MANAGEMENT OF PAVEMENT NETWORK MAINTENANCE AND REHABILITATION PLANNING USING SHUFFLED COMPLEX EVOLUTION

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This paper presents an approach for optimization of segment-linked maintenance and rehabilitation plan for a pavement network by using shuffled complex evolution. It extends the works of Nunuo and Agyei (2000) by improving the exploration-exploitation balance of the algorithm and by using a realistic pavement deterioration model to solve the problem of multiple maintenance and rehabilitation activities. An example to maximize the serviceability of the road network under a fixed budget and minimum serviceability level policy is also presented. The result of the optimization process using a part of Kanagawa prefecture road network showed very good results with reasonable computational times.

[Key Words] *pavement network optimization, modified shuffled complex evolution, pavement performance model,*

1. INTRODUCTION

Pavement management systems support agencies in developing efficient policies to monitor, maintain and repair deteriorating pavements in road networks. The successful implementation of pavement management systems has made them popular among agencies responsible for managing road networks and has warranted a significant amount of research in the field of infrastructure management. The major components of pavement management systems consist of collecting and monitoring information on the current pavement condition, developing pavement performance models for predicting future pavement conditions, and programming for pavement maintenance and rehabilitation.

Pavement maintenance and rehabilitation programming at network level is understood to be a complex process, especially when it is undertaken to optimize a pavement network with multiple options of maintenance and rehabilitation under conditions of a segment linked solutions[1) 2), 3), 4)]. The complexity of programming is mainly due to the multiplication factor of the number of options upon which to select the optimum combination of maintenance and rehabilitation actions to achieve the agency's objectives. For example, if you have a pavement network of 10 segments, 3 maintenance and rehabilitation options, under a planning horizon of 5 years, there will be a total of about $3^{10*5} = 7.2\text{x}10^{23}$ possible combination of maintenance activities to be considered. Likewise, with so much information to optimize, the possibility of landing into a local optimal is very high, to handle these two complexities, a formulation that minimizes computational cost while producing global optimal results is preferable.

This paper is concerned with the development of the programming of maintenance and rehabilitation of pavement at a network level. It extends the previous research in this area into two directions, first, improving the balance between the exploration-exploitation actions in the shuffled complex evolution method by improving the initial population formulation by introducing the randomized systematic choice of the initial feasible solution, and second, using the realistic pavement deterioration model developed by the authors to evaluate the pavement condition. The earlier research[2,4] focused on simple boundary setting in initiating the initial population without paying much attention to the possibility of limiting the exploration capacity of the algorithm. In the same work, a non-realistic pavement deterioration

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model was used, in which the effect of segment characteristics to the future condition and consequently to the choice of maintenance or rehabilitation option was unrealistic.

This paper is organized as follows; first, a brief description of the pavement maintenance and rehabilitation programming is presented, second, the general information concerning the shuffled complex evolution algorithm will be presented followed by a more concise presentation of the modification done in this work, third, the use of the method will be demonstrated by an example from Kanagawa prefecture road network. Towards the end, a discussion of the results of this example will be given followed by conclusions and proposition for future researches.

2. M&R PROGRAMMING

During planning for maintenance of a road network, engineers are faced with the decision to determine which road segment to repair, when to repair, and what treatment to use. Likewise, when engineers want to plan for rehabilitation activities the same thinking is applied. However, the common practice is the combination of the two, maintenance and rehabilitation, in this respect, yet another decision will face engineers, this is, what combination of the maintenance and rehabilitation actions to use. Optimization techniques have been commonly used as aids in making such maintenance and rehabilitation management decisions. For example, Feighan et al. developed a dynamic programming model to accomplish this task[5)], Markow proposed use of optimal control theory[6)], Fwa et al. demonstrated an application of integer programming to arrive at an optimal maintenance program[7)], Fwa et al also demonstrated the use of genetic algorithm to attain the optimal maintenance plan[8)]. In 2000, Nunuo and Agyei[2)] presented an evaluation of use of shuffled complex algorithm in decision-making process of pavement management.

The optimization models can be split into five groups based on the ideas under their formulation, these include: 1) those based on heuristics, 2) those based on linear programming approaches, 3) those based on Markov decision models, 4) those which are expert systems, and 5) those built on random search techniques. Their aim is to decide how much to spend and what action to take on each of the usually large number of facilities under an organization's control, for example, stretches of road under the control of a highway authority, stretches of railway track under a railway company, and individual bridges controlled by highway or railway authorities.

Heuristic methods were first used by Jansan[9)], while Sirajuddin[10)] suggests a heuristic based on the greedy-algorithm approach, using the improvement in facility per unit of money spent for each type of repair action. The linear programming models[11), 12)], usually assume a discrete classification of the degradation states of the facility and a deterministic model of deterioration under the various maintenance and repair actions. The objective is then to find the minimum cost over a finite horizon or the minimum average cost over an infinite horizon for the whole number of facilities given certain acceptable minimum standards. Alfelor & McNeil[13)] use this model for railway track maintenance, but have to address the extra problem that it is sometimes cheaper to repair a continuous section rather than smaller non-adjacent subsections within that continuous section. Ravirala & Grivas[14)] use the goal programming extension of linear programming to cope with several objectives in a road and bridge maintenance programme.

