A MULTI-OBJECTIVE APPROACH BASED ON THE GENETIC ALGORITHM TECHNIQUE FOR ROAD PAVEMENT MAINTENANCE

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ABSTRACT

The development of genetic algorithm that allows road pavement maintenance resource optimization pursues two aims: on the one hand the most economical maintenance strategy under given budget constraint, on the other as far as possible the reduction of the accident risk along the road infrastructures under consideration.

Road accidents are closely connected to the altimetrical and planimetrical characteristics of layout, to the traffic conditions, and to the weather as well as road pavement conditions.

Therefore there are many variables to manage and the traditional optimization techniques often fail to produce suitable management performance regarding both the budget target and road safety target.

However, the multi-objective approach, based on a genetic algorithm model, seems to be a suitable technique for road pavement maintenance since it allows the selection of an optimal solutions set, known as the Pareto optimal solutions set, and the assigning of a fitness rank to each solution, based on the trade-off between economical and road safety features.

In this paper such an approach was developed by examining some of the Sicilian motorways, and the results have highlighted the feasibility and capability of this approach in programming the maintenance of road pavements.

Keywords: genetic algorithm, pavement maintenance, multi-objective optimization

1. INTRODUCTION

The planning of road maintenance involves a search for solutions or strategies that combine reliability with economy of resources.

Pavement is one of the elements on which, more than any other, enormous resources are spent, since to a large extent, traffic safety depends upon its structural and functional efficiency.

If on one hand the need to guarantee high levels of safety and functionality implies maintaining the pavement in excellent repair, on the other hand, motorway companies often find themselves struggling with insufficient availability of funds.

Thus, it is important to identify priorities in intervention and to rationally plan maintenance work.

From the above, it is clear that a basic conflict exists between the objectives that are being proposed: if on the one hand, maintaining pavement in a good state of repair requires a significant economic effort, on the other hand, the interest of the motorway company is that of keeping maintenance costs down. Both of these objectives are legitimate and at the same time contradictory in nature.

To identify the best management strategy, it is necessary to use a mathematical tool that is able to offer a multi-objective approach to the problem, so that the minimum economic resources, under budget constraints, may produce the maximum effect in terms of safety.

The genetic algorithm (GAs) technique fully meets this requirement.

Having formulated a function for the risk state of a motorway infrastructure, this technique was applied as a decisional system for road pavement maintenance of the A18 Messina-Catania motorway, a route of about 160 km.

2. BACKGROUND

In the beginning, the application of GAs to pavement management was analyzed by Fwa et al. (1994) to solve an optimal pavement repair program at the network level for a given rehabilitation schedule, subject to several forms of resource and operation constraints: production requirements, budget constraint, manpower availability, equipment availability, and rehabilitation schedule constraints.

GA formulation is a key step in the solution process in which a GA representation of the problem is established. This is achieved by representing the decision variables in a string structure similar to chromosomes in natural evolution.

The decision variables are the respective amounts of maintenance work, measured in workdays, assigned to each of the 48 maintenance treatment types. The 48 treatment types refer to maintenance repairs arising from four distress forms of three maintenance-need urgency levels on four highway classes. The coded string structure of GA representation would thus consist of 48 cells. Each cell can assume an integer value of workdays from 0 to 45.

The earlier single-objective analyses performed by Fwa et al. (1994) offered solutions that maximized the work production in total workday units.

In a later study Fwa et al. (2000), in addition to maximizing work production, considered the following two additional objective functions: (1) Minimization of the total maintenance cost; and (2) maximization of overall network pavement condition.

The selection of good solutions was based on the so-called Pareto-based fitness evaluation procedure by comparing the relative strength of the generated solutions with respect to each of the adopted objectives.

Bosurgi et al. (2005) proposed an optimization procedure for the management of resurfacing interventions on flexible pavement. The optimization problem was faced by programming a genetic algorithm that manages the decisional process on the basis of two indicators, referring respectively to the Sideway Force Coefficient of pavement and to predicted accidents. The above indicators have been defined through predictive models elaborated with neural networks.

The SFC prediction model has SFC values during the analysis period and cumulated traffic in input, SFC values at the end of the analysis period in output.

In the accident prediction model, considered variables were relative to the geometric characteristics of the motorway, to the environment context, to the climatic and use condition, to the pavement condition and to the total number accidents that occurred during the analysis period.

