Ant Colony Optimization- Artificial Neural Network Technique for Backcalculation of Pavement Layer Moduli

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ABSTRACT

Backcalculation technique is used to estimate the effective pavement layer moduli from surface deflections measured using Falling Weight Deflectometer (FWD) and these moduli values are useful inputs for the mechanistic analysis and estimation of the remaining life of pavements. Number of backcalculation programs have been developed based on iterative and optimization techniques with an effort to achieve global solution((Reddy 2003)). Among the optimization techniques, Genetic Algorithms and Ant Colony Optimization (ACO) are very recent methods which have successfully been used in the past for solution of several complex problems that are known to have local minima. This paper presents an ACO-based model (BACKANT) developed for backcalculation of layer moduli for three layer pavement systems. ACO for backcalculation of layer moduli has been proved to be very effective.

INTRODUCTION

Falling Weight Deflectometer (FWD) has been popularly used for testing in-service pavements to estimate the elastic moduli of pavement layers as it is possible to simulate the field conditions compare to any other available methods. The surface deflections measured using FWD can be used for backcalculating the layer moduli often termed as effective layer moduli. The surface deflections measured using FWD along with other input data such as thickness of layers, Poisson ratios of layers, standard loading conditions are used to estimate the effective layer moduli using backcalculation program. These are moduli which, when used as inputs to layered elastic theory, produce structural responses (deflections) similar to the observed values. In ((Ullidtz and Coetzee 1995)) a detailed review of the salient features of various backcalculation programs was presented . Almost all these procedures use elastic layered theory for the analysis of pavements. Most of the backcalculation methods follow iterative approaches in which the moduli are varied in each step till satisfactory matching is attained between the known and computed deflections. The methods differ mostly in the techniques used for the selection of new set of moduli. However, most of the iterative approaches are sensitive to the initial seed moduli. The solution surface of the backcalculation problem is known to contain a number of local optima. A good backcalculation algorithm should have the ability to reach closer to the global optimum. Because of the features of the search algorithm used in them, Ant colony optimization Algorithms (ACO) are being used extensively for the solution of several complex optimization problems. Following works have backcalculation details (Shuo et al. 1996; Fwa and Chandrasegaran 2001; Shuo et al. 1998; Fwa et al. 1998; Shuo et al. 1997), This paper presents the details of an Ant colony optimization algorithm based model, BACKANT, developed for the backcalculation of pavement layer moduli from surface deflections measured using FWD. The model uses linear elastic layered theory for the analysis of pavements in its forward calculation algorithm. The working of the model has been demonstrated using hypothetical pavement problems

ANT COLONY OPTIMIZATION

The Ant Colony Optimization (ACO) metaheuristic is a relatively recent approach to solving optimization problems by simulating the behaviour of real ant colonies ((Dorigo et al. 1996)). The ACO metaheuristic models the behaviour of ants, which are known to be able to find the shortest path from their nest to a food source. Although individual ants move in a quasi-random fashion, performing relatively simple tasks, the entire colony of ants can collectively accomplish sophisticated movement patterns and can find the shortest route between their nest and a food source . Ants accomplish this by depositing a substance called *pheromone* as they move. This chemical trail can be detected by other ants, which are probabilistically more likely to follow a path rich in pheromone. This chemical trail can be detected by other ants, which are probabilistically more likely to follow a path rich in pheromone.To show how trail information can be utilized to adapt to sudden unexpected changes in the terrain, a brief example is given below (see Fig. 1). In Fig. (1 a) a colony of ants is traveling in both directions between point A and point B. Each ant knows which direction to take because of the pheromone trail that is present from point A to point E Fig. (1 a). An object is placed in the middle of the path (1 b). Since the object is not placed symmetrically on the trail, the path B-C-D is shorter than the path B-F-G-H-D. The ants that are at points B going to point D, and the ants at point B going to D have to make a decision whether to turn left or right. Since there is no pheromone in either direction, the ant has an equal probability of turning right or left. Initially the first ants turn left or right equally, which means that the same number of ants are taking the B-C-D path as the B-F-G-H-D path. The ants traveling the B-C-D path will arrive at point D before the ants traveling the B-F-G-H-D path. The ant that traveled along the B-C-D path will leave pheromone along the B-C-D path. An ant that is traveling in the opposite direction and is at point D will detect more pheromone along the D-C path, since not only are ants going from D to C, but ants are starting to arrive from C to D. On the D-H path ants are not yet arriving from the B-F-G-H-D path because it is longer than the B-C-D path. The exact same thing is occurring at point B. Therefore, probabilistically more ants will begin taking the D-C-B path. Eventually the pheromone level on the D-C-B path will be so dominant that all of the ants will choose this path as in Fig. (1 c). This will also hold true for the ants traveling from point B to D. Hence the ants, using their highly effective pheromone based communication method, are able to find the shortest path between point B and D.

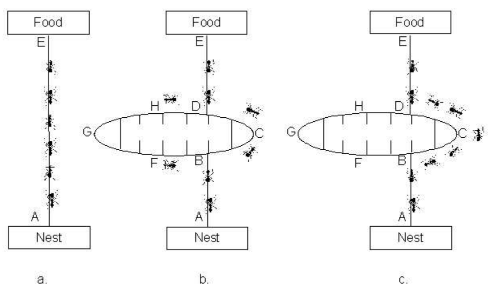

FIG. 1. Biological ants finding shortest path .

