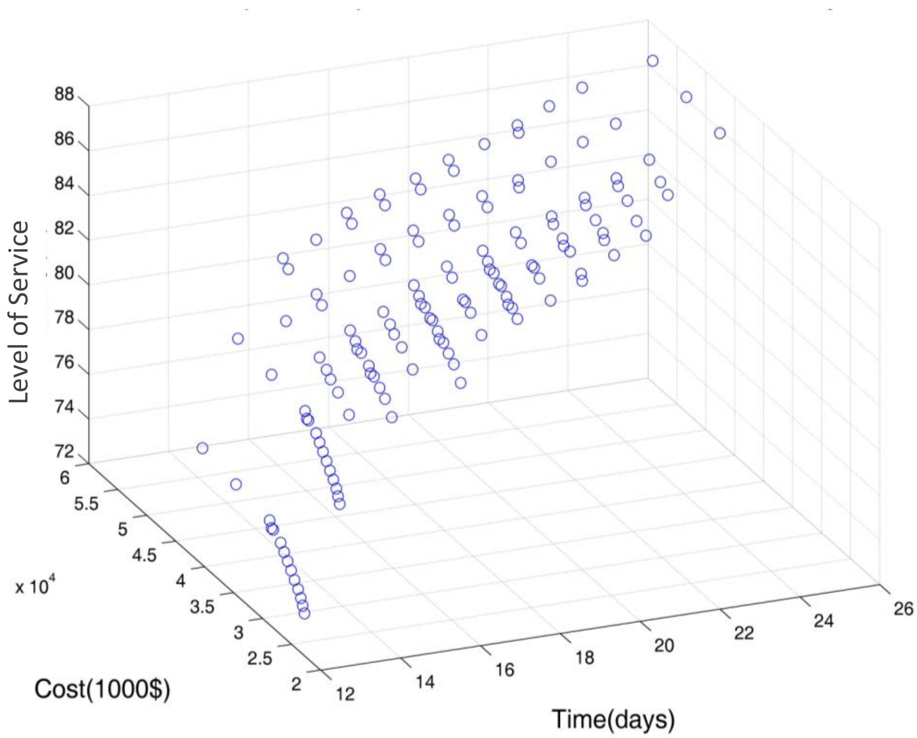


Figure 20 Pareto front of Multi Objective optimization of Time-Cost-Level of Service of example 2

5

Conclusion

5.1 Conclusions

The objectives of highway maintenance projects for the asset items are multiple and there exist various options for the maintenance of different asset items. To achieve the optimal strategy for allocation of the maintenance options to deteriorating assets an approach for multi-objective decision making is needed.

The present research developed a generic framework for sustainable highway maintenance and presented its application in solving 3 Objective and 4 Objective problems. Main focus was on the multi-objective optimization based on multi-colony ant colony optimization. An advanced framework for multi-colony ant colony optimization is presented to minimize time, cost, and environmental impact of the highway maintenance projects while maximizing the improvement in level of service. The designed model searches for near optimal solutions for the MR&R techniques combination in the delivery of highway maintenance projects. First, mathematical formulation of decision objectives, decision variables and constraints are developed. Then, having the objective functions the process of preparation of data for time, cost, level of service and environmental impact is explained. The model was validated in two ways: (i) by comparison with existing case examples that proved the robustness of the proposed algorithm; (ii) by implementing the model on a standard scalable test problem that also proved the capability of the proposed model in generating near optimal non-dominated solutions. In the next stage the non-dominated solutions of the stage of multi objective optimization are ranked using a Multi-Criteria Decision making (MCDM) technique. SMART technique was selected for this prioritization step based on the literature review and comparative study of MCDM techniques.

Finally, the proposed approach was implemented on two case studies: (i) A pavement maintenance project to optimize the pavement maintenance strategies. This case example was first optimized with three objectives of Cost, Level of Service and Environmental Impacts. Then the same example was evaluated based on the four objectives of time, cost, and level of service and environmental impacts; (ii) a three objective optimization of roadway maintenance project with different asset items. This project was optimized based on two different precedence network diagrams for scheduling and the two sets of non-dominated solutions are reported for these variations of the case study.

The results of the research benefits decision makers by providing them with optimal solutions for infrastructure asset management while meeting national goads towards sustainability and performance-based approach. Moreover, it provides a tool to run sensitivity analysis to evaluate annual budget effects and environmental impacts of different maintenance resource allocation scenarios. Application of the proposed approach is implemented on highway asset items but it is not limited to roadways and is applicable to various infrastructure asset systems.