Expert systems are increasingly used in determining how to distribute the repair and maintenance effort. Khan et al.[15)] outlined the expert system used by the Californian highway authority while Corby et al. [16)], and Harper & Majidzadeh[17)] outlined three other expert systems. Neural-network and genetic-algorithm approaches to the road-maintenance optimization problem have been developed by Fwa et al.[18), 8)]. In the works of Liu et al.[19)], the long-term maintenance cost of a network of bridges is solved using a genetic algorithm on the set of possible maintenance strategies. Razaqpur et al.[20)] on the other hand use a combined dynamic programming and neural-network approach to the same problem. The dynamic programming copes with the timing problem of when to repair and the neural net handles which bridges in the network to repair.

The above literature confirms two things, one, the importance of the programming methods and consequently the number of researches, and two, the quest to improve the results of the previous methods through decreasing computation cost as well as improving the global optimal results. With the emerging of the new techniques in the optimization fields, more researches are expected. The current research too is geared towards improving the works of the previous researchers.

Pavement maintenance and rehabilitation programming are aimed at providing with the agency information through which maintenance planning is done for short term (one year), medium term (5 to10 years) and long term (more than 10 years). Indeed, the short term or yearly plans are the most important, because they are the decisions that will be set for implementation in the immediate future. On the other hand both the medium term and long term plans do have some degree of flexibility depending on the update information of the system under analysis which, depends on the short term plan results. This importance is reflected in the way the initial population is formulated in this research.

There are common objectives of road-network maintenance and rehabilitation programming system specified by highway agencies. These include: to minimize the present worth of overall maintenance and rehabilitation expenditures over the planning horizon; to minimize road-user costs by selecting and programming maintenance and rehabilitation activities to reduce disruptions and delays to traffic; and to maintain the highest possible level of overall network pavement condition with the resources available. Therefore, the formulation of the problem is either single or multi-objective. In this research the objective is to maximize the benefit reaped through maintenance and rehabilitation actions under the constraint of the yearly budget. It is therefore a single objective formulation.

3. SHUFFLED COMPLEX EVOLUTION

The Shuffled Complex Evolution Method (SCEM) is a general-purpose global optimization program. It was originally developed by Duan as part of his doctoral dissertation work at the university of Arizona[21)]. The method has since been modified[21), 22)] to be applied to the general optimization problem, rather than the original design for hydraulic parameter identification problems. The SCEM is a hybrid of four types of optimization approaches. It consists of a combination of random and deterministic approaches, the concepts of clustering, the concept of a systematic evolution of a complex of points spanning the space in the direction of global improvement, and the concept of competitive evolution. It is largely based on a controlled random search algorithm developed by Price[23)].

Evolution algorithms are metaheuristics that emulate the process of evolution in which a population of solution is created, and new solutions are found through probabilistic combination and mutation of solutions in the population[24)]. There are many different implementations with varying rules for generation of new solutions. The SCEM expands on this concept by dividing the solution space into several complexes. New solution points in each complex are generated using Nelder Mead[25)] Algorithm reflections and contractions in combination with evolutionary methods. The addition of random search elements aids the algorithm in identifying new neighborhood of interest and escaping neighborhood of local minima. In keeping with competitive nature of evolution, better solutions are more likely to be used as parents in the creation of new solutions. New complexes are periodically formed through recombination and shuffling of all current solutions. Appendix A and B summarize the method as describe in works of Duan et al. [21), 22)].

(1) Shuffled Complex Evolution (SCE) procedure

The SCE procedure is the main framework of the SCEM algorithm. It contains all the four principles that SCEM algorithm is based on (i.e. controlled random search, competitive evolution, clustering and shuffling). The complete procedure as designed by Duan et al.[21), 22)] is represented in Appendix A, and is outlined as follows:

i) A "population" of points is selected randomly from the feasible parameter space.
ii) The population is partitioned into several complexes, each with $2n + 1$ points, where n is the number of parameters to be optimized.
iii) Each complex is evolved independently based on the downhill simplex method (Nelder Mead Algorithm).
iv) The population is periodically shuffled to share information, and new complexes are formed.
v) Evolution and shuffling are repeated until the specified convergence criteria are satisfied

(2) Competitive Complex Evolution (CCE) procedure

The competitive complex evolution procedure forms an important part of the SCE procedure [step iii)]. The CCE procedure employs the down hill search method of Nelder and Mead in generation of offspring. The procedure that is developed by Duan et al.[21), 22)] is shown as Appendix B. The Nelder-Mead Simplex is chosen because it is robust, easy to be programmed and fast. A simplex is a geometrical figure consisting, in n dimensions, of $(n+1)$ points. If any point of a simplex is taken as the origin, the n other points define vector directions that span the n-dimension vector space. Through a sequence of elementary geometric transformations, the initial simplex moves by reflection, expansions or contractions. But in the CCE procedure only the reflection and contraction processes are used. For determining the appropriate transformation, the method uses only the values of the objective function at the considered points. After each transformation, a better one replaces the current worst point.