A solution to the problem is represented by a chromosome where as genes as programming years correspond to every homogeneous section. For every gene a numeric code represents a possible kind of maintenance intervention.

In optimal allocation of the maintenance interventions two optimization problems were defined separately: minimization of the estimate accidents and maximization of the average SFC of the whole infrastructure.

Chootinan et al. (2006) introduced a multi-year pavement maintenance programming methodology that is able to explicitly account for uncertainty in pavement deterioration. This is accomplished with the development of a simulation-based genetic algorithm approach that is capable of planning the maintenance activities over a multi-year planning period.

In this study two maintenance goals commonly used in the networks-level pavement maintenance optimization are considered: pavement-performance maximization and maintenance-cost minimization.

The previous two optimization problems were combined to the bi-objective model in which both maintenance goals are simultaneously optimized. That is, the maintenance plan that costs less and provides higher pavement performance is more preferable. Both objectives are given a weight and combined into a single objective value.

As in the previous case, the chromosome is coded as a series of T-year maintenance activities for all pavement segments.

3. MULTI-OBJECTIVE OPTIMIZATION

A general multi-objective optimization problem consists of a number of objectives to be optimized simultaneously and is associated with a number of inequality and equality constraints. Such a problem can be stated as follows :

Minimize (or Maximize) $f_i(x) \quad (i = 1,\ldots,N)$ subject to: $\begin{cases} g_i(x) = 0 & j = 1,\ldots,M \\ h_k(x) \le 0 & k = 1,\ldots,K \end{cases}$

The f_i are the objective functions, N is the number of objectives, x is a vector whose p components are the design or decision variables.

In a minimization problem, a vector x_1 is said to be partially less than another vector x_2 when :

$$\forall i \quad f_i(x_1) \le f_i(x_2) \qquad (i = 1,\ldots,N)$$

and there exists at least one i such that $f_i(x_1) < f_i(x_2)$

Then it is said that solution x_1 dominates solution x_2.

A common difficulty with a multi-objective optimization problem is the conflict between the objectives : in general, none of the feasible solutions is optimal for all the objectives. Then, a solution of the Pareto set is a solution which offers the least objective conflict.

GAs select individuals according to the values of the fitness function. However, in a multi-objective optimization problem, several criteria being considered, the evaluation of the individuals requires that a unique fitness value, referred to as a dummy fitness be defined in some appropriate way. To achieve this, by application of the definition of non-dominance, the chromosomes are first classified by fronts. The non-dominated individuals of the entire population define front 1; in the subset of remaining individuals, the non-dominated ones define front 2, and so on; the worst individuals define front f, where f is the number of fronts.

Once the individuals have been ranked by fronts, they are assigned the following dummy fitness values :

$$f_i = \begin{cases} 1/r & \text{in case of minimization} \\ r & \text{in case of maximization} \end{cases}$$

where r is the rank of the front.

Because GAs use a population of individuals, their framework permits identification of a whole set of optimal or, more precisely, non-dominated solutions that define the Pareto set.

The population should be characterized by species in order to obtain a whole set of trade-offs among the objectives. In order to achieve diversity (i.e. maintain individuals all along the Pareto front), a non-dominated sorting procedure in conjunction with a sharing technique has been implemented, first by Goldberg in and more recently by Horn (1994a, 1994b) and Srinivas (1995). Then, the objective is to find a representative sampling of solutions all along the Pareto front. This study refers to the algorithm of Srinivas and Deb (1995), called the Non-dominated Sorting Genetic Algorithm (NSGA). It makes use of a selection method by ranking those emphasizing the optimal points. The sharing technique or niche method is used to stabilize the sub-populations of the good points. It uses such a strategy because one of the main defects of GAs in a multi-objective optimization problem is the possible premature convergence. In some cases, GAs may converge very quickly to a point of the optimal Pareto set and as the associated solution is better than the others (it is called a "super individual"), it breeds in the population and, after a certain number of generations, a population composed by copies of this solution only is obtained!

Likewise, it is possible to obtain a Pareto set composed only of a few elements. It is to avoid such a situation that the non-dominated sorting technique is combined with the niche method any time a solution is found in multiple copies ; then, its fitness value is decreased and, in the next generation, new different solutions appear, even if they are not so performant. The fitness values decrease because the different niches to which belong the different optimal solutions have been identified and treated.