5.2 Research Limitations

Current research aimed at considering as many asset items as possible. But, an important issue for this purpose was availability of the needed data. In some groups of asset items needed data could not be obtained and previous inspections are not having the required data. The attempt of research was collecting the data of actual projects for a sub set of asset items. However, one of the limitations of the research is not having a comprehensive data set for all the asset items along with time, cost, level of service and environmental impact data. Therefore, the model was applied to a subset of asset items and the data was used to the extent that they are available. When data is unavailable synthetic data was generated to test the feasibility of the research framework.

In the multi criteria decision making process using SMART it is expected that a decision maker or group of decision maker determine the weights of attribute. It might be carried out using panels or surveys to gauge the preferences of decision makers. However, in the current study these weights are based on the assumptions made by the author.

5.3 Contribution to the body of knowledge

The main objective of this research was to develop a multi-objective multi-asset decision support system for roadway asset management that considers time, cost, level of service and environment. The contribution of this research would be beneficial to decision makers in infrastructure and transportation agencies. The main contributions are as follows:

i. There have been many studies reported in the literature presenting the application of decision making techniques for individual highway asset items such as bridge maintenance systems or pavement maintenance systems or combination of these two major asset groups. However, few previous attempts have been made to consider more asset items for the infrastructure asset management. The proposed model for roadway asset management develops a decision support system for roadway asset management to select optimal MR&R techniques while taking into account various asset items.

ii. There had been studies reviewed in the literature that reported successful application of multi objective optimization for two objective and/or three objective optimization of time, cost, performance and environmental optimization. However, there remains room for a multi-objective optimization model that considers all four conflicting objectives in roadway asset management. One of the contributions of the current study is development of multi-objective optimization approach to simultaneously optimize four conflicting roadway asset management objectives. The model not only considers time and cost as two important objective of projects' MR&R but also looks for optimal way of delivering the projects with maximum possible improvement in level of service and meanwhile protecting and enhancing natural environment. Therefore, meeting national goals towards sustainability and performance-based approach.

iii. Previous studies applied different techniques for the multi–objective optimization among which genetic algorithm is one of the popular techniques. The current study contributes to the body of knowledge by development and validation of an alternative meta-heuristic technique for multi objective optimization of highway asset management projects based on a multi-colony ant colony optimization. This algorithm is modified to match the characteristics of the roadway maintenance projects. The application procedure of this algorithm is discussed and presented in Figure 3. The proposed algorithm is validated to ensure the validity of the results and proposed solutions.

5.4 Possible future research areas

5.4.1 Data collection and implementation of the proposed model on other cases

One of the limitations of the research was lack of data set for all the asset items that includes the information on their time, cost, level of service and environmental impact index. Therefore, the model was implemented on a subset of asset items and synthetic data was generated when data was unavailable. In order to compare the results the proposed framework with the current practice it is worthwhile implement a data collection project to gather the required data to perform the multi- objective optimization framework to a project with a full set of data. The proposed approach can also be used by DOTs to perform an analysis on the maintenance projects once the data collection phase is improved to collect a comprehensive data set.

Application of the proposed model was implemented on the roadway asset management. However, its application is not limited to roadways and is applicable to various infrastructure systems such as water and wastewater systems. The results of condition assessment can be analyzed for multi-objective optimization based on the proposed approach of this research.

5.4.2 Time dependent infrastructure condition prediction and maintenance optimization

Currently most of the research works are focused on the present performance of the asset items. However, identification of distresses and predicting deterioration of aging highway asset items are challenges faced by many road authorities. The prediction of the future condition of asset items makes maintenance activities more efficient and provides the information needed for MR&R optimization within different time scopes. Maintenance optimization in this case will be implemented on the future targets. For example the effort of the multi objective optimization model would be allocating the maintenance options that will result in the highest possible level of service in ten years after the date of MR&R. A research on deterioration curves for different roadway asset items along with the proposed framework of this research will contribute for the more efficient decision makings in the transportation asset management.

Using the proposed roadway asset management approach the deterioration modeling of asset items can be added as a module to make level of service optimization more efficient. The framework for using deterioration prediction for extracting the Level of Service improvement in the proposed model is shown in Figure 21 .

