Probabilistic Segment-linked Pavement Management Optimization Model

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Abstract: Pavement management systems (PMSs) are increasingly important tools in the decision-making processes regarding the maintenance and rehabilitation of road pavements. A new optimization model to be used within network-level PMSs is presented in this paper, together with a genetic-algorithm heuristic to solve the model. The model assumes decisions to be segment linked, thus overcoming the principal drawback of the widely used Arizona PMS. The objective of the model is to minimize the expected total discounted costs of pavement maintenance and rehabilitation actions over a given planning time span, while keeping the network within given quality standards. The model was applied to three test problems involving the road network of Coimbra, the third-largest Portuguese city. The results obtained for these problems clearly indicate that the model is a valuable addition to the road engineer's toolbox.

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Introduction

Pavement management systems (PMSs) are increasingly important tools in the decision-making processes regarding the maintenance and rehabilitation of road pavements.

The history of these systems, briefly summarized in Markow (1995) and Thompson (1994), dates back to the 1960s. The first PMSs were developed for large mainframes as a means of organizing pavement management data and calculating indicators for work productivity, material requirements, maintenance costs, and so forth. By 1980 a major change had occurred, as PMSs had become direct decision-making tools, capable of identifying minimum-cost solutions for network-level pavement management problems. In those days, the utilization of mathematical optimization techniques was severely limited because their application required expensive hardware and unfriendly software. In spite of this, the first modern network-level PMS, prepared for the Arizona Department of Transportation (DOT), was judged attractive enough to be adopted by several other DOTs, both inside and outside the United States (including Alaska, Connecticut, Kansas, Finland, Hungary, and Portugal). More recently, from 1990 onward, advances in computing technologies, in terms of both speed and user-friendliness, allowed PMSs to become interactive decision-aid tools, capable of providing policymakers with answers to "what-if" questions in short periods of time.

This paper contains a new, probabilistic segment-linked mixed-integer optimization model for network-level PMSs developed at the University of Coimbra, Portugal. The model assumes that the evolution of pavement condition states is probabilistic, and that decisions are associated with road segments. This feature is especially important because it allows PMSs to "communicate" very easily with geographic information systems (GISs), thus making input and output operations quicker and easier.

The paper is divided into five sections. The first section consists of a brief presentation of the two main alternative optimization-based network-level PMSs—the Arizona probabilistic system and the Singapore segment-linked system. The planning principles underlying the new model are stated in the second section. The third section contains a detailed description of the model. The results obtained with the model for the road network of Coimbra, the third-largest Portuguese city, using both branch-and-bound (a general mixed-integer optimization method) and a genetic-algorithm heuristic, are presented in the fourth section. The final section comprises a synthesis of the conclusions reached so far and a statement of prospects for future research.

Alternative Systems

Arizona System

The Arizona system is based on a (continuous) linear optimization model expressing the objective of minimizing the expected agency discounted costs of pavement maintenance and rehabilitation (M&R) actions over a given planning time span, while keeping the network within given quality standards (Golabi et al. 1982; Wang et al. 1994; Wang and Zaniewski 1996). Maximization of service quality and minimization of agency costs were both considered initially, but the Arizona DOT eventually selected the cost minimization approach. Some of the authors involved in the development of the Arizona system have recently reconsidered the quality maximization approach (Liu and Wang 1996; Wang and Liu 1997).

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The model is applied separately to each road category, defined as a function of traffic loadings and climate conditions. At present, the Arizona DOT distinguishes 15 road categories, 45 types of pavement condition states, and six types of M&R actions, from ''routine maintenance'' to ''heavy asphalt concrete layer plus friction course'' (i.e., 11.5 cm ACFC). The deterioration of pavements over time is described by a set of Markov chains (Ang and Tang 1975), one for each road category, specifying the probability of transition between any two condition states.

Like any other linear optimization model, the model used in the Arizona system is relatively easy to solve, at least when the problem size does not exceed certain, quite large, limits. The Arizona DOT uses NOSLIP, a specific native 32-bit OS/2-based code developed at the civil engineering departments of the Universities of Arizona and Arkansas. But any good commercial linear optimization package, and there are many available today, will surely also be efficient for the job.

The application of the model determines the M&R actions to apply to proportions of the roads in each category, for each year of the planning time span. The exact segments of the road network where the actions are to be applied are not identified. Therefore, considerable additional work is, in principle, needed to define a proper M&R plan. One of the authors directly involved in the development of the Arizona PMS recognizes that the system, though being an effective tool for generating annual budget estimates, does not provide a comprehensive methodology for selecting M&R actions (Wang 1992). He also recognizes that this would only be possible through a different approach, based on mixed-integer optimization techniques.

Singapore System

An interesting alternative to the Arizona system is currently being developed in Singapore (Chan et al. 1994; Fwa et al. 1994, 1996), evolving from earlier work on highway routine maintenance programming (Fwa and Sinha 1986; Fwa et al. 1988).

One of the distinctive features of the Singapore system is that it associates M&R actions with road segments, and not just with road categories; i.e., it explicitly identifies the segments of the road network where M&R actions should be applied.

The objective of the Singapore system may be to minimize agency and/or user costs, or to maximize service quality. It may also be any combination of both. For each segment and year, various types of actions are considered, from ''do nothing'' to ''structural overlay.'' In between these extremes, actions like ''crack sealing'' and ''pothole patching,'' taken individually or in combination, may be considered. The latest implementation of the system comprises a total of nine alternative actions. This means that even for a small 20-segment, four-year problem the number of alternative M&R plans to be evaluated is huge (approximately 2.2×10^{76}). The distress parameters used to describe pavement condition states are total cracked area, rut depth, total disintegrated surface, and the American Association of State Highway and Transportation Officials present serviceability index. Their evolution over time is assumed to be deterministic, and is given as a function of traffic loading, pavement age, and structural numbers. The decision to take action, as well as the nature of the actions to take, depends on the values taken by the distress parameters. In particular, these values are not allowed to exceed certain levels, called warning levels.