In essence, the SCEM begins with an initial population of points sampled randomly from the feasible space. The population is portioned into one or more complexes each containing a fixed number of points. Each complex evolves based on a statistical reproduction process. Periodically, the entire population shuffled and points are reassigned to complexes to ensure information sharing. As search progresses, the entire population tends to converge towards the neighborhood of the global optimum, provided the initial population size is sufficiently large.

For an evolutionary algorithm (EA) to be successful two important facets of the search space need to be addressed, these are exploration and exploitation of the search. Exploration is responsible for sampling of areas of the search space that are likely to contain points of high fitness. Exploitation consists of extracting maximum information possible at a local level. The success of an EA run depend heavily on its achieving a delicate balance between exploration and exploitation. If the exploration power is too weak, then the population loses its diversity very quickly and the search converges to a sub optimal solution. On the other hand, if exploitation pressure is very low, the EA search behaves like a random search process [25].

Indeed the success of SCEM, which follows under EA group, depends very much on the two processes, exploration, and exploitation of the solution space. The exploration of the solution space is directly linked to the initial solution formulation and the process of choosing the initial solution to enter the exploitation stage. While the exploitation process is linked with the way the initial solution space is evolved towards the direction of global optimal solution as explained above. The SCEM as developed by Duan et al. [21), 22)], is very powerful in both the second part of exploration process and exploitation process. In essence, the important add-on to this algorithm is the initial solution formulation. Though unanimously recognized as a crucial step in EAs, initialization of population of potential solutions has not been paid much attention so far in the infrastructure programming problems[26].

The first attempt to use SCEM in infrastructure Management was done by Nunuo and Agyei[2]. In this work, except for the initial population formulation algorithm, the other parameters and algorithms as developed by Duan et al. [21), 22)] were used. In other words, in order to use the SCEM algorithm in the pavement maintenance and rehabilitation programming, one is required to develop an algorithm that creates an initial solution to be used by the two routines of the SCEM, Competitive Complex Evolution (CCE) and Shuffled Complex Evolution (SCE).

In the current research, the algorithm that creates the initial solution space was modified to improve the exploration of the pavement maintenance and rehabilitation solution space, and consequently of the SCEM algorithm. In order to explain the difference between the initial formulation and the current formulation better, the previous algorithm and areas that have been modified are explained in the next section.

4. MODIFIED INITIAL POPULATION ALGORITHM

Various population-evolution-based search strategies, including the SCEM, use random data generator to generate the initial population. As the search proceeds, the population converges toward an optimum in one of the many possible regions of attraction. If this region of attraction does not contain the global optimum, then the search converges to a local optimum. The reason for such local minimum convergence could be an insufficiently large initial population size or an initial population that is not well spread in the search space.

Thus, with the aim of having an initial population of points that are well spread in the search space, a scheme is proposed to locate the initial population points which considers the characteristics of the problem at hand. The reason for using such a generated initial population is that this increases the exploratory capability of the search algorithm, which should result in a superior balance between exploration and exploitation of the SCEM algorithm.

The optimal programming of rehabilitation and routine maintenance activities is a combinatorial problem. Indeed the solution space of the problem is very large and it depends on the initial condition of the pavement. In turn the choice of the maintenance actions in early years is controlled by the initial condition and the agency policy. In essence, the choice of the maintenance and rehabilitation actions in the initial year of programming plays a very important role in the succeeding years road condition and consequently in the choice of the maintenance or rehabilitation actions in the later stage.

In order to achieve the required exploration process, choice of the SCEM parameters that improves the ability to include as many options in the solution space was also done. The number of control parameters to the SCEM algorithm include m, the number of points in a complex, q, the number of points in a sub complex, p, the number of complexes, α, the number of consecutive offspring generated by each sub complex, and β, the number of steps in-evolution taken by each complex. Duan et al.[27] proposed a range of appropriate selection of these parameters. This current research uses this guideline to select the parameters used in the formulation as follows:

$$m = 2n \;;\; q = n+1\;;\; \beta = 1\;;\alpha = 1\;;\text{ and } p = 5.$$

Where n = number of parameters being estimated. Another key process is the initiation of the initial year action randomly.

In the present research the solution space is initiated first by randomly selecting the action to be applied in the first year of the planning horizon, followed by the systematic selection of actions governed by, from the second year, the agency's policy and pavement segment condition. **Fig. 1** shows the algorithm that creates the initial years maintenance actions. By choosing the first year maintenance action randomly we increase the chance of exploring as much as possible the large solution space of the problem. And by setting the number of points in the complex to be *2n* we make it possible for the algorithm to generate systematically the solution space using twice the complete loop of the initial solution algorithm. However, when choosing the maintenance and rehabilitation options randomly there is the possibility of landing into an option that may not meet the minimum criteria in which case the next better option is chosen as indicated in the **Fig. 1** (i.e. j= j +1).