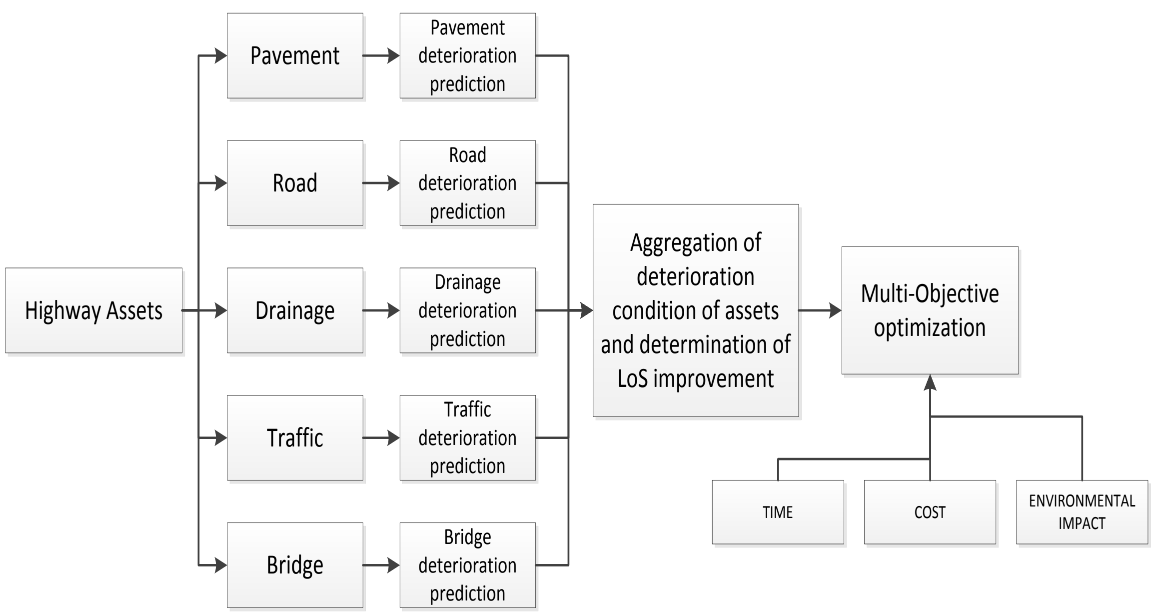


Figure 21 Framework for deterioration prediction for further studies based on current research

5.4.3 Improving the developed multi-colony ant colony optimization algorithm

There are particular improvements possible that can make the proposed algorithm even more robust and efficient. A procedure which guides the colonies to focus on different regions of the objective space will be beneficial to prevent from algorithm's pre-mature. One of the procedures used in the MOACO algorithm is the local search and developing other local search methods to be combined with the current algorithm or utilization of other known algorithms might be contributing to the algorithm's efficiency. Moreover, for tacking large scale problems a procedure for parallel ant colony optimization based on parallel computing might be developed.

This procedure should be able to increase the quality of the solutions found in a given fixed time compared to present algorithm. In other words, for reaching the same quality of solutions the algorithm would need a smaller amount of processing time. In addition the algorithm would be able to solve the large scale problems with a fraction of the time needed with the present approach.

5.4.4 Improvements to multi-criteria decision making process for the prioritization of the solutions

Group decision-making is aggregating different individual preferences on a given set of alternatives to a single collective preference. As the decision making process for prioritization of the final solutions most of the time involves multiple decision makers with different skills, experience and knowledge of the problem. A group decision making process can improve the second stage of the proposed framework in this research.

Different knowledge and priority of the group members are expressed by voting powers both for weighing the criteria and qualifying the alternatives against the criteria. Setting up panels, surveys and interviews for collecting the data should be carried out. The results of this effort will make a more reliable process for making a final decision on selecting the MR&R strategy.

Furthermore, for measuring the impact of variations in the weight factors and also the values a sensitivity analysis of the weights might be performed to consider the effect of weight on the outcome of the prioritization.

6
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Appendix A:
An overview of Maintenance Techniques

In this appendix a general description of the maintenance techniques introduced in the first case study is given. These information are adapted from Cerea (2010) and the descriptions are inspired by the current literature, agencies websites, the National Asphalt Pavement Association (2009) and the information and notes that are adapted from Cerea (2010).

Crack Seal

This technique is widely used and it is one of the cheapest alternatives. For a long time the typical preventive maintenance of the pavements had been the crack seal. It prevents the intrusion of water and incompressible materials inside cracks. Crack cleaning is a very important step and often requires the use of specialized workers, as well as the laying down of the sealant.

Movements of working cracks require the sealant to be capable of remaining adhered to the walls of the crack, elongating to the maximum opening and recovering to the original dimensions without ruptures.