The nonlinear integer optimization model defined in the Singapore approach, for which no explicit mathematical formulation is given, is solved through a genetic-algorithm heuristic called PAVENET-R. Genetic-algorithm heuristics are inspired by Darwin's theory of natural selection. Since they were introduced by Holland (1975), they were successfully applied to a large number of complex engineering optimization models (Goldberg 1989; Michalewicz 1996; Mitchell 1996). Their utilization within the Singapore system was yet another success. However, it must be said that PAVENET-R was tested on a single problem, and that little information had actually been supplied on the quality of PAVENET-R solutions. Useful data about the quality of the heuristic would have been provided if PAVENET-R solutions were compared to global optimum solutions (obtained through complete enumeration) on small test problems.

Planning Principles

Pavement management systems are mainly aimed at helping decision makers to plan M&R actions. To be successful, a planning process must simultaneously deal with short-term (one year), medium-term (up to 10 years), and long-term issues (more than 10 years), and prepare decisions for the short, the medium, and, possibly, the long term. Short-term decisions are undoubtedly the most important ones, because they are the decisions that will be set for implementation in the immediate future. Both medium- and long-term decisions are less important because, within a flexible approach to the planning process, they can be changed if necessary, in response to updated information about the evolution of the system under analysis (i.e., in this case, the road network pavements). However, it is essential to keep the medium term and the long term in sight for two reasons—first, because short-term decisions must take into account the future evolution of the system, which depends on medium- and long-term actions; second, because short-term actions modify the framework within which medium- and long-term decisions will be made.

The approach to PMSs implicit in the model presented later derives from this view of the planning process. In fact, the model is designed to help identify the optimum short-term M&R actions to be taken under a feasible, optimum medium-term strategy for network-level pavement management. Within the medium-term strategy, concern for long-term pavement behavior issues is expressed through requiring road network pavements to be above a given average quality level at the end of the planning time span. The higher this level is, the easier it will be to keep road network pavements in good condition in the distant future. The strategy is established with reference to the expected (average) pavement states of individual road segments, which, taken together, define the most likely state for the road network as a whole.

Application of the model on a yearly basis (i.e., a new run every year) allows both the determination of the optimum M&R actions to be implemented in the immediate future and the identification of any corrections that may need to be made in the medium-term strategy. The strategy can, and will, in principle, change over time, in response to changes in the decision environment (pavement states, M&R action costs, and likewise).

Before concluding this section, the writers would like to emphasize their idea that models cannot be viewed as replacements for policymakers in any planning process, because, by definition, models do not fully capture reality. The word ''optimum'' employed before applies only to models, not to real-world problems. Hopefully, the optimum decisions indicated by the models will help policymakers make good decisions. But they are not enough to guarantee them.

Optimization Model

The model used in the Arizona system is probabilistic, but not segment linked. The model used in the Singapore system is segment linked, but deterministic. A new mixed-integer optimization model for network-level PMSs is presented in this section. The model is probabilistic and segment linked. That is, the model takes the uncertainty inherent to the evolution of pavement states into account, and explicitly identifies the segments of the road network where the M&R actions should be applied. To the best of the writers' knowledge, the only optimization model combining these characteristics reported in the literature is the dynamic programming model proposed in Mbwana and Turnquist (1996).

Like any other optimization model, the new model contains three basic ingredients—decision variables, an objective function, and constraints.

The decision variables represent both the instruments that can be applied to change the state of a system (here, the road network pavements) and the state itself. In this case, the instrumental and state variables are, respectively

$Y_{sat}=1$ if M&R action a is applied to segment s in year t; $Y_{sat}=0$ otherwise

$X_{sjat}\geqslant 0=$probability that segment s is in state j at the beginning of year t when M&R action a is applied

The objective function expresses the objective underlying the intervention in the system as a function of the decision variables (all, or part of them). In this case, the objective is to minimize the expected total discounted costs of M&R actions over the planning time span. This objective can be stated as follows:

$$\min \sum_{s=1}^{S} \sum_{a=1}^{A} \sum_{t=1}^{T} C_{at} W_s L_s Y_{sat}$$

where S=number of road segments; A=number of M&R actions; T=number of years in planning time span; C_{at}=discounted cost of applying action a in year t per unit of paved area; W_s=width of segment s; and L_s=length of segment s.

The constraints express any conditions that the system and the decisions that will change its state must meet. In this case, constraints are needed to represent the impact of M&R actions upon pavement states, to describe the evolution of pavement states over time (starting from a known initial pavement state), and to represent any requirements imposed on model solutions.

The impact of M&R actions upon pavement states can be expressed as follows:

$$\sum_{j=1}^{J} X_{sjat}=Y_{sat}\,;\quad \forall s=1,\ldots,S;\quad a=1,\ldots,A;\quad t=1,\ldots,T$$

where J=number of pavement states.

According to these constraints, if a given action is applied to a given segment in a given year (i.e., when $Y_{sat}=1$), the possible pavement states of the segment are those corresponding to the application of the action (once solved, the model determines the best possible states and their probability of occurrence). Conversely, if the action is not applied (i.e., when $Y_{sat}=0$), all pavement states corresponding to the application of the action are impossible (i.e., $X_{sjat}=0$).