Our work modifies the weaknesses that could be identified from the previous work in this area. A clear observation of the flow chart of the algorithm used in work of Nunuo and Mrawira [4] would reveal two things. Firstly, the generated initial solution contains a

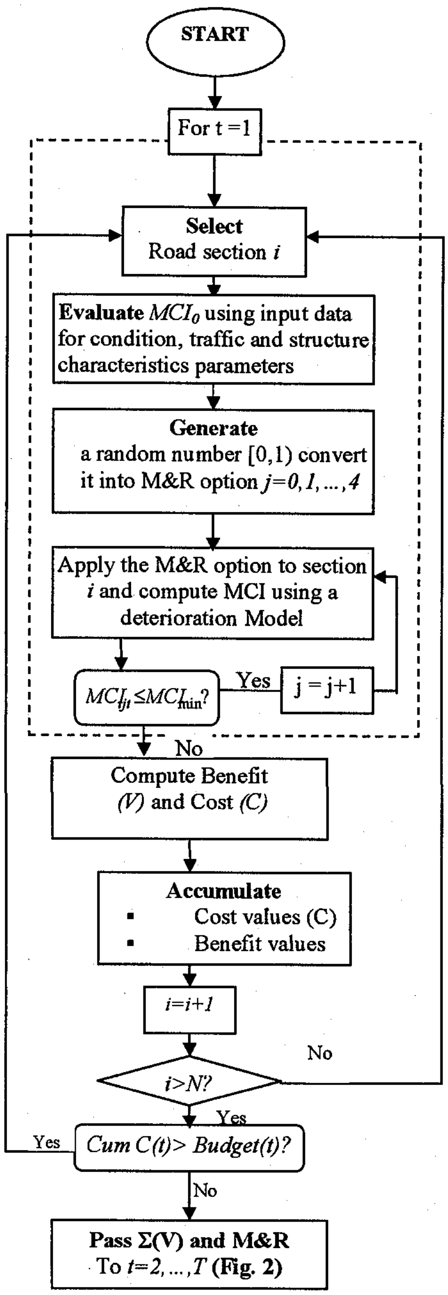

Fig. 1 Initial solution algorithm for first year

set of local minimums that are depending on the maximum pavement condition as its constraint to be included in the solution space, as such this will require many evolution runs to improve the solution and hence longer computation time. Secondly, the alternative action chosen when the initial one has failed is not correct. If the previous action causes the segment to have a larger than maximum condition, then their algorithm proposes to choose yet a bigger action which obviously will not pass the test for inclusion in the initial solution. This will cause the initial population generation algorithm to run many times to generate enough solution, and thus increase the computation time. Another key observation is that there is little possibility that their formulation will generate the whole initial solution population, which is equal to $(2n+1)*p$. This is because of the combinatorial and non-continuous nature of the maintenance and rehabilitation programming problem.

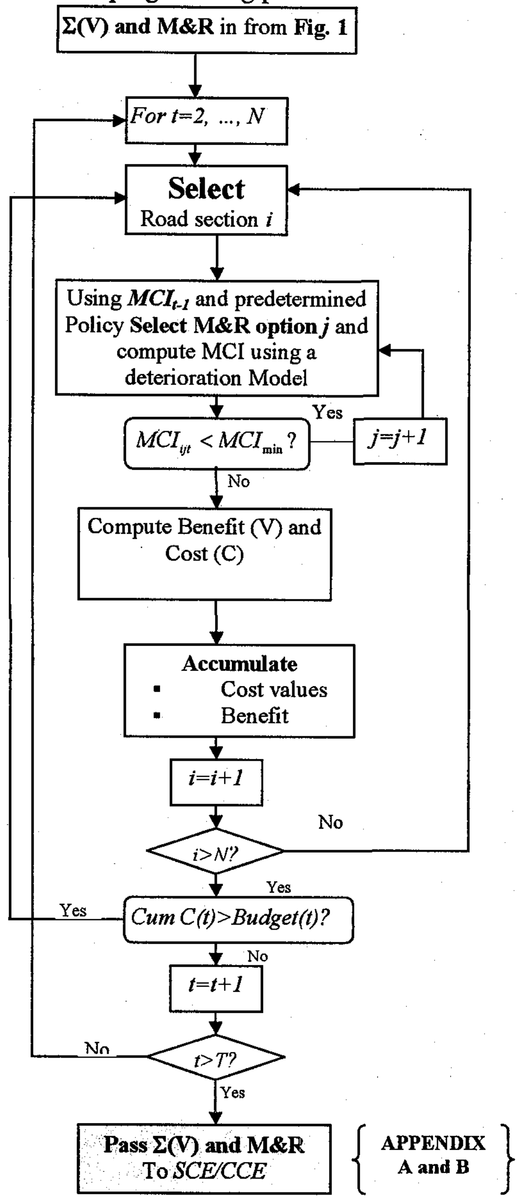

Fig.2 Initial Solution Algorithm for year *2,...,T*

However, the current research algorithm being controlled by the random number, could be run as many times as possible to generate the initial solution and the solution would be spread across the combinatorial solution space. **Fig. 2**, which generates the remaining points of the solution space from the second year until the end of the programming horizon, is a systematic algorithm. It chooses the maintenance and rehabilitation options using a pre-selected policy. In this study and in the example to be described latter, the policy is such that the program chooses the M&R

option using the following criteria: MCI $\leq$ 3.5 ="4"; 3.5< MCI $\leq$ 5.0 = "3"; 5.0 < MCI $\leq$ 6.0 = "2"; 6.0 < MCI $\leq$ 8.0 = "1"; and MCI > 8.0 ="0". This procedure reflects the actual engineering practice of maintenance and rehabilitation programming, where the medium-term and long-term plan depends on the short-term plan, in this respect the first year options.

