Comparison of Termite spatial Correlation Optimization and Genetic Algorithm in Traffic signal Coordination

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***Abstract*—This article proposes a novel method for solving traffic signal coordination problem under over-saturated conditions. This problem is a large combinatorial optimization problem formulated as a dynamic optimization problem. The algorithm derives optimal green times for a network consisting of 20 interconnected signals using a recently proposed optimization algorithm called termite spatial correlation optimization (TSCO) algorithm. The algorithm tries to do so by incorporating proper queue dissipation along with maximizing number of vehicles precessed by the network in the congestion period. The resulted green times and fitness values have been compared with those derived using state of the art GA algorithm. TSCO is shown to outperform GA algorithm effectively in terms of fitness value as well as overall function evaluations.**

***Keywords*—Signal Coordination, Genetic Algorithm, Termite spatial Correlation Algorithm, Optimization.**

I. Introduction

Traffic engineering is an important optimization problem that benefits the common people in day to day life. Normally the sufficiency of size of road and limited vehicle movements poses no problem but the voilation of these conditions caused significant delays. The ever increasing volume of traffic in contemporary cities and the constraint of size of roads are not able to meet the requirements of smooth traffic flow. This has led to a very common phenomenon in current cities known as Over-saturation. Over-saturation occurs when a signalized intersection cannot process all arrived vehicles at the end of a green period; thus, a queue is developed and carried over to the next green period. If corrective steps are not taken,the growing queue blocks the intersection and reduce the capacity of intersection networks. Providing an optimal solution for the over-saturation problem is a very cumbersome task. Since all the arterials in a network are interdependent and also time dependent, the optimal selection of all the variables in each traffic cycle becomes computationally costly.

One way to solve this problem could be to renewal and expansion of the already present traffic network. But this solution results in high cost of infrastructural modifications which is not always sensible. More efficient solution would be to improve mobility and efficiency of already present traffic network. Such traffic models involves use of efficient signal coordination strategy. In last few decades various researchers have developed different signal coordination models with some more recent ones even tackling the problem of traffic-congestion/over-saturation. Such strategies generally involves maximization of vehicles processed by the queue or minimization of travel times of vehicles. The condition of over-saturation had been studied by various researchers [1], [5], [7]. Congestion was divided into two categories in form of saturation and over-saturation with saturation condition involving formation and growth of queue with a local delay effect that does not affect other intersections in the network[6].Earlier research involved development of control policies for minimization of travel costs which though worked well in under-saturated situations but failed miserably in over-saturated conditions. Later proposal [2] used blockage and queue removal as the prime objective. Further strategy is to generate a set of green times such that the vehicles processed within the network in a given time gets maximized. This involves generation of green signals such that number of vehicles released at each signal are maximized during congested periods such that queue formation is minimized [3], [4], [5]. Further offsets are generated for proper traffic progression. Testing of performance of different algorithms on a given model is necessary to find best optimization algorithm that should be applied. Luca and Putha [8] have compared Genetic Algorithm and Ant Colony optimization on a given traffic model.

The next section discusses the traffic model used in this paper. The problem formulation is describes in Section III which is followed by Section IV in which describes the algorithms used. The results and the plots are described in Section V followed by Conclusion and future work.

II. Traffic network model

This study uses base signal network problem (BSNP) as the traffic model for over-saturated network study taken from [14]. Figure 1 shows various signals present in the network and the links connecting them. Signals are coordinated along single arterial that crosses coordinated parallel arterials. The network uses a two phase plan without any kind of turning movements at all of the 20 signals (N=20). In total there are 49 links connecting these signals. Links at coordinated paths are shown with thick solid lines while those along non coordinated paths are shown with dashed lines. North-south arterial from signal 20 to 5 and east-west arterial from signal 20 to 16, from 11 to 15, from 10 to 6 and from 1 to 5 are coordinated as represented by solid lines in the traffic model figure. The two arterials

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from signal 20 to 5 and from signal 10 to 6 are assumed to carry heavy traffic of 2000 vehicles per hour per lane (vphpl). Further the arterials from signal 1 to 5, from signal 11 to 15 and from 20 to 16 enters at a rate of 1800 vehicles per hour per lane (vphpl). Traffic enters all other arterials at 1,500 vphpl.

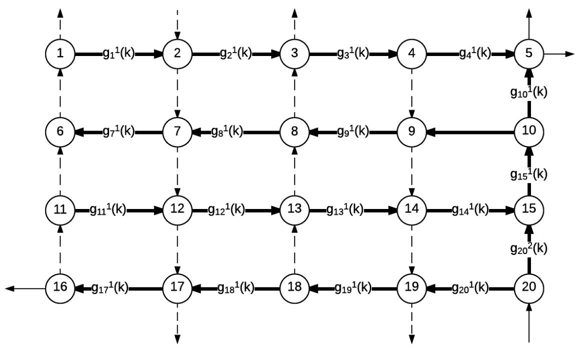

Fig. 1. One way arterials with 20 signals

III. Formulation of traffic problem

Let f_c be the network performance function or objective function as formulated in Equation 1. The function consists of two parts with first part representing number of vehicles processed by the the network and second being disutility function. Disutility function represents the occurrence of a queue on signal approaches along coordinated arterials. The main objective of this function is to maximize the number of vehicles processed by the system and minimize the queue formation at the coordinated paths. In the objective function K is the period of over-saturation in terms of number of cycles, and $D_{i,j}(k)$ is the departure flow at signal j coming from signal i at cycle k. A non-negative weighting factor, $l_{i,j}$, is the distance between signal i and j, and $q_{i,j}(k)$ is the number of vehicles in the queue approaching signal j coming from signal i at the beginning of cycle k. L_p is a set of streets carrying coordinated movements, and $\mu_{i,j}(k)$ is a positive disutility factor whose values are determined based on a queue management strategy. For this paper $\mu_{i,j}(k)$ has been taken to be 1 for all i and j in the network. The traffic problem formulation has been taken from [15].