The evolution of pavement states over time is described by Markov transition probabilities, as follows:

Objective-function

Minimize expected total discounted M&R costs

$$\min \sum_{s=1}^{S} \sum_{a=1}^{A} \sum_{t=1}^{T} C_{at}\ W_s\ L_s\ Y_{sat}$$

Constraints

Impact of M&R actions upon pavement states

$$\sum_{j=1}^{J} X_{sjat} = Y_{sat},\quad \forall\ s=1,\ldots,S;\ a=1,\ldots,A;\ t=1,\ldots,T$$

Evolution of pavement states

$$\sum_{a=1}^{A} X_{sjat} = \sum_{a=1}^{A}\sum_{k=1}^{J} P_{kja}\ X_{ska,t-1},\quad \forall\ s=1,\ldots,S;\ j=1,\ldots,J;\ t=2,\ldots,T+1$$

Initial pavement states

$$\sum_{a=1}^{A} X_{sja1} = Q_{sj},\quad \forall\ s=1,\ldots,S;\ j=1,\ldots,J$$

Pavement quality standards

$$\sum_{s=1}^{S}\sum_{a=1}^{A} W_s\ L_s\ X_{sjat} \le M_{jt} \sum_{s=1}^{S} W_s\ L_s,\quad \forall\ j\in U;\ t=2,\ldots,T+1$$

Maximum number of heavy M&R actions

$$\sum_{a=2}^{A}\sum_{t=1}^{T} Y_{sat} \le 1,\quad \forall\ s=1,\ldots,S$$

Annual budget

$$\sum_{s=1}^{S}\sum_{a=1}^{A} C_{at}\ W_s\ L_s\ Y_{sat} \le B_t,\quad \forall\ t=1,\ldots,T$$

Non-negativity constraints

$$X_{sjat}\ge 0,\quad \forall\ s=1,\ldots,S;\ j=1,\ldots,J;\ a=1,\ldots,A;\ t=1,\ldots,T+1$$

Zero-one constraints

$$Y_{sat}\in\{0,\ 1\},\quad \forall\ s=1,\ldots,S;\ a=1,\ldots,A;\ t=1,\ldots,T$$

Fig. 1. Summary of optimization model

$$\sum_{a=1}^{A} X_{sjat}=\sum_{a=1}^{A}\sum_{k=1}^{J} P_{kja}X_{ska,t-1}\,;\quad \forall s=1,\ldots,S;\quad j=1,\ldots,J;\quad t=2,\ldots,T+1$$

where P_{kja}=transition probability from state k to state j when action a is applied to the pavement.

The initial pavement state for each segment, and therefore the values for variables X_{sja1}, must be known in advance; that is

$$\sum_{a=1}^{A} X_{sja1}=Q_{sj}\,;\quad \forall s=1,\ldots,S;\quad j=1,\ldots,J$$

where $Q_{sj}=1$ if the initial state of segment s is j; $Q_{sj}=0$ otherwise.

Many different requirements on model solutions may be considered. In this case, constraints were included to guarantee that appropriate standards for pavement quality will be verified, to ensure that heavy M&R actions will not be carried out too frequently, and to guarantee that the annual budget for M&R actions will not be exceeded.

The pavement quality constraints are as follows:

$$\sum_{s=1}^{S}\sum_{a=1}^{A} W_sL_sX_{sjat}\leqslant M_{jt}\sum_{s=1}^{S} W_sL_s\,;\quad \forall j\in U;\quad t=2,\ldots,T+1$$

where M_{jt}=maximum (expected) proportion of paved area permitted to be in undesirable state j at the start of year t; and U=set of undesirable states.

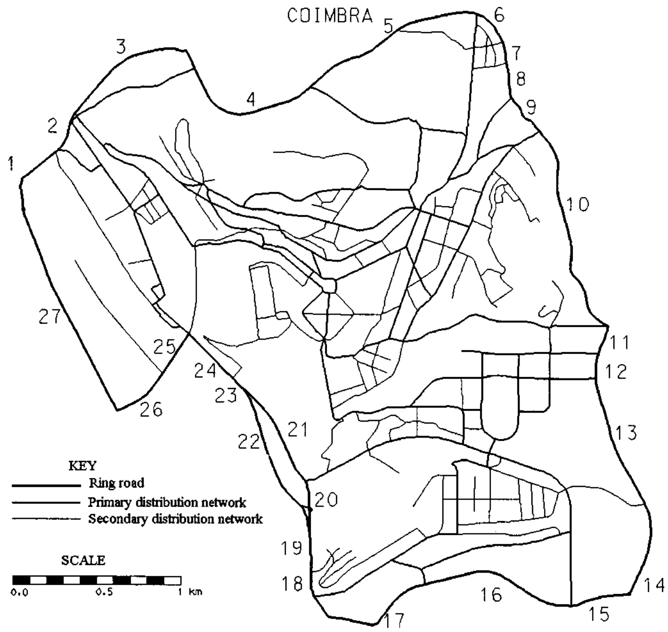


Fig. 2. Coimbra's road network

These constraints ensure that the proportions of paved area expected to be in undesirable states in a given year will not exceed some predefined values. These values can be selected either to guarantee that the area of low-quality pavements will steadily decrease over the planning time span, or to guarantee that the area of low-quality pavements will be small enough at the end of the planning time span.

The heavy M&R actions constraints are as follows:

$$\sum_{a=2}^{A}\sum_{t=1}^{T} Y_{sat}\leqslant 1;\quad \forall s=1,\ldots,S$$

These constraints ensure that only one M&R action other than routine maintenance (Action 1) will be applied to each road segment over the planning time span, thus avoiding frequent disturbance of traffic flows in the segment. Instead of one action, two or more could be considered, through changing the right-hand side of the equation to 2 (or more).

The annual budget constraints are as follows:

$$\sum_{s=1}^{S}\sum_{a=1}^{A} C_{at}W_sL_sY_{sat}\leqslant B_t;\quad \forall t=1,\ldots,T$$

where B_t=discounted annual budget for year t.

These constraints ensure that the budget available for M&R actions in the different years of the planning time span will not be exceeded.