5. SCEM FORMATION IN PAVEMENT OPTIMIZATION

The overall scheme of the SCEM algorithm as used in optimisation of maintenance and rehabilitation actions in the road network is depicted in **Fig. 3**. It has three main parts, the initial population formulation that is attained by algorithms represented in **Figs. 1** and **2**. It is then followed by a shuffled complex evolution (SCE) algorithm which has a competitive complex

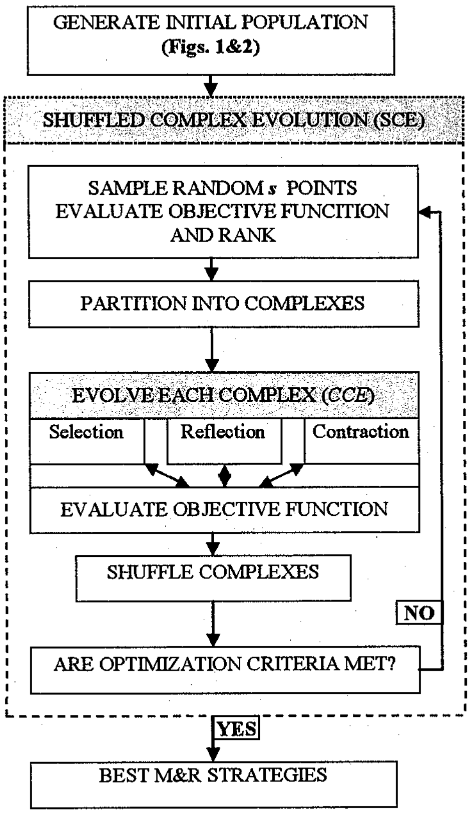

Fig.3 SCEM formation for optimisation of pavement maintenance and rehabilitation (M&R) actions

evolution (CCE) algorithm embedded in it. The algorithms SCE and CCE are coded according to the original algorithm developed by Duan et al.[21), 22)]. The SCE procedure is repeated until either of the following criterions is satisfied:

- Convergence criteria, the change of the M&R value (= benefit/cost) between consecutive runs does not exceed a chosen percentage. This percentage is chosen depending on the agents level of accuracy. It is usually between 0-10%;
- Maximum number of runs has been exceeded before convergence criteria is achieved. This is set depending on the complexity of the problem, the maximum number of runs should be set such that it is possible to have achieved convergence, it should be at least 5000.

6. DESCRIPTION OF AN EXAMPLE PROBLEM

(1) General description of the problem characteristics

The road network used to demonstrate the application and performance of this optimisation formulation consists of 30 pavement segments with length of 0.1km. They constitute a 3 km stretch of Route *129* in Kanagawa Prefecture. The characteristics and other problem formulation are shown in **Table 1**. In Kanagawa prefecture, the maintenance and rehabilitation are governed by the maintenance condition index (MCI) of the segment in question. A rough policy that is used in Kanagawa Prefecture and is proposed by the Japan Road Association[28)], suggests the following maintenance level options:

- $5 \leq MCI < 10$ - Routine maintenance;
- $3 \leq MCI < 5$ -Minor repair; and
- $MCI < 3$ -Major repair.

In this demonstrational example, minor repair was assumed to mean milling and overlay; while the major repair means reconstruction of asphalt concrete layers, and reconstruction.

Objective function of this optimisation program is to maximize the benefits that are reaped from applying maintenance or rehabilitation actions on the pavement segment during the planning horizon.

In this study, benefit is defined as the product of the improvement attained during the programming horizon as a result of applying maintenance or rehabilitation option to a pavement segment and the traffic that travels onto that section, **Fig. 3** and Equation 1 elaborates more.

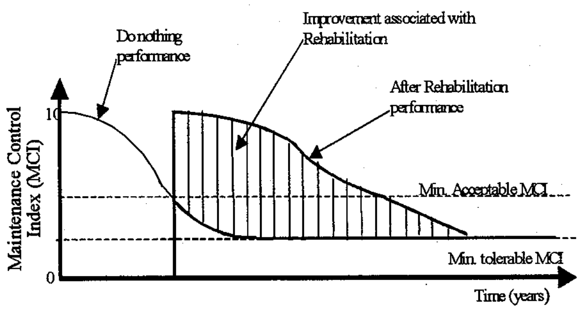

Fig. 4 schematic intepretation of M&R benefit

Benefit (V) resulting from maintenance or rehabilitation action is given by:

$V = L_i \times \Delta MCI_{ij} * AADT_{it}$ ....(1)

Where;

L_i =Length of the road section rehabilitated, i

ΔMCI_{ij} = Improvement reaped from rehabilitation, option j, for the section i (the shaded area of the curve in **Fig.3**),

$AADT_{it}$ =Annual Average Daily Traffic for pavement section i *and in year t*The complete programming formulation is expressed mathematically as follows:

$$\text{Maximize: } \sum_{i=1}^{N}\sum_{j=1}^{S}\sum_{t=1}^{T} X_{ijt} * V_{ijt} \quad \text{.......(2)}$$