The various steps of the method are the following :

- Before performing the selection step on the available population of solutions, it first identifies the non dominated individuals (according to the criteria). These individuals define front 1. The probability of reproduction of these individuals is very high.
- It then assigns the same dummy fitness f_i to the non dominated individuals i of front 1 (generally, the dummy fitness f_i is equal to 1).
- To maintain the diversity, the dummy fitness of the individuals is then shared: it is divided by a quantity proportional to the number of individuals around it, according to a given radius. If the individual has numerous neighbours, a large number of similar solutions exist and the fitness value is split in order to favour diversity in the next generation. This phenomenon is called a niche. Then after a niche has been isolated and treated for each individual of the current front, it assigns a new dummy fitness value, namely $\frac{f_i}{m_i}$.
- After the above sharing has been performed, the non dominated individuals are temporarily ignored from the population. For the new current front, we first assign to the each individual belonging to this front the same dummy fitness which is the minimum of the $\frac{f_i}{m_i}$ found in the previous front.
- This process is iterated until all the population has been visited.
- As a dummy fitness value has now been assigned to each individual in the population, selection, crossover and mutation can be applied in the usual manner.

In the case of a minimization problem, the population is sorted by assigning a greater dummy fitness to the best individuals: the individuals of front 1 have a greater fitness than the individuals of front 2 that, in turns, have a greater fitness than the individuals of front 3, and so on ; as a result, the Pareto optimization becomes a maximization.

4. METHOD

The multi-objective approach implies the definition of at least two functions, in this case representing the degree of safety offered by the road infrastructure, and the costs of maintenance.

The GAs technique was applied to an important Italian motorway, the A18 Messina-Catania, using a method as follows:

- Creation of a functional and geometric database, which first analyses the characteristics of the infrastructure in question, then carries out discretisation of the same, into functional units;
- Creation of a database of accident rates, requiring selection of the factors that concur to cause an accident and the formulation of a function that links these factors to the accident rate itself;
- Elaboration of the data, consisting of a programming phase and an optimization phase.

4.1 Selection of indicators of the state of infrastructure

The first phase consists of acquiring data regarding the plano-altimetrical geometry of the route, the surface characteristics of the pavement, weather and climate conditions, and traffic divided into heavy and light vehicles.

The entire route of the A18 was divided into Functional Units (FU), made up of planimetric segment-circular curve sequences (clothoid is not present) so that their length was between one and two kilometres.

Each FU that is geometrically characterised in this way is a distinct element, defined by the same conditions of the state of pavement and climatic conditions.

Previous studies carried out on the A18 [Bevilacqua et al. 1998, 1999a, 1999b] through the use of Neural Networks had already identified, using a precise hierarchical scale, the concauses that determine accidents.

On the basis of this research, a set of indicators was selected to represent each FU, made up of :

- Average Daily Traffic of passenger cars only, ADT_L;
- International Roughness Index, IRI;
- Sideway Force Coefficient, SFC;
- Curvature index, $I_T = \frac{\sum_i \frac{L_i}{R_i}}{\sum_i L_i}$;
- Gradient index, $I_P = \frac{\sum_i L_i \cdot p_i}{\sum_i L_i}$;
- Weather-climate index, $I_k = \frac{\text{annual height of rain}}{\text{n°of annual wet days}}$.
- Accident rate Indicator, I_a, equal to the number of accidents registered corresponding to the generic FU.

The period of analysis covers five years from 2000 to 2004 and significant observations total 237.

Since it is not easy to work with the numerical values of input indicators, we decided to subdivide the variation interval of each indicator into classes in order to refer to a single representative value for an entire class, and then create identification initials for that class.

The number of classes for each indicator depends on the need to describe in detail the data and on the importance assigned to certain characteristics in terms of determining accident occurrence; for some of these characteristics, the extra detail is due to the fact that maintenance intervention is based directly on these characteristics. The following table shows the variation domain and the classes for each indicator:

Table 1 Variation domain ranges for each indication and number of orresponding classes

Indicator	Ranges of domain	N. classes
IRI	1- 4.15	3
SFC	40.5 - 70.5	3
ADT_L	2800 - 26800	3
It	0.00012 - 0.00152	2
Ip	(-0.031) - 0.039	2
Ik	1.0 - 7.0	2
Accident range	0-17	

4.2 Definition of the risk state function

The risk state function was formalised on the assumption that the relation linking the number of accidents to the 6 chosen indicators, is linear for each of the considered functional units.