This particular behavior of ant colonies has inspired the Ant Colony Optimization meta-heuristic algorithm, in which a set of artificial ants co-operate to find solutions to a given optimization problem by depositing pheromone trails throughout the search space.

In ACO the functionality of real ant colonies is exploited in artificial ant colonies in order to solve discerte optimization problems. They are based on a colony of artificial ants i.e. simple computational agents that work cooperatively and communicate through artificial pheromone trails ((Dorigo and Di Caro 1999)) . ACO algorithms are essentially construction algorithms : in each algorithm iteration , every ant constructs a solution by travelling on a construction graph $G = (\mathbf{X}, \mathbf{L}, \mathbf{C})$, where $\mathbf{X} = \{x_1, x_2, \ldots, x_n\}$ is a set of points at which decisions have to be made, $\mathbf{L} = \{l_{ij}\}$ is a set of options (j) available at each decision point (i), and $\mathbf{C} = \{c_{ij}\}$ is the set of costs associated with $\mathbf{L} = \{l_{ij}\}$. A set of final constraints Ω $(\mathbf{X},\mathbf{L})$ may be assigned over the elements of $\mathbf{X}$ & $\mathbf{L}$. A feasible path over G is called the solution (φ) and a minimun cost path is an optimal solution($\varphi*$). The cost of a solution is denoted by $f(\varphi)$ and cost of the optimal solution by $f(\varphi*)$ ((Dorigo and Di Caro 1999)).

Once the problem has been defined in the terms set out above, the ACO procedure can be applied. The main steps in the algorithm are shown in Algorithm 1 and include:

1. Trial solutions are constructed incrementally as artificial ants move from one decision point to the next until all decision points have been covered.
2. Choose a solution component at each decision point. When solutions are generated by all the ants and iteration is said to be completed. The cost of the trial solutions generated is calculated.
3. Pheromone is updated after the completion of one iteration (t) .

Let l_{ij} denote the jth choice at decision point i .The probability that ant k chooses l_{ij} solution component at iteration t is given by

$$p_{ij}(k,t) = \frac{[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}]^{\beta}}{\sum_{l_{ij}}[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}]^{\beta}} \quad . \tag{1}$$

where for l_{ij} , $\tau_{ij}(t)$ is concentration of pheromone at iteration t and η_{ij} is heuristic factor. $\eta_{ij} = 1/c_{ij}$ is heuristic factor which favors options having smaller local costs, and α and β are exponent parameters that control the relative importance of pheromone and heuristic factor respectively.

Algorithm 1: Procedure for Ant Colony Optimization Algorithm

```
Algorithm:ACO steps
input ACO parameters;
initialize trail;
while Termination criteria not true do
    for each ant k do
        while all decision points not visited do
            find p_ij;
            add solution component;
            local trail update ;
        end
        evaluate solution;
        update iteration best solution;
    end
    global trail update ;
end
print best found solution;
```

It should be noted that the addition of the local heuristic factor η_{ij} is analogous to providing real ants with sight, and is sometimes called "visibility" ((Dorigo et al. 1996)). Artificial ants can also be provided with memory to ensure that each decision point is only visited once. After an ant chooses solution component l_{ij} , trail associated with it is decreased according to Eqn. 2.

$$\tau_{ij}(t) = (1-\gamma)\tau_{ij}(t) + \gamma\tau_0 \quad . \tag{2}$$

where γ is adjustable parameter between 0 to 1. Equation (2) is known as Local update rule (Dorigo and Gambardella 1997). This is done to promote exploration by inducing ants to visit new areas of the search space.

Once an iteration has been completed, and trial solutions have been constructed by all ants , the pheromone trails are updated in a way that reinforces good solutions. The general form of the pheromone update equation ((Dorigo et al. 1996)) is as follows:

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Delta\tau_{ij} \quad . \tag{3}$$

where τ_{ij} is concentration of pheromone associated with l_{ij} at iteration t ; and ρ is coefficient representing pheromone persistence; and $\Delta\tau_{ij}$ is change in pheromone concentration associated with l_{ij} as a function of the trial solutions found at iteration t. The pheromone persistence coefficient (ρ) has to be less than one and simulates pheromone evaporation. This enables greater exploration of the search space and avoids premature convergence to suboptimal solutions as it reduces the difference in pheromone concentration between options at each decision point. In addition, evaporation reduces the likelihood that high cost solutions will be selected in future cycles. There are many methods in the literature for calculating the change in pheromone concentration $\Delta\tau_{ij}$. In one of the first methods used in (Dorigo et al. 1996),,$\Delta\tau_{ij}$ is given by following equation

$$\Delta\tau_{ij} = \sum_{k=1}^{m}\Delta\tau_{ij}^{k} \quad . \tag{4}$$

where m is the number of ants in the colony.