Hot in-place recycling

This process consists in softening the existing asphalt surface with heat, removing the surface material, mixing the milled material with a recycling agent, adding virgin asphalt and if required aggregates to the material and finally replacing the material on the pavement. Hot in-place recycling (HIR) is known to be a green technique for the rehabilitation of pavements and a cost-effective way to use already existing in-place materials. It is an on-site, in-place method that rehabilitates deteriorated asphalt and minimizes the use of new materials. The process corrects surface distresses not caused by structural inadequacy, such as cracks, ruts, holes and bumps.

The process of hot in-place recycling is cheap and less traffic control is needed than other methods. In addition, elevations and overhead clearences are preserved.

Micro-surfacing

Micro-surfacing is a polymer-modified cold-mix paving system that can remedy a broad range of problems on streets and highways. Micro-surfacing is now routinely used in more than 30 states in preventive maintenance programs and for rut filling and texturing moderate to heavy volume roads, over both asphalt and concrete pavements.

Mill and resurfacing

Typically, in preventive maintenance a 1 inch-milling and a 1,5 inches resurfacing is a good alternative to simple overlay. Thanks to the low thicknesses involved the milling process acts as a small "scrub" of the surface, with low costs and emissions. The effect is practically the same as the one obtained with a thin overlay with the benefit of maintaining the previous surface level. This may be a requirement for some works which involve roads bounded by sidewalks or subterranean parts. Moreover, it prevents the accumulation of an excessive number of asphalt layers, improving vertical load transmission to the deepest layers.

Novachip

An ultrathin friction course is a formulation of hot-mix asphalt with gap-graded aggregates placed on a polymer-modified asphalt emulsion tack-coat. The total thickness of the wearing surface goes from 0.375 to 0.75 inches. Its application is typically used to seal the surface in order to minimize weathering, raveling, and oxidation. Candidate roads for an ultrathin friction course should typically present ruts less than ½ inch deep, moderate cracking to no cracking, and minor to no bleeding. Novachip is an ultrathin friction course whose primary objective is to restore the skid resistance and the surface impermeability. The few other advantages are excellent adhesion, reduced rolling noise, reshaping of existing pavements.

Novachip consists of a layer of hot pre-coated aggregates over a binder spray application. The tack coat is generally a polymer-modified and emulsified emulsion. Such type of coating offers a strong bonding between the chippings. Thus, due to the immediate application of the binder, chippings are perfectly held in position and whip-off is completely avoided.

Overlay

This thin asphalt overlay is a preventive maintenance technique that helps for extending the life of pavements that are still in good condition. The thickness of these overlays are 1,2-1,5 inches, and the aggregates have a small maximum size. There are several advantages in using a thin overlay, including a longer service life and a lower life-cycle cost when placed on structurally sound pavements, or the ability to maintain grade and slope with minimal drainage and avoid loose stones after the initial construction. Good production and construction practices are obviously paramount to obtain a good performance. Warm-mix asphalt may add further benefits by allowing the asphalt mix to be transported farther or to be laid in colder weather conditions. Reclaimed asphalt pavement (RAP) should be incorporated into surface mixes to maximize the economy and enhance performance, especially rut resistance. Milling the existing pavement surface can enhance the overlay performance and moreover it can provide recycled material for the future. It is expected that a thin asphalt overlay may last more than 7 years on a good, low-distress surface and from six to ten years on a concrete pavement.

Slurry Seal

Slurry Seals are a mixture of asphalt emulsion, graded aggregates, mineral filler, water and other additives. A traveling paver is used to place the mixture on a continuous basis. The paver measures the mix components and put them in a predetermined order into a pug mill.

The resulting slurry material is a free flowing composite material that is spread using a spreader box over the existing road surface. The consistency of the slurry material allows it to spread over the pavement, wetting the latter, and forming an adhesive bond to the pavement.

Appendix B:
Environmental analysis of pavement treatment techniques

In this appendix the process of life cycle analysis for treatment options introduced in case study 1 is analyzed. The analysis is adapted from Cerea (2010) and for clarification of the process the process is represented for two of the treatment options. For more information on other techniques see the reference.

Inputs are the mix design, the percentage of RAP for hot-mix and warm-mix asphalts, the type of aggregate for Slurry Seal and Micro-surfacing, the percentage of crushed aggregates and the distance from the asphalt plant. Emissions and energy are divided into: (i) Production of materials (ii) Laying down.

Overlay

1) Deciding the mix design in terms of percentage of bitumen, aggregates and filler. Thickness=1.5”.