The multiple linear regression on an initial sample of 237 observations was submitted to the following statistical tests:

R^2 e R^2_{adj} , Student test T, Leverage test, Variance Inflaction Factor test, Ramsey RESET test, Breusch-Pagon test in the Cook-Weisberg version, and the Jarque-Bera test.

After several tests, the I_t and I_k parameters are resulted not relevant and the following relation was obtained on a final sample of 230 observations:

$$RS = 8.354441 - 7.250908\, I_p - 0.1291383\, SFC + 0.3960943\, IRI + 0.0000377\, ADT_L \qquad \text{(Eq. 1)}$$

Table 2 Parametres of the third relation of multivariate linear regression

N°inc	Coef.	Std. Err.	t	P>|t|	[95% Conf.Interval]	
Ip	-7.25091	3.889339	-1.86	0.064	-14.9151	0.413282
SFC	-0.12914	0.015901	-8.12	0	-0.16047	-0.09781
IRI	0.396094	0.184389	2.15	0.033	0.032744	0.759445
ADT_L	3.77E-05	1.39E-05	2.71	0.007	1.03E-05	6.51E-05
constant	8.354441	1.272436	6.57	0	5.847026	10.86186
Number of obs=230		**R^2**= 0.5761		**Adj R^2**=0.5685		

The total number of risk states is 54, considering all the possible combinations of the identified classes of state indicators.

Therefore, each UF is characterised by a particular RS value.

4.3 Programming Model

4.3.1 Definition of the intervention strategies

The types of intervention to be carried out on the road in question depend on the state of wear of the pavement, and since this varies so much, a whole range of intervention solutions needs to be available.

The description of these intervention solutions is external to the purpose of the present work, but it is important to emphasise that the model requires a definition of each basic activity under each type of intervention.

Defining the basic activities implies a description of the specific jobs to be carried out, and of the basic cost of each job per m of road. The sum of the costs of each job for each intervention represents the basic cost per m of the same, c_k.

The table below shows the average costs obtained, according to a Sicilian market survey regarding the four most common maintenance solutions for motorway pavement.

Table 3 Intervention therapy and relative prize

Intervention Solutions	Price [€/m]
Surface Repair	144,59
Coating renewal	240,21
Asphalt layers renewal	365,80
Pavement Repair	491,65

Among the possible solutions, we must also include solution 0, that is, the choice not to apply any solution, which has a corresponding cost of 13 Euros according to market research, which allows for cleaning and inspection expenses.

An operative strategy on the entire road network is obtained when for each FU, the type of solution and the time for intervention is established.

The available budget, B, for maintenance over a given period of time, is a given factor in the problem, and depends upon the management policy of the company. Such a factor is a strong conditioning element, since out of the whole range of possible strategies for the network in question, one must first exclude all the strategies whose costs exceed the budget.

4.3.2 Application of Markov's theory

Once an S series of possible strategies for intervention on the network has been assumed, it is necessary to predict the Risk State for each individual Functional Unit at the end of the maintenance work planning period.

The probability model for the forecast is the stationary Markovian model, based on the assumption that the probability at t+1, that the variable X, in this case the Risk State, will assume the value i_{t+1} depends exclusively on the value of the variable considered corresponding to the time t immediately before, and not on the sequence of values that X assumes in times t-1, t-2, …,1, 0.

Indicating the *probability of transition (one step)*, with p_{ij} , that is the probability that at time t+1 the system will be in state j, having been in state i at time t, all the conditions of transition of the system from one state to another due to the effect of the generic intervention can be summed up in the k[th] Transition Matrix:

$$\overline{\overline{P_k}} = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,54} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,54} \\ \cdots & \cdots & \cdots & \cdots \\ p_{54,1} & p_{54,2} & \cdots & p_{54,54} \end{pmatrix} \qquad \text{(Eq. 2)}$$

$\overline{\overline{P_k}}$ is a square matrix of 54*54 elements, for which the following condition is given:

$$\sum_{j=1}^{54} p_{ij} = 1 \qquad \text{(Eq. 3)}$$

The number of transition matrices is equal to the possible typologies of intervention.