The another method is Rank-based Ant system (AS_{rank}) introduced in (Bullnheimer et al. 1997). In the AS_{rank}, the solutions created by the ants are ranked according to how well they solve the problem. Then, the paths associated with the top ranked ants (a number defined by λ) are adjusted using a global update scheme. In addition to the best solutions found during a given iteration, the best solution found from all the cycles is stored as an elite solution. The intensity of trail on the paths making up the rest of solutions are not adjusted. The AS_{rank} global update process begins by computing the amount of trail to be added to the solution that represents the best solution from all cycles. The change in trail $\Delta\tau_{ij}$ is calculated as

$$\Delta\tau_{ij}^{e} = \frac{1}{f(\varphi^{e})} \quad . \tag{5}$$

where $f(\varphi^e)$ is the cost of the solution found by the elite ant. Next, the change in trail $\Delta\tau_{ij}^{\mu}$ for the ranked ants is computed as

$$\Delta\tau_{ij}^{\mu} = (\lambda - \mu)\frac{1}{f(\varphi^{\mu})} \quad . \tag{6}$$

where μ = rank a solution received between 1 and λ and $f(\varphi^{\mu})$ is the cost of the solution receiving rank m. Eqs.(5) and (6) are only applied to the l_{ij} if it is part of the ranked ants solutions. This component may be a part of more than one solution, so the total amount of trail added to the solution component l_{ij} is

$$\Delta\tau_{ij}^{r} = \sum_{\mu=1}^{\lambda-1} \Delta\tau_{ij}^{\mu} \quad . \tag{7}$$

This update rule was found to significantly improve the quality of the results obtained by the AS((Dorigo et al. 1999)) Some recent results in the literature (Stützle and Hoos 2000; Stützle and Dorigo 1999) show that ACO performs especially well when coupled with a local search routine. In local search neighbourhood of the best found solution is searched for improvements.

DEVELOPMENT OF ANN MODELS FOR COMPUTATION OF SURFACE DEFLECTIONS

The computational effort required in backcalculation algorithm is mainly for computing the surface deflections for different sets of layer moduli. In the GA-based backcalculation models, the surface deflections are, in general, computed several thousand times. Thus, any reduction in the time required for computing surface deflections will result in significant reduction in the total time. The development of ANN models for computation of surface deflections for different types of flexible pavements is discussed in the following sections of the paper. The ANN models were developed using MATLAB software (MATLAB R 12, 2000).

Artificial neural network (ANN) is an electronic model of the neural structure of the brain and learns from experience (Swingler 1996). The fundamental processing unit in an ANN is the artificial neuron, which simulates the basic functions of a natural neuron.

Feed forward back-propagation network, which is commonly used for various applications, has been adopted for the present problem. A typical back-propagation network has an input layer, an output layer and at least one hidden layer. The number of layers and the number of processing units in each layer are to be appropriately selected. Once the network is created, it is made to learn from training data consisting of a set of known input-output pairs. Training inputs are applied to the input layer and the outputs obtained at the output layer are compared with the actual outputs. The differences between the computed and actual outputs are back propagated to the preceding layers and the connection weights are adjusted in proportion to the error. Once trained, the network is tested for its performance using a test data set, which is different from the training data set. The trained and tested network can be used for computation of the surface deflection for any given set of inputs (layer moduli, Poisson ratio values, thicknesses and radial distance). Though the process of training and testing the ANN is a time consuming task, the computation of the output using a trained ANN usually takes little time. This makes the ANN a computationally effective tool for solving many complex problems. ELAYER computes surface deflection at any radial distance (measured from the center of a circular loading plate). It uses number of layers in the pavement, thicknesses, elastic moduli and Poisson ratio values of pavement layers as inputs. A standard load of 40kN acting over a circular contact area of 150mm radius is considered for analysis. This loading arrangement corresponds to the standard load applied to the pavement surface using the falling weight deflectometer (FWD).

The inputs considered in the present case are layer moduli (E1, E2,) and Poisson ratio values (1, 2, .), layer thicknesses (h1, h2,) and the radial distance (r) at which the deflection is computed. The output from the ANN model is the surface deflection of the pavement at the radial distance (measured from the center of the load) selected.

TABLE 1. Ranges of moduli and thicknesses considered for generation of data base

Pavement System	Name of the layer	Parameter	Maximum Value	Minimum Value
3-layer	Bituminous-Surface	Thickness	500	50
		Modulus	2000	400
	Granular-Base	Thickness	700	100
		Modulus	600	50
	Subgrade	Modulus)	100	20
4-layer	Bituminous-Surface	Thickness	500	50
		Modulus	2000	400
	Granular-Base	Thickness	600	100
		Modulus	600	100
	Granular-Subbase	Modulus	300	50
		Thickness	500	100
	Subgrade	Modulus	100	20

Separate ANN models were developed for three and four layer pavement systems. The networks were trained using synthetic training data generated using elastic layered programme, ELAYER (Reddy, 1993), for typical ranges of layer thicknesses, elastic modulus and Poisson ratio values. The ranges of input parameters considered for generating the training data are given in Table **??**. Poisson ratio values are considered in the range of 0.3 to 0.5. A number of hypothetical pavement sections with different combinations of pavement parameters, randomly selected using the ranges given in Table **??**, were analyzed using ELAYER program. Surface deflection was computed at a radial distance (measured from the center of the loading plate) selected randomly to lie in the range of 0 to 2000mm. The ranges of pavement parameters were selected to be representative of typical in-service and newly constructed pavements on Indian highways. The range of radial distance has been taken to correspond to the radius of typical surface deflection bowls expected under the action of a 40kN load. The loading configuration adopted for generating the data-base is shown in figure 2. A single wheel load of 40kN acting over a load contact area of 150mm radius was considered. The corresponding contact pressure is about 0.56 MPa.

Three and four-layer pavement systems were evaluated. Four thousand data sets, consisting of the input-output pairs, were generated for each type of pavement system for developing the ANNs. The inputs consisted of layer moduli, Poisson ratio values, layer thicknesses and radial distance and surface deflection was the output. Out of the 4000 randomly generated input-output pairs, 3000 pairs were used for training the networks. 500 pairs were used for validation of the network during the training process while the remaining 500 pairs were used for testing the final ANN.