A summary of the model is presented in Fig. 1.

Model Solving

Section Overview

The results obtained with the new model for a set of test problems using branch-and-bound and a genetic-algorithm heuristic are presented in this section. The test problems are described in the first part of the section. The second part contains the results obtained through branch-and-bound, the most popular general mixed-integer optimization method (Wolsey 1998). This method is relatively simple to apply, because it is available through good, reliable commercial software, but it can only deal with small models. The third part contains the results obtained through the genetic-algorithm heuristic.

Table 1. Length, Width, and Condition State of Road Segments

Segment	Length (m)	Width (m)	GDI
1	440	10	2
2	244	10	1
3	906	10	3
4	885	10	2
5	1,114	10	4
6	227	10	2
7	118	10	3
8	199	10	3
9	253	10	4
10	900	10	6
11	171	10	4
12	140	10	2
13	760	10	3
14	541	10	5
15	354	10	5
16	921	10	7
17	815	10	4
18	136	10	5
19	226	10	7
20	289	10	4
21	637	10	5
22	900	10	6
23	89	10	3
24	358	10	4
25	271	10	2
26	352	10	2
27	1,251	10	3

Test Problems

The problems used to test the two solution methods involved the definition of an optimum four-year M&R plan for the road network of Coimbra (with approximately 100,000 inhabitants). Coimbra has a three-level urban road network with a total of 75 km and 254 segments (Fig. 2). The first level is the ring road, with 14 km and 27 segments. The second and third levels are the primary distribution network, with 32 km and 119 segments, and the secondary distribution network, with the remaining 29 km and 108 segments. The 65 km of local access streets were not considered in the study. The four-year planning time span was adopted because of computational reasons. For a longer planning time

Table 2. Types and Costs of M&R Actions

Action number	Description	Cost (euros/m^2)
1	Routine maintenance	0.05
2	Slurry seal	0.55
3	Microasphalt concrete	1.75
4	Asphalt concrete (4 cm)	2.50
5	Asphalt concrete (6 cm)	3.70
6	Asphalt concrete (5 cm+8 cm)	7.50

Table 3. Maximum Proportion of Paved Area in Undesirable Condition States at End of Planning Time Span

GDI	Maximum proportion
5	0.20
6	0.10
7	0.10
8	0.05
9	0.05

Table 4. Branch-and-bound Solution Information

	Problem	
Item	Nine-segment	27-segment
Number of integer solutions	6	13
Best solution (euros)	72,669.6	277,226.4
Best lower bound (euros)	72,669.6	209,942.1
Difference to best (%)	0.0	32.0
Total computing time (min)	49.3	1,987.9
Best solution computing time (min)	31.3	1,609.6
Percentage of total	63.4	81.0

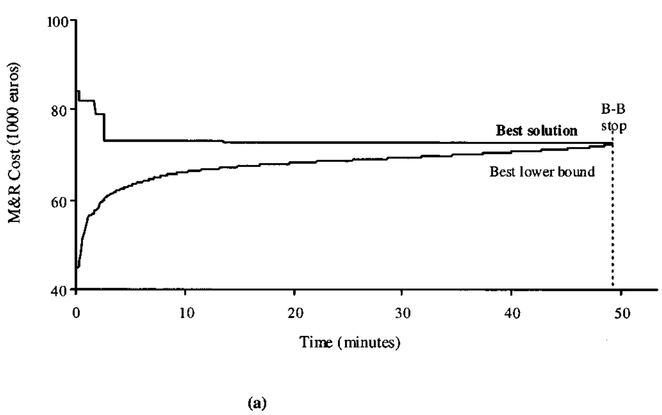
span, it would have been impossible to solve the model through branch-and-bound even for moderate-sized networks. Consequently, it would have been impossible to assess the quality of genetic-algorithm solutions against branch-and-bound solutions. In real-world applications of the model, the planning time span should be longer (say, 10 years), to permit a better evaluation of the trade-off between light and heavy M&R actions.

To gain insight into the performance of solution methods, three distinct, increasingly more complex problems were considered.

- A nine-segment problem, corresponding to the north section of the ring road (Segments 1–9),
- A 27-segment problem, corresponding to the entire ring road (segments 1–27), and
- A 254-segment problem, corresponding to the entire urban road network.

The first two problems were solved both through branch-and-bound and the genetic-algorithm heuristic. The third one was only solved through the genetic-algorithm heuristic, because it was far too large to be handled with branch-and-bound.

Part of the data used in this study, more specifically in the ring road problems, are presented in Tables 1–3. Table 1 identifies the length and width of the ring road segments, and the initial state of their pavements as given by a global degradation index (GDI). This information was taken from SIGPAV (Ferreira 1996, 1998), a GIS-based system consisting of a road database and a pavement evaluation tool. The GDI was determined by the VIZIR method, a visual distress score method developed at the Laboratoire Central de Ponts et Chaussées, in France (Autret and Brousse 1991). This method classifies pavement states into nine categories. Category GDI=1 corresponds to the best states; Category GDI=9 corresponds to the worst ones. Table 2 describes the six different types of M&R actions considered in this study, and the corresponding unit costs. The actions range from routine maintenance to the application of two layers of asphalt concrete (of 5 and 8 cm). Table 3 displays the maximum proportions of paved area allowed to be in undesirable states at the end of the planning time span. Alternatively, they could have been defined for some intermediate years or for all of the years included in the planning time span.