Each element of the transition matrix is defined as a composite transition and is the probability that the set of indicators placed respectively in classes a, b, c, d before the intervention, move to classes e, f, g, h as a consequence of intervention k. Such probability is obtained as a product of each single simple transition probability of each indicator, considered as independent events.

Therefore if the combination of classes [a, b, c, d] represents the generic risk state i, while the combination [e, f, g, h] represents the status j, the transition p_{ij} of the generic UF is computed as follows:

$$p_{ij} = P(a,b,c,d \rightarrow e,f,g,h) = P_{I_1ae} \times P_{I_2bf} \times P_{I_3cg} \times P_{I_4dh} \qquad \text{(Eq. 4)}$$

The single factor of the product is the transition probability of one of the 4 considered status indicators and can be computed analyzing the historical data tracing the percentages of networks that pass from one class to the other of the generic indicator during a year as a consequence of the k[th] intervention [Marchionna, 2002].

The reference database concerning the period 2000-2004 provided the necessary information to determine the probability, as described above, on the basis of the chronology and typology of maintenance intervention performed.

The variables of the optimization problem are the percentages of length of the road network Λ_r^a which are in a given risk state r, during the generic year *a* of the programming period.

If we assume that year *a* is the moment in which we plan the interventions for the following year *a*+1, the current state of the road pavement is that of year *a*, while the road pavement conditions expected as a consequence of the intervention strategy selected are those of the year a+1.

In addition we indicate as λ_{rk}^{a} the length percentage of the entire road network that in the year a is at state rth and is programmed to undergo the generic intervention k, and as λ_{rk}^{a+1} the length percentage that in the year a+1 is at state r as a consequence of the kth intervention.

The formulas are:

$$\Lambda_r^a = \frac{L_r^a}{L_{tot}} \qquad \lambda_{rk}^a = \frac{L_{rk}^a}{L_{tot}} \tag{Eq. 5}$$

Thus defined the variables of the problem, naturally we obtain:

$$\Lambda_r^a = \sum_{k=0}^{4} \lambda_{rk}^a \qquad \sum_{k=0}^{4}\sum_{r=1}^{54} \lambda_{ik}^a = 1 \qquad \sum_{k=0}^{4}\sum_{r=1}^{54} \lambda_{ik}^{a+1} = 1 \tag{Eq. 6}$$

To define the initial conditions it is necessary to compute the length quantities of the road network which are in one of the 54 risk states during year a, the year in which planning takes place. We obtain a vector $\overline{\Lambda}^a$ of dimension 54 that is made of the 54 length percentages Λ_r^a.

Within quantity Λ_r^a a component will undergo intervention 0, one component intervention 1, and another component generic intervention k and so forth, therefore for each intervention strategy we obtain the k vectors $\overline{\lambda}_k^a$ of simple percentages λ_{rk}^a:

$$\overline{\Lambda}^a = \overline{\lambda}_0^a + \overline{\lambda}_1^a + \overline{\lambda}_2^a + \overline{\lambda}_3^a + \overline{\lambda}_4^a \tag{Eq. 7}$$

which written as a matrix is:

$$\overline{\Lambda}^a = \begin{bmatrix} \Lambda_1^a \\ \Lambda_2^a \\ \cdots \\ \Lambda_{54}^a \end{bmatrix} = \begin{bmatrix} \lambda_{1,0}^a \\ \lambda_{2,0}^a \\ \cdots \\ \lambda_{54,0}^a \end{bmatrix} + \begin{bmatrix} \lambda_{1,1}^a \\ \lambda_{2,1}^a \\ \cdots \\ \lambda_{54,1}^a \end{bmatrix} + \begin{bmatrix} \lambda_{1,2}^a \\ \lambda_{2,2}^a \\ \cdots \\ \lambda_{54,2}^a \end{bmatrix} + \begin{bmatrix} \lambda_{1,3}^a \\ \lambda_{2,3}^a \\ \cdots \\ \lambda_{54,3}^a \end{bmatrix} + \begin{bmatrix} \lambda_{1,4}^a \\ \lambda_{2,4}^a \\ \cdots \\ \lambda_{54,4}^a \end{bmatrix} \tag{Eq. 8}$$

The transition conditions are represented by the equation that expresses the product of the rth column of the transition matrix of the generic intervention k for the vector $\overline{\lambda}_k^a$.