A number of trial networks were trained to evaluate the performance of different network architectures. The Backpropagation training method was adopted. The transfer function used was Tansig except for the output layer where Purelin function was used. In the training process, the input-output pairs were presented to the network repeatedly. Each training iteration or 'epoch' consists of presenting each input-output pair once. The performance of the network was evaluated after each epoch. A typical training exercise might require several iterations (epochs) to be completed before satisfactory performance is achieved. The early stopping facility available in MATLAB (MATLAB R 12, 2000) was utilized. The error term, represented by the Mean Square Error, in the deflections, computed for the 500 validation input-output pairs, was monitored during the training process. The validation error normally decreases during the initial phase of training. However, when the network begins to overfit (situation arising when ANN works well only with the training data) the data, the error on the validation set will typically begin to increase. When the validation error

TABLE 2. Final network architectures selected for different pavement systems

Pavement system	Number of inputs	Network structure (*)	Mean Square Error in deflections for 500 validation data	% of deflection data within an error of	
				2%	5%
3-layer	9	9-12-1	1.732*10-5	72.6	98
4-layer	12	12-15-1	1.828*10-5	71.1	94

increased for a specified number of iterations, training is stopped and the weights at the minimum of the validation error were saved. 3-layer network architecture, with one input layer, one output layer and one hidden layer, was considered. The number of neurons (processing units) in the input layer is equal to the number of inputs. Output layer has one neuron for the single output (surface deflection) being computed. The number of neurons in the hidden layer was varied and the performance of the resulting architectures was evaluated before a final network was selected. Performance was evaluated in terms of the mean square error (MSE) term representing the differences between computed and actual surface deflections for the 500 validation examples. Details of the final ANN architectures selected for different pavement systems and their performance are presented in table 2. These architectures were selected from a number of architectures investigated for each type of pavement system. Table 2 also shows the performance of the selected networks.

The final selected ANN models were tested with the 500 test input-output pairs randomly selected out of the initial 4000 data sets generated. The performance of the models with the test data is shown in figures 4. It can be observed from the figures that the networks perform satisfactorily in predicting the surface deflection for all the four types of pavement systems considered. For each of the four systems, in only one to two cases only (out of 500 test data) the error in the computed deflection was more than 10The ANN models developed in the present study can be used for computation of surface deflection for any combination of layer thicknesses, moduli and Poisson ratio and for any selected radial distance within the ranges for which the models were developed. The only limitation of the models is that the loading considered was 40kN applied over a circular contact area applied at a pressure of 0.56 MPa. However, the deflection data available for backcalculation of layer moduli of highway pavements are usually normalized to correspond to a load of 40kN.

APPLICATION OF ANT COLONY OPTIMIZATION FOR BACKCALCULATION OF PAVEMENT MODULI

As pointed out in ((Dorigo and Gambardella 1997)) , the key to the application of ACO technique to new problems is to identify appropriate representation of the problem in graph $G=(\mathbf{X}, \mathbf{L}, \mathbf{C})$ In order to apply ACOAs to backcalculation problems, **X** is the set of variables , which is in our case is equal to the number of moduli to be calculated. The number of moduli required to be calculated is equal to the number of layers of the pavement considered . In this work 3 and 4 layer pavements have been considered. One decision point is associated with moduli of each layer. At each decision point, there are a number of options which ants can choose. The number of options are governed by the lower and upper limit of moduli and the precision required. Each choice represents the value of moduli. Number of choices(nc_i) for a variable i can be calculated as

$$nc_i = \frac{(ulimit_i - llimit_i)}{precision_i} + 1 \ . \tag{8}$$

Hence **L** becomes $\{l_{i,1}, l_{i,2}, l_{i,3}, \cdots, l_{i,nc_i}\}$ for $i = 1, 2, \ldots, nv$. where nv is the number of variables. Ants construct solutions by travelling from bottom of the pavement towards the surface. Whenever they encounter a new layer they make a decision for appropriate moduli value of that layer. l_{ij} represents the jth moduli value for ith layer . With every l_{ij} , pheromone trail τ_{ij} is associated. At iteration t , l_{ij} is chosen with a probabiity

$$p_{ij}(t) = \frac{[\tau_{ij}(t)]^\alpha}{\sum_{j=1}^{nc_i}[\tau_{ij}(t)]^\alpha} \ . \tag{9}$$

by ant k. In this way values with high pheromone trail are chosen by ants with a greater probability.

Eventually ants reach the surface after making decision for moduli value of all the layers. Moduli value for all layers make a complete solution. The cost function associated with a particular solution ($f(\varphi)$) can be calculated as

$$f(\varphi)=\sum_{i=1}^{n}(D_i-d_i)^2\ . \tag{10}$$

where, D_i and d_i are measured and computed deflections respectively and n is the number of sensors. While measured deflections are obtained from the structural evaluation of pavement using FWD, the moduli values generated in a particular solution set are used in elastic layered theory to get computed deflections. Deflections are computed using ANN based program (Williams and Gucunski 1995) **ELAYER program, which was developed for the analysis of flexible pavements based on linear elastic layered theory ((Reddy 1993)). A typical pavement structure considered for analysis using ELAYER is shown in Fig. 5 . $f(\varphi)$ represents the RMS error between the observed and computed deflections. The minimum cost path $f(\varphi*)$ is the optimal solution and has cost(RMS error) equal to zero. This corresponds to effective backcalculation of moduli and other variables if any. The problem formulation required for the optimization of backcalculation of pavement moduli is different from that used for other combinational optimization problems, such as the traveling salesman problem, in the way the cost associated with a solution component is not defined. This because cost associated for a solution can be assessed after it has been constructed in its entirety. So the set $\mathbf{C}$ is not defined for this problem. So that is why no heuristic factor η_{ij} is associated with a solution component l_{ij}. There are no constraints associated with a solution so $\Omega(\mathbf{X},L)$ is empty.