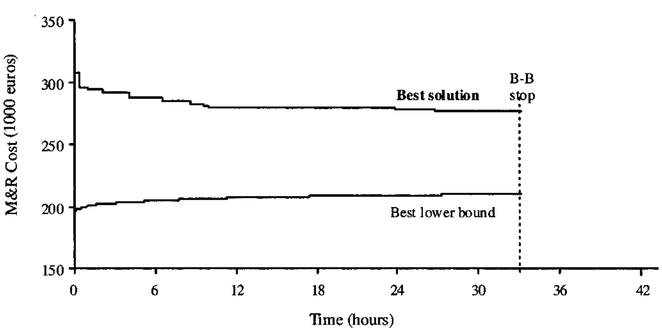


Fig. 3. Evolution of branch-and-bound solutions over time: (a) nine-segment problem; (b) 27-segment problem

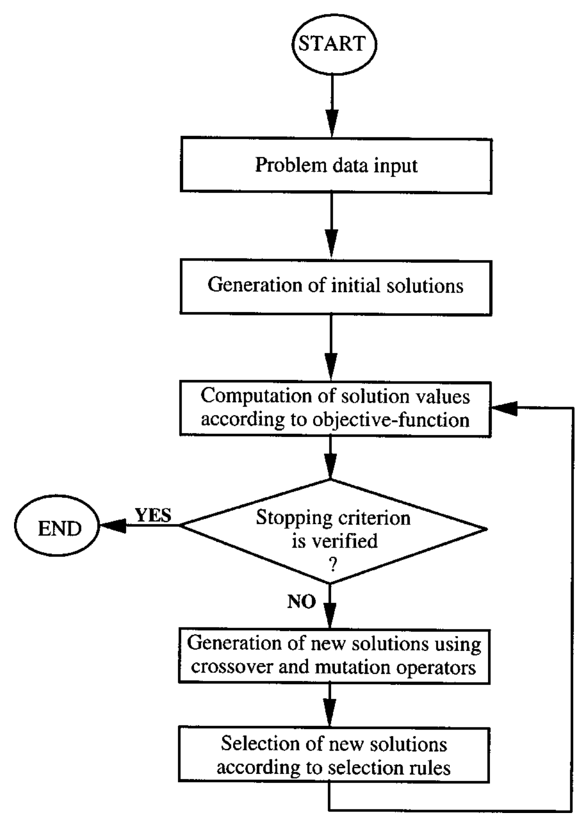


Fig. 4. Flowchart of genetic-algorithm heuristic

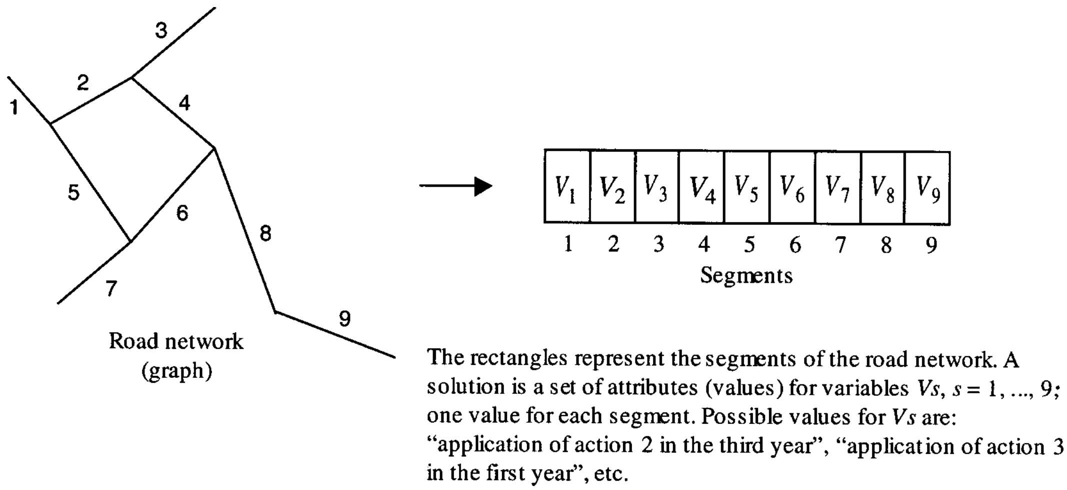


Fig. 5. Solution coding

But this would make the number of feasible solutions smaller, thus making the search performed by the genetic-algorithm heuristic easier (in principle).

Other data used in this study were the annual budget for M&R actions, the rate used for discounting costs, and the Markov transition probabilities. The maximum annual budget for the 9-, 27-, and 254-segment problems was assumed to be 40,000, 120,000, and 360,000 euros, respectively (the euro is the new European currency). The discount rate was assumed to be 5% per year. This is the discount rate for public investment indicated by the Portuguese central bank. The transition probabilities were taken from the PMS of the Instituto das Estradas de Portugal (the Portuguese Road Administration), which is based on the Arizona PMS.

Branch-and-bound

The application of branch-and-bound was made using the mixed-integer optimization package XPRESS-MP (XPRESS-MP 1997) on a 450 MHz personal computer (PC). This package was chosen because it combines a friendly Windows 95/98 interface with a very efficient solver.

Even though powerful PC hardware and software were used, the model was quite difficult to solve. In the nine-segment problem, it was possible to identify a guaranteed optimal solution (72,669.6 euros over the four-year planning time span), but the search procedure took approximately 49.3 min of computing time (Fig. 3 and Table 4). It should be noted, however, that a good