Such scalar product results in a numerical value expressing the sum of the network percentages which as a consequence of the intervention k pass from the 54 risk states in which they were during year a to the jth risk state in year a+1.

$$\lambda_{jk}^{a+1} = \sum_{r=1}^{54} (\lambda_{rk}^{a} \cdot P_k(r, j)) \qquad \text{(Eq. 9)}$$

$$\Lambda_{j}^{a+1} = \sum_{k=0}^{4} \lambda_{jk}^{a+1} = \sum_{r=1}^{54} \sum_{k=0}^{4} (\lambda_{rk}^{a} \cdot P_k(r, j)) \qquad \text{(Eq. 10)}$$

In matrix form the first of the two relations, specifically for intervention 0, becomes:

$$\begin{bmatrix} \lambda_{1,0}^{a+1} \\ \lambda_{2,0}^{a+1} \\ \ldots \\ \lambda_{54,0}^{a+1} \end{bmatrix} = \begin{bmatrix} P_0(1,1) & P_0(2,1) & \ldots & P_0(54,1) \\ P_0(1,2) & P_0(2,2) & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ P_0(1,54) & \ldots & \ldots & P_0(54,54) \end{bmatrix} * \begin{bmatrix} \lambda_{1,0}^{a} \\ \lambda_{2,0}^{a} \\ \ldots \\ \lambda_{54,0}^{a} \end{bmatrix} \qquad \text{(Eq. 11)}$$

Note that the transition matrix of the matrix product is not the $\overline{\overline{P_0}}$ of the Equation [5], but its transposed.

The vector $\overline{\Lambda}^{a}$ represents the distribution of the network percentages during the various risk states before carrying out the generic maintenance strategy s, the vector $\overline{\Lambda}^{a+1}$ represents the same distribution as a consequence of the strategy s ($\overline{\Lambda}^{a} \neq \overline{\Lambda}^{a+1}$).

The first goal function of the programming model is a measure of the danger level of the road network and represents the degree of safety and functionality of the infrastructure following the maintenance interventions selected for each basic section of the network under examination. This can be computed with the following formula:

$$\Theta = \sum_{r=1}^{54} \sum_{k=0}^{4} \lambda_{r,k}^{a+1} \cdot RS_r \qquad \text{(Eq. 12)}$$

The second goal function matches indeed the cost Cs of each intervention strategy, computed with the following formula:

$$C_S = \sum_{m=1}^{M} \sum_{k=0}^{4} L_{mk}^{a} \cdot c_k \qquad \text{(Eq. 13)}$$

where L_m is the longitudinal extension of the m[th] Functional Unit (m=1,2,…,M).
The two criteria are reasonably in contrast. In order to considerably reduce the danger level of the network it is necessary to intervene with more incisive therapies, therefore spending a bigger amount of resources. If a minor cost strategy is selected obviously you cannot solve the functionality conditions of the whole network, instead an intervention priority must be decided for those areas that present major criticality for the circulation safety.

4.4 Optimization Method: Genetic Algorithm

The calculation process of the Genetic Algorithm follows a set of elementary instructions that are applied repeatedly until obtaining convergence to a set of solutions known as the Pareto optimal front.

The original population of chromosomes, each representing a maintenance strategy, is generated randomly. The main steps of each application are:

1. Selection of a population of popSize elements using the Roulette Wheel selection procedure: once the cumulative fitness has been generated and a random number between zero and the fitness rank has been extracted from the whole population (as a sum of all the fitness), there is a selection of the individual with a fitness rank immediately below the extracted random number. This procedure is applied as many times as there are individuals in the population.
2. Updating of the population applying crossover and mutation operators.
   The first is applied after random popSize/2 selection of couples of individuals. Then the mutation operator randomly selects a gene from each string, and with a probability that depends on the rate of mutation, substitutes the value with one of five possible values (0,1,…,4).
3. Calculation of the W matrices of the percentages of road pavement that are found respectively in the various risk states and that are to undergo different maintenance interventions according to the proposed strategies.
   Matrix products are calculated to obtain the WW matrices of the same percentages expected following maintenance, and finally, risk state functions and costs for each population string are calculated.
4. Classification of the solutions according to the following dominance rules:
   $f_1(x_1) < f_1(x_2) \text{ e } f_2(x_1) \leq f_2(x_2) \quad or \quad f_1(x_1) \leq f_1(x_2) \text{ e } f_2(x_1) < f_2(x_2)$
   Dummy Fitness values are assigned which are the inverse of the rank, substituting previously obtained fitness ranks with this single value which represents a compromise of the two.
5. Adoption of fitness cut techniques using the niche method to avoid premature convergence of the genetic algorithm.
6. Calculation of the cumulative fitness using values obtained after the cut technique.