BACKANT FOR BACKCALCULATION OF PAVEMENT LAYER MODULI

BACKANT is an Ant Colony Optimization (ACO) Algorithm based program developed for the backcalculation of effective layer moduli of flexible pavements using surface deflections measured by FWD.

BACKANT can be used for backcalculating layer moduli of pavements consisting of different number of layers. Thickness and Poisson ratio of the pavement layers are used as inputs to the program. Layer thicknesses can be obtained from construction records, by cutting open the pavement crest or by non-destructive methods. Typical values of Poisson ratio, within practical ranges, can be taken for analysis without significantly affecting the layer moduli backcalculated or the critical pavement responses computed. It is possible to select different sensor configuration in this model, i.e. different number of deflection measuring sensors can be used with varying configurations (radial distances from the center of loading plate). Similarly, it is possible to select single or dual loading plate with different load magnitudes. In this system, load is transmitted to the pavement through a single loading plate of $150mm$ radius. Surface deflections are measured at six locations at radial distances (at a spacing of $300mm$).

The main objective of the backcalculation program is to select a set of layer moduli within a given range in such a way that the deflections computed using these moduli are close to the measured (known) deflections. The objective function selected is given as

$$\text{minimize}\ \ OBJ=\sum_{i=1}^{n}(D_i-d_i)^2\ . \tag{11}$$

where, D_i and d_i are measured and computed deflections respectively and n is the number of sensors. While measured deflections are obtained from the structural evaluation of pavement using FWD, the moduli values generated in a particular solution set are used in elastic layered theory to get computed deflections. Deflections are computed using ELAYER program, which was developed for the analysis of flexible pavements based on linear elastic layered theory ((Reddy 1993)). A typical pavement structure considered for analysis using ELAYER is shown in Fig. 5 .

Unlike in iterative procedures, backcalculation-using ACO does not require seed moduli. Only the lower and upper bounds of the layer moduli (range of moduli) are required. The discrete step size can be used to control the desired accuracy of backcalculated values. ACO parameters such as number of ants, number of iterations, trail importance factor α pheromone evaporation ρ are given as inputs to the program. The solution with the best objective function obtained in different generations is stored and given as the final output (back calculated moduli) along with the corresponding objective function value. It is important that ACO parameters such as number of ants, number of iterations, trail importance factor α pheromone evaporation ρ , are selected in an optimal way so that the ACO works satisfactorily for the given type of problem. Based on a study conducted for the determination of optimal ACO parameters for typical three layer pavement systems, the following ANT parameters have been selected. Flow chart for the algorithm is shown in algorithm 2.

Algorithm 2: Steps in BACKANT

input ACO parameters and pavement system;
initialize trail ;
while *Termination criteria not true* **do**
    for *each layer v* **do**
        for *each ant a* **do**
            find p_{vu} for component l_{vu};
            choose layer moduli;
            local trail update ;
        end
    end
    find cost(RMS error) for all ants;
    global trail update ;
end
print best found moduli and RMS error;

VALIDATION OF BACKANT

To evaluate the performance of BACKANT, the program was tested with a number of hypothetical and field pavement sections.

Backcalculation of Pavement Moduli for Hypothetical Sections

With hypothetical pavements, the performance of the program can be evaluated not only in terms of the closeness of the computed and observed deflections but also by comparing the backcalculated moduli directly with actual moduli. Table 7 shows the details of hypothetical pavement sections selected.

TABLE 3. Pavement systems considered

	Three layer					Four layers								
	Moduli(MPa)			Height			Moduli(MPa)				Height			
No	E1	E2	E3	h1	h2	No	E1	E2	E3	E4	h1	h2	h3
1	1500	350	50	125	500	6	1000	500	250	50	175	275	420
2	600	225	60	150	700	7	1500	500	200	65	00	250	425
3	950	350	55	150	450	8	2300	900	450	75	150	225	350
4	2200	440	80	75	250	9	1400	600	275	55	125	300	400
5	1300	300	75	110	300	10	1200	375	300	85	110	300	375

Single wheel load of magnitude 41kN acting over circular contact area of 150 mm radius was considered for the computation of deflections (refer Table7). Poisson ratio value of the first layer was taken as 0.45 while a value of 0.4 was assumed for the remaining layers.

The ranges of moduli are chosen from the regression equations developed for the estimation of layer moduli from surface deflections and thicknesses. This helps to guide the search in proper space and direction and thereby increasing the probability of reaching the global solution. Upper and lower bounds of moduli were selected using the modulus value estimated from appropriate regression equation and the corresponding value of the standard error of estimate. The moduli ranges considered for different pavement sections are given in Table 7. Precision used in the calculation of layer moduli values (discrete values) in BACKANT is given in the Table 7. Note that High, Low and Precision refer to the upper limit ,lower limit and precision for discrete values of pavement moduli.