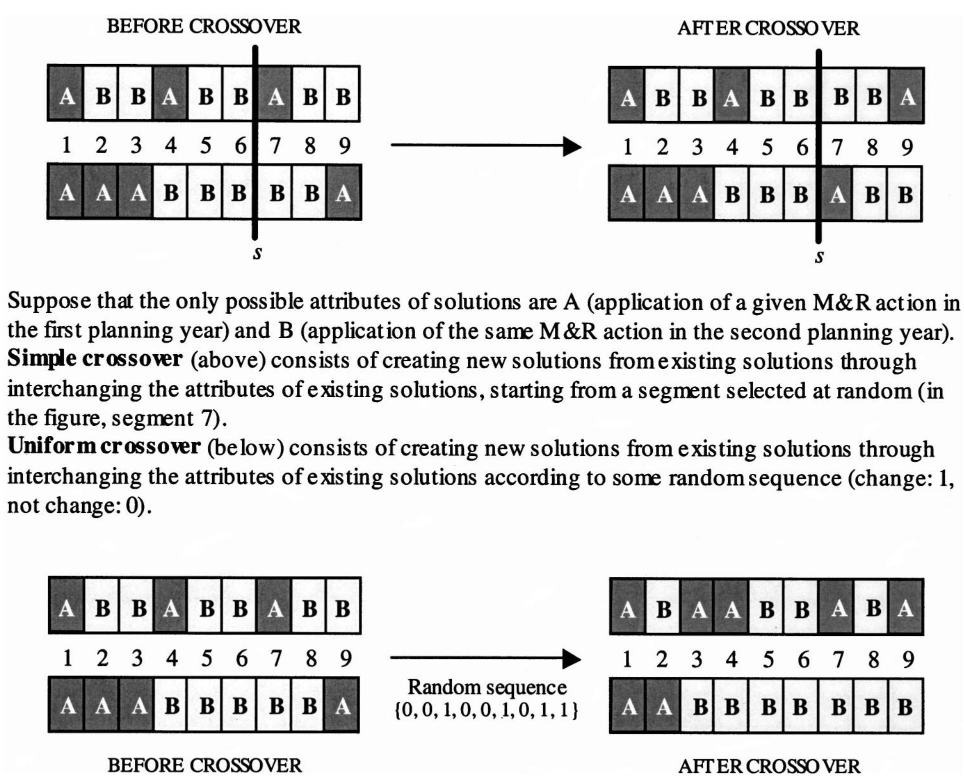
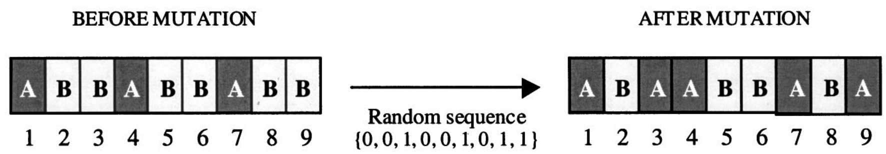


Fig. 6. Crossover operations



Suppose that the only possible attributes of solutions are A (application of a given M&R action in the first planning year) and B (application of the same M&R action in the second planning year). **Mutation operations** consist of creating new solutions from existing solutions through changing the attributes of existing solutions according to some random sequence (change: 1, not change: 0).

Fig. 7. Mutation operations

solution (73,265.3 euros) was found in only 2.6 min. In the 27-segment problem the search procedure stopped before completion. After 33.1 h of computing time, the best solution found (277,226.4 euros) was still a long way from the best optimum solution possible at this stage of the search, known as the best optimum solution lower bound (209,942.1 euros).

Genetic Algorithms

As one could expect, the application of a general method like branch-and-bound only allowed the identification of the optimum solution for the smallest (nine-segment) problem. For larger problems, two basic alternatives may be considered—to develop a specialized (exact) method, exploring the particular mathematical structure of the problem to be solved; or to develop a (specialized) heuristic method. The second alternative is much easier to implement, but it does not guarantee that a global optimum solution to the model will be found. However, if the heuristic is properly designed, it will provide either a global optimum solution or a good local optimum solution, close to a global optimum solution.

In this study, a heuristic method based on genetic-algorithm principles was used to solve the model. Genetic-algorithm heuristics can be briefly described as follows (Fig. 4). They start with an initial population of chromosomes, or, within an optimization framework, solutions. Each chromosome (solution) consists of a given number of genes, or, within an optimization framework, attributes (the possible values taken by instrumental decision variables; i.e., in this case, variables *Y*). The population of solutions evolves over time through reinsertion, crossover, and mutation. Reinsertion is the transfer of the best solutions of the existing population to the next generation. Crossover is the interchange of some attribute or attributes between two existing solutions. Mutation is the transformation of some attribute or attributes of an existing solution. Selection of solutions takes place in such a way that only the best solutions from successive generations survive, thus avoiding the occurrence of overpopulation. Through this process, the quality of solutions will progressively tend to improve, leading eventually to a population consisting only of optimum or near-optimum solutions. In-depth presentations of genetic-algorithm principles can be found in Mitchell (1996) and Chan et al. (1994). The latter presentation is made within the framework of pavement management systems.

Table 5. Complete List of Alternative Parameters and Operators

Parameters/operators	Values		
Population size	100	200	300
	500	1,000	2,000
Crossover operators	C1	C2	C3
Mutation operators	M1	M2	M3
Selection rules (r,c,m)	(0,50,50)	(10,40,50)	(20,30,50)
	(0,70,30)	(10,60,30)	(20,50,30)
	(0,85,15)	(10,75,15)	(20,65,15)
	(0,95,5)	(10,85,5)	(20,75,5)
	(0,100,0)	(10,90,0)	(20,80,0)

Note: All possible combinations of population size, crossover operators, mutation operators, and selection rules have been tested.

Any implementation of a genetic-algorithm heuristic involves making decisions on several issues. These include solution coding, population size, initial solution, selection rules, crossover operations, mutation operations, constraint handling, and the stopping criterion.