Table A.1 Materials and weight of an asphalt overlay
(Adapted from Cerea (2010))

MIX DESIGN	Asphalt Concrete	Bitumen	Aggregates	Filler
[t/m3]	2.45	1.02	2.65	
% mix	100	5%	90%	5%
thickness [m]	0.038			
[t/m2]	0.0931			
R.A.P. [%]	30%			

2) Weight per square meter of each material.

The Weight of asphalt is assumed to be equal to 2450 tons/m3. Table 2 represents the CO2 emissions and MJ usage of energy per ton for the production of each material. The values of KgCO2 and MJ per square meter are calculated by multiplying them to the specific weight (tons/m3) and the thickness (m).

Table A.2 Weights of single materials (Adapted from Cerea (2010))

MATERIALS		Weight [t/m2]	Energy [MJ/t]	CO2 [Kg/t]
Bitumen		0.003	4602.64	256.50
Tack coat emulsion		0.001	3490.00	221.00
Aggregate [%]				
60%	crushed	0.035	38.85	7.46
40%	pit-run	0.023	19.36	6.25
RAP processing		0.028	42.00	8.69
Manufacture				
	HMA	0.093	314.16	21.99
	WMA	0.0931	190.80	17.93

3) Emissions corresponding to the Equipment utilized as well as energy consumption. The equipment used along with the amount of emissions and energy consumptions for the current maintenance technique is shown in Table 3.

Table A.3 Machinery used (Adapted from Cerea (2010))

Choose machinery	Model	[l/h]	[km/h]	[MJ/m2]	[g/m2]
Paver	AP600	31,3	0,972	0,387	28,48
Roller	CB534D	24,5	4	0,777	57,17

4) Transportation emissions and energy consumption and calculations.

Distance between asphalt plant and working place is an input. Transportation of milled material is considered.

Table A.4 MJ and CO2 consumed for an HMA Overlay (Adapted from Cerea (2010))

OVERLAY		Energy [MJ/m2]	CO2 [Kg/m2]
Machinery	km		
Lorry transport Km	1	0,066	0,004
Tack Coat		0,491	0,036
Pavers		0,387	0,03
Roller		0,777	0,06
Mat production			
Bitumen		11,84	0,660
Tack Coat Emulsion		3,49	0,221
Aggregate	crushed	1,26	0,24
	pit-run	0,27	0,09
RAP processing		0,93	0,19
Manufacture	HMA	23,09	1,62
TOTAL		**42,60**	**3,14**

Warm mix asphalt needs modified bitumen, thus an estimation of the real emissions as a result of a warm mix overlay must consider a 3% polymer modified bitumen. Table 6 represents the energy consumption and CO2 emissions.

Table A.5 Modified Bitumen used in WMA (Adapted from Cerea (2010))

MATERIALS	Weight	Energy	CO2
	[t/m2]	**[MJ/t]**	**[Kg/t]**
Modified bitumen	0,0026	6997	331

Table A.6 MJ and CO2 consumed for a WMA Overlay (Adapted from Cerea (2010))

	WMA
Energy [MJ/m2]	39,69
CO2 [Kg/m2]	3,038

Mill and resurfacing

The first three steps are similar to the overlay technique. Table 7 represents the environmental impacts of equipment in this technique.

Table A.7 Machinery used (Adapted from Cerea (2010))

Choose machinery	Model	[l/h]	[km/h]	[MJ/m2]	[g/m2]
Miller	PL2100S	105	2.16	0.875	64.41
Paver	AP600D	31.3	0.972	0.387	28.48
Roller	CB534D	24.5	4	0.777	57.17

4) Calculations

Distance between asphalt plant and working place is an input. Inputs are: distance between plant and working place and distance between working place and waste storage.

Table A.8 MJ and CO2 consumed for a Milling + HMA Overlay (Adapted from Cerea (2010))

MILL AND RESURF.		Energy [MJ/m2]	CO2 [Kg/m2]
Machinery	**km**		
Lorry transport Km	1	0,084	0,006
Miller		0,875	0,064
Milled mat. Transp.	1	0,059	0,004
Tack Coat		0,491	0,036
Pavers		0,387	0,03
Roller		0,777	0,06
Mat production			
Bitumen		15,00	0,836
Tack Coat Emulsion		3,49	0,221
Aggregate	crushed	1,37	0,26
	pit-run	0,45	0,15
RAP processing		1,17	0,24
Manufacture	HMA	29,25	2,047
	WMA	17,76	1,669
TOT	**HMA**	**53,40**	**3,95**
	WMA	**41,92**	**3,57**