The process is repeated the same number of times as the number of generations, placing the population fitness values in a matrix entitled ‘Genetic Algorithm Results’.

This matrix includes all the solutions provided by the Algorithm throughout the various generations, from which the best or dominant solutions are selected, representing the “Pareto Front”.

In order to select the Optimum Final Strategy (OFS) from this curve, various criteria may be followed, expressed in the following relations:

$$OFS = \min[Ci] \quad \text{(Eq. 14)}$$
$$OFS = \min[\Theta i] \quad \text{(Eq. 15)}$$
$$OFS = \min[CMi] \quad \text{(Eq. 16)}$$
$$OFS = \min[Dist_i] \quad \text{(Eq. 17)}$$

with $Ci \leq B$.

Where:

$$C_{Mi} = \frac{C_i}{\Theta_{initial} - \Theta_i} \quad [\text{ € / (n°accidents x FU) }] \qquad \text{(Eq. 18)}$$

where $\Theta_{initial}$ is the danger in year *a* before carrying out any intervention, and is obtained as follows:

$$\Theta_{initial} = \sum_{r=1}^{R} \sum_{k=0}^{K} \lambda_{r,k}^{a} \cdot RS_r \qquad \text{(Eq. 19)}$$

Where:

$$\mathrm{Dist}_{\mathrm{i}} = \sqrt{\left(\frac{\Theta_i - \Theta_{\min}}{\Theta_{\max} - \Theta_{\min}}\right)^2 + \left(\frac{C_i - C_{\min}}{C_{\max} - C_{\min}}\right)^2} \qquad \text{(Eq. 20)}$$

5. ANALYSIS OF RESULTS

The model was applied by acting differently on the generation of some chromosome populations: in the case called R the starting population, made up of 100 chromosomes, was entirely generated randomly; in the other case called RE in the starting population, made up of 95 chromosomes generated randomly, 5 extreme chromosomes were inserted, these represented a strategy consisting in the same intervention on the whole network.

Every starting population was exposed to an evolutionary process according to 100, 200 and 300 iterations.

For both the procedures, R and RE, 7 starting populations were taken into account and, at the end of the iterative process, in addition to determine the Pareto’s front and the number of distinct solutions belonging to the front itself, the best solution was found according to the criterion of the minimum distance.

The results and some representative diagrams of Pareto’s front are shown in the following tables (Tables 4 and 5, Figures 1 and 2).

Finally, for each analysed case, the diagrams for n° of iterations and chromosomes of the front were elaborated, they helped to understand the quantitative evolution of the Pareto’s front. In figures 3 and 4 the diagrams related to the R300a and RE300a cases are shown.

By examining the results of the R procedure we observe as, generally speaking, after an increase of the number of optimal solutions related to the increase of the iteration number, it follows that the best solution for each case does not differ significantly from the others.

An analogous trend is found also in the RE case. In this case, the number of optimal solutions, in addition to grow significantly when the iteration number increases, shows better results, if compared with the same outcomes of the R procedure, both from a quantitative (number of distinct optimal solutions) and qualitative (chosen solution according to the criterion of the minimum distance, which is better in the RE procedure than in the R procedure) point of view.

Finally, a significant outcome is the greater rapidity, found for the RE procedure, to arrive at the number of the front solutions compared with the trend shown in the R cases, which are both displayed in diagrams 3 and 4.

In conclusion, we can affirm that the RE procedure, not completely random, seems to have more reliable performances, both relating to the results and to the rapidity of choice. Generally speaking, due to the importance of the problem we have faced, it could be considered a reliable threshold of the number of solutions equal to 300.