Solution coding defines the way the attributes of a solution are represented. In this implementation, each solution is represented by as many attributes as the number of road segments (Fig. 5), and each attribute is represented by a variable describing the application of feasible sequences of M&R actions to the segment (“feasible” here refers to the fact that only one action other than routine maintenance can be applied to the segment over the M&R planning time span). For instance, the variable associated with segment *s*, V_s, may represent attributes such as “application of routine maintenance only to segment *s*,” “application of Action 2 to segment *s* in the first year (and routine maintenance in the other years),” “application of Action 3 to segment *s* in the fourth year,” and so forth. In total, variable V_s may take $(A-1)\times T+1$ different values (where *A* is the number of M&R actions and *T* is the number of years). Variable V_s corresponds to the different possible decisions for segment *s*. The total number of segment decisions for the entire network is therefore $[(A-1)\times T+1]\times S$ (where *S* is the number of road segments). The computation of the total cost for a network solution can be extremely fast if different possible segment costs are calculated at the outset. This makes this type of solution coding particularly efficient.

Population size (i.e., the number of solutions in each generation), *N*, must be carefully chosen because, if the population is too small, the risk of premature convergence of the algorithm (to a poor local optimum solution) will be serious, and, if it is too large, the effort needed to run the algorithm will be excessive. Several alternative population sizes were tested in this study.

Initial solutions should vary in quality, in order to avoid premature convergence of the algorithm. In this implementation, they were generated at random.

Selection rules are the rules that define the evolution of the population over successive generations. In this implementation, each new population is generated from the existing population according to a reinsertion rate, *r*, a crossover rate, *c*, and a muta-

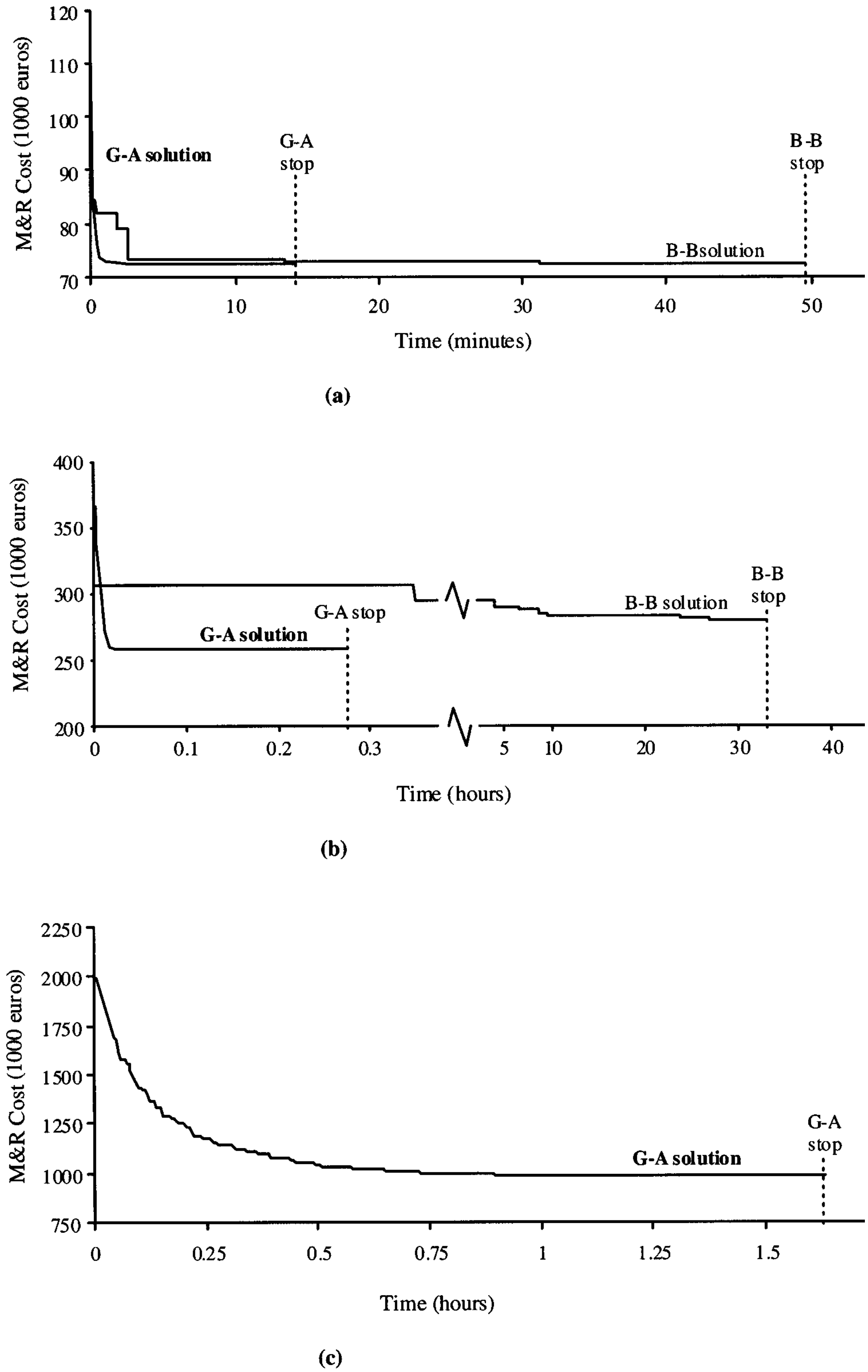


Fig. 8. Evolution of genetic-algorithm solutions over time: (a) nine-segment problem; (b) 27-segment problem; (c) 254-segment problem

tion rate, *m*. These rates define the percentage of solutions in the new population that are obtained by reinsertion, crossover, and mutation. Several alternative selection rules were tested in this study.

Crossover operations may be simple or uniform. Simple crossover consists of interchanging contiguous attributes between two solutions (Fig. 6). Uniform crossover consists of interchanging attributes at random between two solutions. Pairs of solutions involved in crossover may be chosen according to several criteria. In this implementation, three common crossover operators were considered—simple crossover between quality-consecutive solutions, C1; simple crossover between best solutions and randomly chosen solutions, C2 (in successive couplings, only solutions not previously involved in crossover may be chosen); and uniform crossover between best solutions and randomly chosen solutions, C3.