Parameters for four layer were as follows Number of ants $m = 500$, Elitist-ants =30,Ranks for rank-based update (λ) = 30, maximum number of iterations = 100, Pheromone evaporation constant (α) = 0.5, local

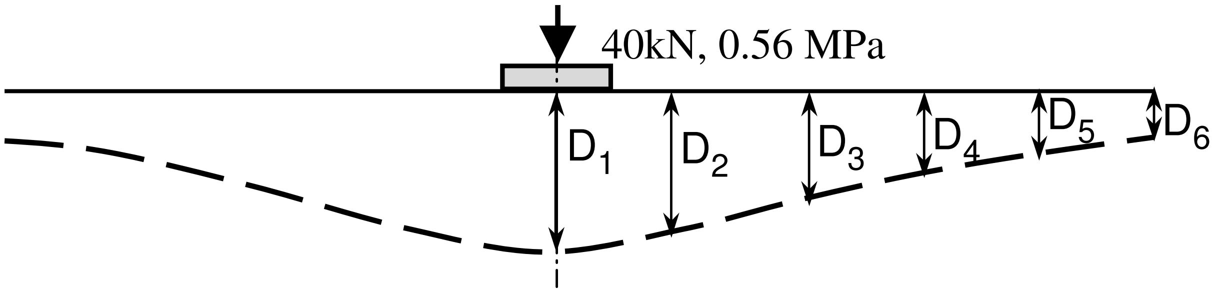

FIG. 2. Typical loading considered for analysis

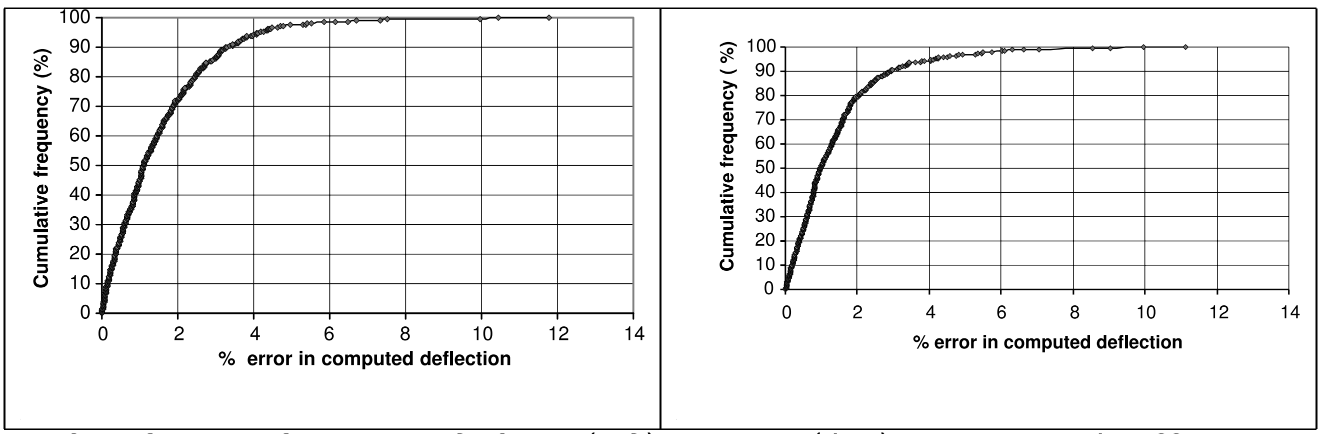

FIG. 3. Performance of ANN model for 3-layer (left) and 4-layer (right) system tested with 500 data

TABLE 4. Deflections for various pavement systems

#	Computed deflections (mm) at surface deflection of					
	0	300 mm	600 mm	900 mm	1200 mm	1500 mm
1	0.4882	0.3384	0.2612	0.2166	0.1808	0.1509
2	0.5842	0.3080	0.2195	0.1753	0.1447	0.1218
3	0.5153	0.3298	0.2506	0.2044	0.1675	0.1377
4	0.5050	0.3483	0.2292	0.1642	0.1205	0.926
5	0.5230	0.3423	0.2291	0.1671	0.1248	0.973
6	0.4394	0.2920	0.2305	0.1938	0.1638	0.1423
7	0.4838	0.3060	0.2185	0.1726	0.1383	0.1163
8	0..3016	0.2066	0.1630	0.1284	0.1109	0.0991
9	0.3937	0.2612	0.2118	0.1793	0.1508	0.1307
10	0.3869	0.2152	0.1739	0.1275	0.1037	0.0871