Subject to:

$$\sum_{i=1}^{N} X_{ijt} < 1 \quad \text{for i = 1,2,3,..., N} \quad \text{.......(3)}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{k} X_{ijt} * C_{ijt} \le B_t \quad \text{for t = 1,2,3,..., T} \quad \text{......(4)}$$

$$X_{ijt} \ge 0 \quad \text{.......(5)}$$

Where,

X_{ijt} = section i (of N total sections) with alternative j (of k M&R alternatives) in year t (of the T total period)

V_{ijt} = present value of annual benefits of section i, with alternative j built in year t

C_{ijt} = the actual treatment cost of section i, with alternative j built in year t,

B_t = total budget for year t

(2) Parameters used

a) General parameters

The major problem parameters are summarised in **Table 1** and they contain; network parameters, pavement section characteristics planning period, traffic parameters, maintenance options, maintenance costs and effects, and rehabilitation history.

b) Deterioration model

The deterioration model used in this programming is developed as part of the pavement management system. The model is a non-linear deterministic one, it uses the maintenance control index (MCI) calculated from in-service condition survey data as its independent variable, and pavement characteristics (initial condition, structure and traffic loading) as its dependent or explanatory variables. The model is indicated as Equation 6. The parameters of the model are estimated using Kanagawa Prefecture Road Network condition survey data and are presented in **Table 2**. This model is simple in its expression, uses a simple estimation method, and readily available data, consequently reducing the cost of model estimation. It therefore, suggests a promising avenue for improving the pavement performance prediction and consequently the pavement management system. The detail of the model formulation and its estimation process are presented elsewhere.

$$MCI_{i,t} = MCI_{i,0} - (EST)^{\alpha_5}(ETL)^{\alpha_8},$$

$$EST = T_{i,0} x C_i^{\alpha_0} + \alpha_1 T_{i,1} + \alpha_2 T_{i,2} + \alpha_3 T_{i,3} + \alpha_4 T_{i,4}$$

$$ETL = \alpha_6 L_{i,\Delta t} + \alpha_7 H_{i,\Delta t} \quad \text{................(6)}$$

where,

$MCI_{i,t}$ = pavement MCI for section i at time t

$MCI_{i,0}$ = pavement initial MCI

$T_{i,0}$ = section thickness between lowest part of subbase and 2m depth

C_i = design CBR of the section i subgrade

$T_{i,1}$ = surface thickness for pavement section i

$T_{i,2}$ = bituminous base thickness for pavement section i

$T_{i,3}$ = mechanical base thickness for pavement section i

$T_{i,4}$ = subbase thickness for pavement section i

$L_{i,\Delta t}$ = cumulative light traffic since construction or reconstruction

$H_{i,\Delta t}$ = cumulative heavy traffic since construction or reconstruction

α_0 to α_8 = model parameters to be estimated

Table 1 Parameter used in problem formulation

Parameter Category	Parameter Adopted
Network parameters	
Number of road segments	10
Planning Period	
Total study period	20 years
Unit planning period	1 year
Traffic parameters	
Heavy traffic number	Number of vehicles with at least 5 tons axle load
Light traffic number	Number of vehicle with axle load less than 5 tons
Budget	
Annual budget	0.11Billion Yen
Warning levels	
Minimum MCI	MCI value=3..5
Maintenance costs	
Routine Maintenance cost	Crack sealing/patching in unit cost per m^2 of surface area (105Yen/m^2)
Rehabilitation cost	
Scrap and overlay surface layer	309.4Yen/m^{2}per unit depth of surface thickness in cm
Asphalt concrete layers reconstructed	251.5Yen/m^2 per unit depth of bituminous base plus the scrap and overlay cost
Reconstruction	177.8Yen/m^2 per unit dept of mechanical base (in cm) and the asphalt concrete layer cost

Table 2 Deterioration parameter values

P	Estimate value	
M_0	Depend on M&R action	
	Routine Maintenance	M_{t-1}+0.5
	Milling and overlay	8.6
	Asphalt layers reconstructed	8.8
	Reconstruction	9.2
α_0	1.335	
α_1	5.867	
α_2	3.515	
α_3	1.535	
α_4	0.699	
α_5	-1.431	
α_6	0.566	
α_7	2.16	
α_8	0.482	

P: parameter

(3) Results

Performance of the SCEM algorithm in this example is summarised by the convergence characteristics of the algorithm. **Figs. 5** and **6** shows the progression of objective-function value and cost values of the successive generations up to 86th generation. It can be seen clearly that the problem starts to converge to the optimum solution from 20th generation after the initial solution (i.e. generation 1), which takes about 91 minutes in a Pentium (R) 4, 2.4GHz CPU and RAM 512MB desktop computer. This is a good time for the computation of 30-segments network, 5-maintenance and rehabilitation options and planning for 20 years.