Table 4 Optimal solutions selected using the minimum distance criteria. Case R

Procedure	Iterations	N° of Pareto's singular chromosomes	FOS	
R100a	100	77	3.16×10^7	1.264
R100b	100	93	3.12×10^7	1.213
R100c	100	101	3.08×10^7	1.207
R200a	200	83	3.03×10^7	1.229
R200b	200	102	3.32×10^7	1.171
R300a	300	117	3.16×10^7	1.242
R300b	300	180	3.058×10^7	1.247

Table 5 Optimal solutions selected using the minimum distance criteria. Case RE

Procedure	Iterations	N° of Pareto's singular chromosomes	FOS	
RE100a	100	237	2.48×10^7	1.208
RE100b	100	395	1.96×10^7	1.316
RE100c	100	189	2.51×10^7	1.210
RE200a	200	414	2.26×10^7	1.162
RE200b	200	326	2.87×10^7	1.494
RE300a	300	252	2.94×10^7	1.426
RE300b	300	304	2.19×10^7	1.165

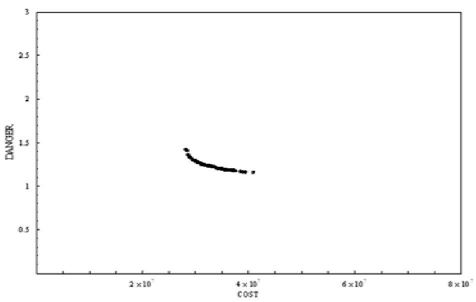

Figure 1 Pareto Front in case R300a

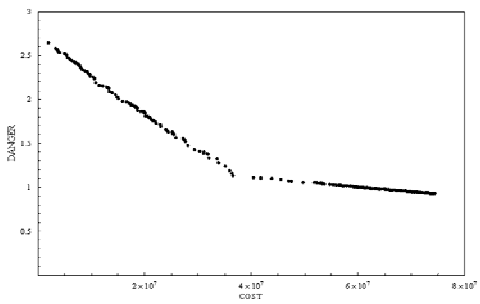

Figure 2 Pareto Front in case RE300a

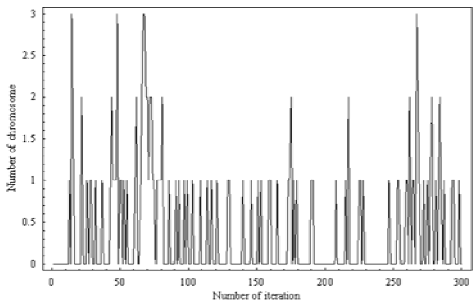

Figure 3 Number of optimal solutions corresponding to each iteration. Case R300a

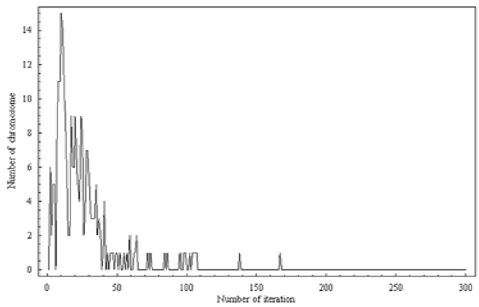

Figure 4 Number of optimal solutions corresponding to each iteration. Case RE300a

6. CONCLUSIONS

The above study resulted in the definition of a model for attribution of resources for road pavement maintenance on the A18 Messina-Catania motorway, which allows an optimal solution to the maintenance problem to be obtained.

Clear benefits were found in the use of Genetic Algorithms in searching for a set of solutions for a compromise between the objectives laid out at the beginning of this study.

The research carried out in this study is innovative in its approach to the problem, which is multi-objective in nature, since it seems that the problem that the decision-maker faces regarding maintenance work, is the divergence that exists between budget requirements and improvement of traffic safety conditions.

It was precisely for this reason that further study was carried out on the method, introducing concepts such as the Pareto optimization criteria which does indeed seem fit for the task.

The results of these formulations show that the procedure that was followed was successful, translating into perfectly identifiable specific maintenance strategies.

However, it should be noted that depending on the generation procedure and the number of preset iterations, the speed of decision and economy of time may vary considerably.

In future, further study, typically required for research of this kind, should focus on the formulation of a risk state function so that these results, already important in themselves, may become even more so.

Furthermore, from a computational point of view, in future it would be beneficial to widen the analysis by involving a greater number of like infrastructures, so as to arrive at more general conclusions.

However, for aims that are applicable in research, this analysis is held to be pertinent to the individual infrastructure, since it possesses specific characteristics, traffic condition, geometry, pavement and so on, which are unlike those of any other.

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