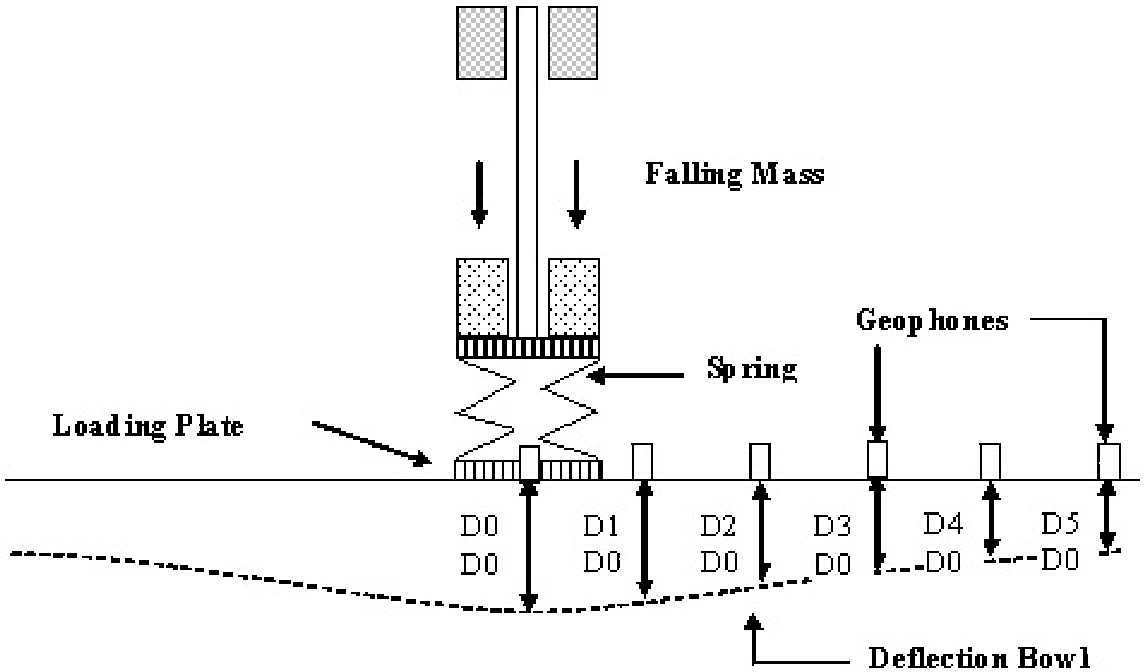

FIG. 4. Falling Weight Deflectometer.

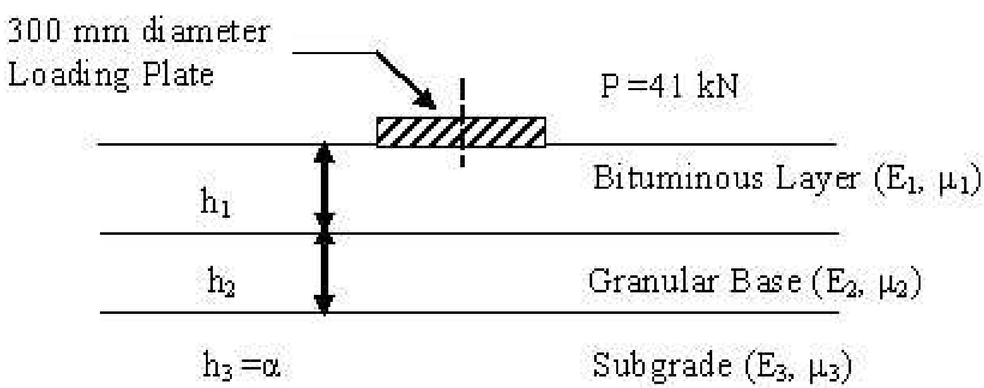

FIG. 5. Typical Structure of a Pavement considered for analysis.

TABLE 5. Ranges of pavement layer moduli considered

System	E1(MPa)		E2(MPa)		E3(MPa)		E4(MPa)	
	Low–High	Precision	Low–High	Precision	Low–High	Precision	Low–High	Precision
3 layered	400–2000	2.0	100–1000	1.0	20–80	0.5	na–na	na
4 layered	200–3500	2.0	50–1250	1.0	40–650	1.0	5–120	0.5

TABLE 6. Predicted pavement moduli for pavements in Table 7

#	RMS-ERROR	Iterations	Reqd. Eval's	E1	E2	E3	E4
1	0.0000	21	9900	1500	350	50.0	na
2	0.0004	20	9450	602	225	60.0	na
3	0.0002	28	12850	954	349	55.0	na
4	0.0000	23	10600	2196	440	80.0	na
5	0.0000	13	6300	1300	300	75.0	na
6	0.0000	30	38750	1000	500	250	50.0
7	0.0000	54	19175	1500	500	200	65.0
8	0.0000	23	30000	2300	900	450	75.0
9	0.0001	72	90875	1438	603	271	55.0
10	0.0000	20	25875	1202	375	300	85.0

update constant(γ) = 0.3, initial value of trail (τ_0) = 1, In local search number of ants was 25 and iterations were limited to 15.

TABLE 7. Results for thickness backcalculation for pavement with three layers.

#Pmvt	RMSe	Iterations	surface	base	subgrade	h1	h2
1	0.000316	74	1375.000	342.000	50.000	140.000	490.000
2	0.000592	80	575.000	220.000	60.000	160.000	700.000
3	0.000000	133	950.000	350.000	55.000	150.000	450.000
4	0.000173	32	2205.000	440.000	80.000	75.000	250.000
5	0.000000	139	1300.000	300.000	75.000	110.000	300.000

REFERENCES

Bullnheimer, B., Hartl, R., and Strauss, C. (1997). "A new rank based version of the ant system — a computational study.

Dorigo, M. and Di Caro, G. (1999). "The Ant Colony Optimization meta-heuristic." *New Ideas in Optimization*, D. Corne, M. Dorigo, and F. Glover, eds., McGraw-Hill, New York, NY, USA.

Dorigo, M., Di Caro, G., and Gambardella, L. M. (1999). "Ant algorithms for discrete optimization." *Artificial Life*, 5, 137–172.

Dorigo, M. and Gambardella, L. M. (1997). "Ant colony system: A cooperative learning approach to the travelling salesman problem." *IEEE Transactions On Evolutionary Computation*, (1), 53–66.

Dorigo, M., Maniezzo, V., and Colorni, A. (1996). "The ant system: Optimization by a colony of cooperating agents." *IEEE Transactions on Systems, Man, and Cybernetics*, 26, 29–41.