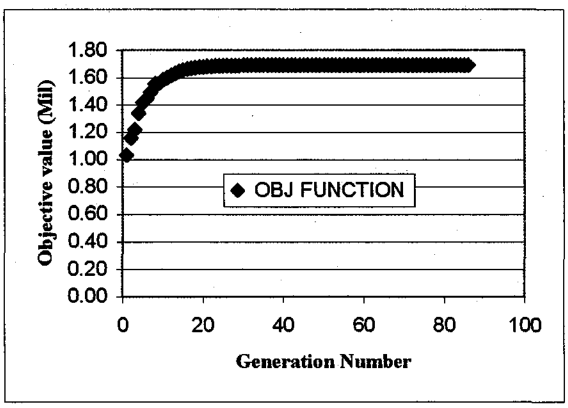

Fig. 5 Convergence progression of objective function value

Another important observation is the distribution of the maintenance and rehabilitation actions within the pavement segments and the planning horizon. The **Figs. 7** and **8** indicates the number of actions proposed in the first generation and those that were suggested in the 20th generation. It is apparent that in the first generation the number of rehabilitation suggested in each year is large compare to those that are suggested in the 20th generation. In the first generation (i.e. **Fig.7**) the results are thought to be containing some local optimal values which over the optimization looping they are changed into global optimal which in this example was achieved after 40 runs. Therefore, the 20th run is achieved after 19 stages of optimization loops. The other reason is, the first year M&R options are chosen randomly, and because the formulation of the optimization problem is based mainly on budget constraint, therefore, the possibility of getting solutions which allows the M&R options to be assigned in such a way that maximum benefits are achieved earlier on when the budget constraint is not violated is big.

The improvement that is seen to be achieved between the first generation and the twentieth generation indicates that the algorithm indeed tries to maximize benefit while minimizing the cost. And because of the consistence that has been shown by the convergence characteristics of the algorithm it can be said that the algorithm reproduces well the planning policy inputs.

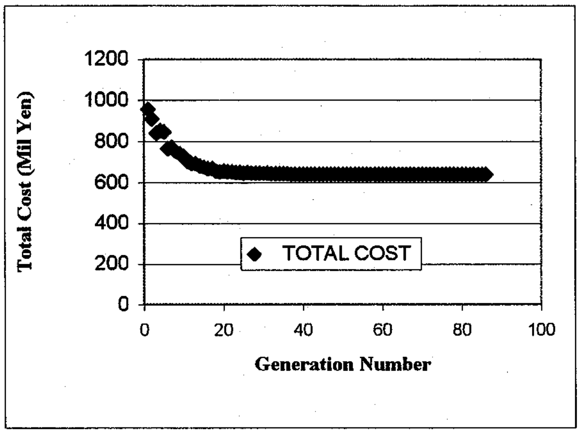

Fig. 6 Convergence progression of M&R total cost

When the results of the algorithm are looked from the view of pavement condition of the network within the planning horizon. It can be seen that the average pavement condition in the first generation is slightly less compared to the average condition of the 20th generation. While the overall pavement condition in first generation is 7.2 that for the 20th generation actions is 7.3. Although, the maintenance and rehabilitation options suggested in the first generation are with higher cost compared to those in 20th generation, the 20th generation gives a slightly better overall pavement condition. The comparison of pavement condition resulting from first generation and 20th generation are depicted in **Fig. 9**

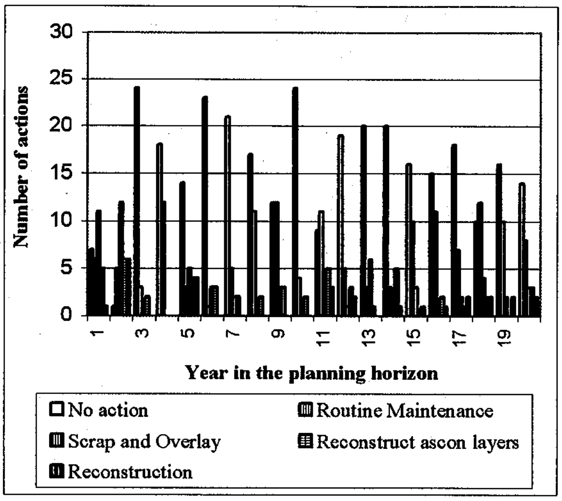

Fig. 7 Number of maintenance and rehabilitation actions suggested in 1st generation

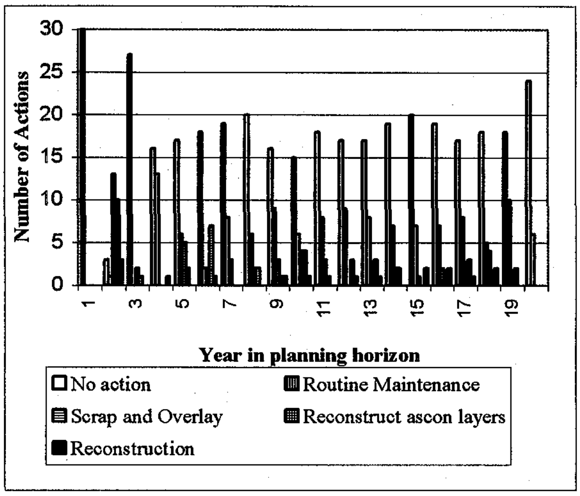

Fig. 8 Number of maintenance and rehabilitation actions suggested in 20th generation