Table 6. Genetic Algorithm Heuristic Solution Information

Item	Problem		
	Nine-segment	27-segment	254-segment
Final best solution (euros)	72,669.6	258,922.2	979,907.6
Best solution after 10% computing time (euros)	73,005.2	259,000.1	1.3363671 million
Difference from final best (%)	0.5	0.0	36.4
Best solution after 50% computing time (euros)	72,669.6	258,922.2	999,636.4
Difference from final best (%)	0.0	0.0	2.0
Total computing time (min)	14.0	16.7	98.0
Best solution computing time (min)	4.4	9.2	81.6
Percentage of total	31.4	55.1	83.3

Mutation operations may involve one or more attributes, of one or more solutions (Fig. 7). In this implementation three common mutation operators were considered—random mutation of all attributes of the *m*-percent-best solutions of each generation, M1; random mutation of one randomly chosen attribute of the *m*-percent-best solutions, M2; and successive random mutation of one randomly chosen attribute starting with the first-best solution, M3.

Constraints 3–6 were handled directly, within the process of generating new solutions. Constraints 2 and 7 were handled indirectly, through dynamic penalty functions (Michalewicz 1996). These functions penalize the objective function by a quantity proportional to the degree of violation (i.e., the distance to feasibility) associated with each constraint.

The stopping criterion defines the moment for the termination of the search made within the heuristic. In this implementation, the search was stopped when no improvement of either the best solution or the average solution (over the entire population) was achieved in 10% of the total number of generations.

After a careful investigation conducted for the nine- and 27-segment problems, it was found that the best performance of the genetic-algorithm heuristic occurs for the following combination of parameters and operators: $N=1{,}000$; $r=10\%$; $c=85\%$; $m=5\%$; crossover operator C3; and mutation operator M1. The various alternative combinations that were studied are described in Table 5. A detailed report on this investigation is presented in Ferreira et al. (1999).

With the combination of parameters and operators indicated earlier, the optimum solution to the nine-segment problem (72,669.6 euros) was found in only 4.4 min; i.e., less than 10% of the 49.3 min required by branch-and-bound (Fig. 8 and Table 6). For the 27-segment problem, the genetic-algorithm heuristic was able to identify in just 2.3 min a better solution than the best solution given by branch-and-bound (277,226.4 euros) after 33.1 h of computing time. Before the heuristic stopped, several solution improvements were accomplished. The best solution determined with the genetic-algorithm heuristic (258,992.2 euros) was 6.5% better than the solution given by branch-and-bound, and was obtained in 9.2 min.

The genetic-algorithm heuristic was also applied to the 254-segment problem defined for the entire road network of Coimbra. The best solution for this problem (979,907.6 euros) was found in 81.6 min. This is a very reasonable amount of time, given the large size of the network. The network can indeed be classified as large because the segments are decision-making segments, not data-collection segments. At the urban level, decision-making segments will often be shorter than 1 km. However, at the state (or country) level, they will normally be longer than 10 km, to avoid frequent changes of pavement quality on a given route.

The results obtained with the genetic-algorithm heuristic for the 27-segment problem are illustrated in Fig. 9. The figure depicts the best M&R plans identified by the heuristic. As one could expect, heavier actions are needed only in the last 2 years. This happens because quality requirements, defined for paved areas in undesirable condition states, apply only at the end of the final planning year. Actions 3 and 6 were never selected for implementation.

Conclusion

This paper presents a new probabilistic segment-linked optimization model for use in PMSs. The model allows maintenance and rehabilitation actions to be defined for specific segments of a road

Period	Road Segment																										
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1			2	1	1	1	1	2	1	2	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2
2	1	1	1	1	1	1	2		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	2	5	2	1	1	1	1	5	2	1	1	5	1	1	5	1	1	5	1	1	5	1	1	1
4	2	2	1	1	1	1	1	1	5	1	1	1	1	5		5	4	1	1	4	1	5	4	1	2	2	1

LEGEND

Routine Maintenance 1

Slurry Seal 2

Micro-Asphalt Concrete 3

Asphalt Concrete (4 cm) 4

Asphalt Concrete (6 cm) 5

Asphalt Concrete (5+8 cm) 6

Fig. 9. Genetic-algorithm solution for 27-segment problem

network, thus overcoming one of the principal drawbacks of the widely used Arizona PMS. The new model is rather difficult to solve. This became clear after using the model on three test problems defined for the road network of Coimbra. The application of branch-and-bound, a general mixed-integer optimization method, was successful only on the smallest test problem (nine segments). This led to the development of a genetic-algorithm heuristic to solve the model. The results obtained with this heuristic for a judicious choice of parameters and operators were quite interesting. A 254-segment problem was solved in 81.6 min of computing time using a 450 MHz PC. The writers estimate that a 1,000-segment problem will take less than 2 h to solve on the 2 GB MHz PCs available today. Assuming that the average length of (decision-making) segments is 0.75 km for an urban network and 15.0 km for a state (or country) network, this means that the model is expected to handle 750 km urban networks and 15,000 km state networks within manageable computing effort.

In the near future, research in this area will follow two main directions. First, the genetic-algorithm heuristic will be tested on a representative sample of road networks and evaluated against the best results provided by branch-and-bound. This will make it possible to ascertain whether the parameters and operators used in the heuristic are the best possible ones, or whether they should be modified. Second, the model will be incorporated into a geographic information system, in order to make input-output operations more rapid and convenient. This will explore one of the main advantages of a segment-linked model. The second line of research will be carried out within the framework of a contract recently signed between the University of Coimbra and the City Council of Lisbon, the capital city of Portugal, for the development of Lisbon's PMS.

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