Fwa, T. F. and Chandrasegaran, S. (2001). "Regression model for back-calculation of rigid-pavement properties." *Journal of Transportation Engineering*, 127(4), 353–355.

Fwa, T. F., Tan, K. H., and Li, S. (1998). "Graphical solutions for back-calculation of rigid pavement parameters." *Journal of Transportation Engineering*, 124(1), 102–104.

Reddy, K. (1993). “Analytical evaluation of flexible pavements,” PhD thesis, Indian Institute of Technology, Kharagpur, India.

Reddy, M. (2003). “Evaluation of in-service flexible pavement layer moduli,” PhD thesis, Indian Institute of Technology, Kharagpur, India.

Shuo, L., Fwa, T. F., and Tan, K. H. (1996). “Closed-form back-calculation of rigid-pavement parameters.” *Journal of Transportation Engineering*, 122(1), 5–11.

Shuo, L., Fwa, T. F., and Tan, K. H. (1997). “Back-calculation of parameters for slab on two-layer foundation system.” *Journal of Transportation Engineering*, 123(6), 484–488.

Shuo, L., Fwa, T. F., and Tan, K.-H. (1998). “Parameters back-calculation for concrete pavement with two slab layers.” *Journal of Transportation Engineering*, 124(6), 567–572.

Stützle, T. and Dorigo, M. (1999). “ACO algorithms for the traveling salesman problem.” *Proceedings of Evolutionary Algorithms in Engineering and Computer Science: Recent Advances in Genetic Algorithms, Evolution Strategies, Evolutionary Programming, Genetic Programming and Industrial Applications (EUROGEN 1999)*, M. Makela, K. Miettinen, P. Neittaanmäki, and J. Périaux, eds. John Wiley & Sons, New York, NY, USA.

Stützle, T. and Hoos, H. H. (2000). “$\mathcal{MAX}$-$\mathcal{MIN}$ Ant System.” *Future Generation Computer Systems*, 16(8), 889–914.

Swingler, K. (1996). Morgan Kaufmann Publishers.

Ullidtz, P. and Coetzee, N. (1995). “Analytical procedures in nondestructive testing pavement evaluation.” *Transportation Research Record No.1482*, 61–66.

Williams, T. P. and Gucunski, N. (1995). “Neural networks for backcalculation of moduli from sasw test.” *Journal of Computing in Civil Engineering*, 9(1), 1–8.

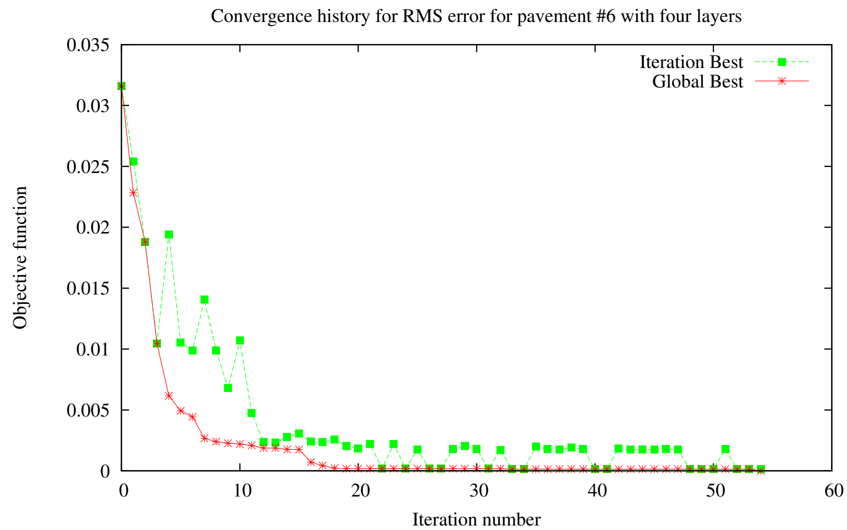

FIG. 6. Convergence of RMS error values for pavement #6.

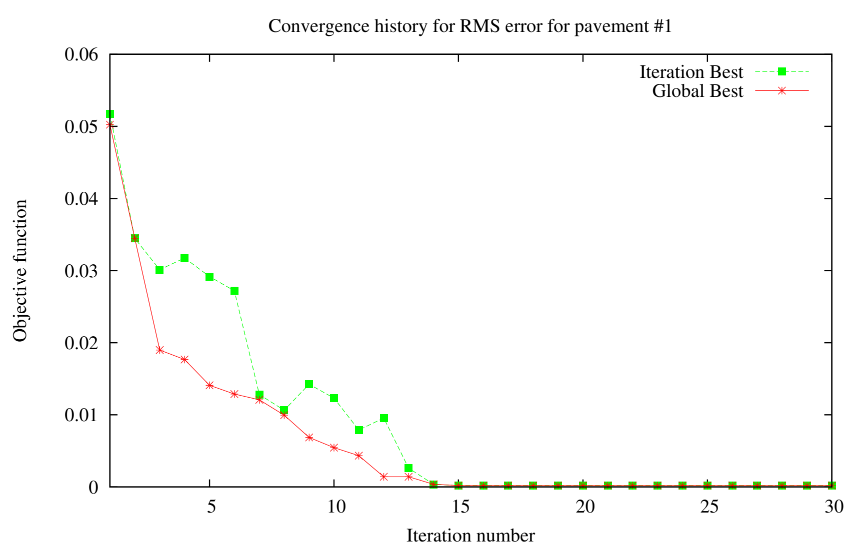

FIG. 7. Convergence of RMS error values for pavement #1.