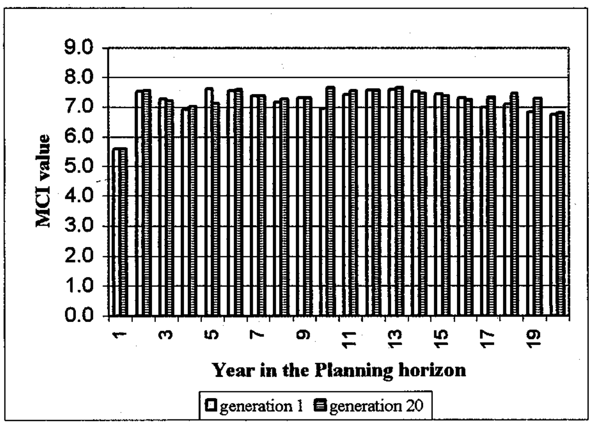

Fig. 9 Average pavement condition resulting from M&R actions suggested by 1st and 20th generation plans

7. CONCLUSIONS AND FUTURE RESEARCH

This paper presented the formulation of shuffled complex evolution method in the pavement maintenance and rehabilitation planning optimization. The importance of generating the initial solution that improves the exploration-exploitation balance of the method was shown. The random choice of the initial options was advocated and proved to be very efficient in the creation of a well-spaced population in the feasible solution space.

The demonstration example has shown that SCEM algorithm could be used to optimize the planning of maintenance and rehabilitation of a road network. The results of the example have shown good results when used to optimize the pavement maintenance and rehabilitation of the portion of Kanagawa prefecture road network. The convergence characteristics and tradeoff between the maintenance and rehabilitation indicates that the formulation is capable of handling the difficult combinatorial problem of maintenance and rehabilitation planning.

However, when looked from the users disturbance, the single objective formulation may seem to overlook the problem of traffic interruptions during maintenance and rehabilitation project implementation. In this aspect, it is suggested that, the current formulation be extended to multi objective in order to be able to include the scheduling of the actions suggested. Similarly, the current formulation seems to take long time to arrive at the converged solution. For example in the demonstration problem, only 20 generations took 91minutes. It is suggested that a further research to code the formulation so that it the competitive complex evolution may done in parallel, in order to minimize the running time.

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APPENDIX A: The Shuffled Complex Evolution Method (SCE)[21), 22)]

Initialise $p \geq 1$ (number of complexes), $m \geq n+1$ (number of points per complex), and $s = p * m$ (sample size). Let $\Omega \subset \Re^n$ be the set of feasible points

1. Generate a sample of s points from Ω assuming a uniform distribution. Evaluate $f(x_i)$ for $i = 1,\ldots,s$. Renumber the points in order of ascending function values so that

$f(x_1) \le f(x_2) \le ... \le f(x_s)$. Let $D = \{(x_i, f(x_i)) : i = 1,..., s\}$.

2. Partition D into p complexes $A^1,..., A^p$ of size m using the following equation:

$$A^k = \{(x_j^k, f(x_j^k)) : x_j^k = x_{j+p(k-1)}, j = 1,..., m\}.$$

3. Evolve each complex using the CCE algorithm found in **Appendix B**
4. Recreate D by combining all points from all complexes and order as in step 1.
5. Determine if termination criteria are met. If not, return to step 2

APPENDIX B: The Competitive Complex Evolution Strategy (CCE) [21), 22)]

Initialise integers $2 \le q \le m, \alpha_s \ge 1$, and $\beta_s \ge 1$. The parameter q determines the number of parent solutions used in each reproduction step

1. Create a triangular probability distribution for the element of A^k. Let $\Pr ob(x_i) = \frac{2(m+1-i)}{m(m+1)}, i = 1,..., m$. Thus, the point x_1^k has the lowest function value and highest probability, while x_m^k has the highest function value and lowest probability. (This distribution ensures the competitive aspect of the evolution process).
2. Sample q different points $u_1,...,u_q$ from A^k following the triangular probability distribution. Store these points in $B = \{(u_i, f(u_i)) : i = 1,..., q\}$
3.
   a) Renumber B in order of ascending function value. Compute
   $$u_g = \frac{1}{q-1}\sum_{j=1}^{q-1} u_j$$
   b) Compute $u_r = 2u_g - u_q$. (This is analogous to the reflection point in the Nelder Mead Algorithm (NMA))
   c) If $u_r \in \Omega$, compute $f(u_r)$ and go to step d). Otherwise, generate the smallest hypercube $H \subset \Re^n$ that contains A^k. Sample a point $z \in H$, evaluate $f(z)$, and set $u_r = z$
   d) If $f(u_r) < f(u_q)$, replace u_q with u_r and go to step f). Otherwise let $u_c = \frac{u_g + u_q}{2}$ and evaluate $f(u_c)$
   e) If $f(u_c) < f(u_q)$, replace u_q with u_c and go to step f). (This is analogous to NMA contraction). Otherwise, sample a random $z \in H$, compute $f(z)$, and set $u_q = z$. (This is mutation step)
   f) Repeat a) through e) α_s times.
4. Insert the member of B into A^k by replacing the q points sampled in step 2. Renumber A^k in order of ascending function values.
5. Repeat steps 1 through 4 for β_s times.

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