$$max.\ f_c = \sum_{k}^{K} \sum_{i,j \epsilon L} l_{i,j} D_{i,j}(k) - \sum_{k}^{K} \sum_{i,j \epsilon L_p} \mu_{i,j}(k) q_{i,j}(k) \qquad \mu_{i,j}(k) > 0, l_{i,j} > 0 \tag{1}$$

Various constraints used in the formulation are shown in Eq. 2-12. $\phi_{i,j}(k)$ of eq. 2 represent the offset between signal i and j at the k^{th} cycle and is calculated as difference between $\tau_{i,j}(k)$ and $\alpha_{i,j}(k)$. $\beta_{i,j}(k)$ is the the time it takes for a stopping shock wave to propagate upstream. $gt_i(k)$ is green time of signal i for k^{th} cycle. $gt^c_j(k)$ is the green time of cross coordinated arterials. $ext\phi_{i,j}(k)$ is extended offset and is measure of neighboring intersection linkage over time. C_i is the cycle length of i_{th} signal and Δ is lost green time. Eq. 7 has been used to formulate lock in constraints using $N(l)$ as set of directed loop nodes, $F(l)$ as set of forward links in loop l and $R(l)$ as set of reverse links in loop l. $q_{i,j}(max)$ is the queue length capacity of the street between signal i and signal j[14]. It is calculated as $l_{i,j}/l_{veh}$, where l_veh is average vehicle length. The number of vehicles processed by the network is calculated in terms of vehicle departure ($D_{i,j}(k)$) which is formualated in eq. 11 using vehicle arrival ($A_{i,j}(k)$) and queue length ($q_{i,j}(k)$). q_{init} is initial queues in the network and s_j is the saturation flow rate.

$$\phi_{i,j}(k) = \tau_{i,j}(k) - \alpha_{i,j}(k) \tag{2}$$

$$gt_i(k) \leq gt_j(k) + \phi_{i,j}(k) + \beta_{i,j}(k) \tag{3}$$

$$gt^c_j(k) = ext\phi_{i,j}(k) + \phi_{i,j}(k+1) - [gt_j(k) + \Delta] - \Delta \qquad (i,j) \epsilon L_p \tag{4}$$

$$ext\phi_{i,j}(k) = C_i(k) + \phi_{i,j}(k+1) \tag{5}$$

$$q_{i,j}(k) \leq q_{i,j}(max) \qquad (i,j) \epsilon L_s,\ k = 1, 2, ...K \tag{6}$$

$$q_{i,j}(k+1) = q_{i,j}(k) + A_{i,j}(k) - D_{i,j}(k) \qquad j \epsilon N,\ (i,j) \epsilon L \tag{7}$$

$$gt_{min} \leq gt_j(k) \leq gt_{max} \qquad j \epsilon N \tag{8}$$

$$q_{i,j}(k) = q_{init} \qquad k = 0,\ (i,j) \epsilon L \tag{9}$$

$$D_{i,j}(k) = min \left\{ \begin{array}{c} q_{i,j}(k) + A_{i,j}(k) \\ q_{i,j}(k) + (\frac{A_{i,j}(k)}{gt_i(k)}) X (gt_j(k) - \frac{q_{i,j}(k)}{s_j}) \end{array} \right\} \tag{10}$$

Eq 2-9 represents the different constraints that has to be included in the system. The calculation of offset is dependent on the street length,the size of the queue, and the speed of vehicle which is calculated in Eq 2. τ is the time which the vehicle will take to reach from one signal to the next signal downstream , calculated by dividing the free space to the platoon speed. α is the time taken by the stopping shockwave too propagate upstream, calculated by dividing the queue length by the starting shockwave speed. The relation between the green time of i_th signal and the j_th signal is calculated by Eq 3 where i is the upstream signal. The green time of the upstream signal must ensure that the total of time required for the propagation of starting shockwave upstream (β), the offset(ϕ) and the green time of the upstream signal(gt_j),must be greater than or equal to the green time of upstream signal(gt_i), so that all the arriving vehicles may depart easily and no queue is formed. Eq 4 represents a relation in form of equality constraint which calculates the green time of the non coordinated arterials. $ext\phi_{i,j}(k)$ represents the extended offset which is the sum of offset calculated over each cycle and the cycle length denoted by Eq 5. Δ is the lost green time which indicates the time during which the intersection is not effectively utilized for any movement. For example, when the signal for an approach turns from red to green, the driver of the vehicle which is in the front of the queue, will take some time to perceive the signal (usually called as reaction time) and some time will be lost before vehicle actually moves and gains speed. The length of queue must not be more than the capacity of the arterial and this constraint is included by Eq 6, where $q_{i,j}(max)$ is the maximum length of the queue that can be accomodated in the arterial avoiding the condition of De Facto Red.De facto red exists when the signal is green but traffic cannot proceed because of backed-up traffic on a receiving street. Eq 7 shows the upper and lower bounds of the green times. In the first cycle,the queue lengths at each of the signal is assumed to be constant and is represented by Eq 8. Eq 9 calculates the number of vehicles departed in a given cycle. Under normal situtation the signal must be able to handle the incoming traffic and the number of departed vehicles must be equal to the sum of the vehicles in the queue and the number of arriving vehicles($A_{i,j}$). Under oversaturated conditions, the queue length may exceed the length of arterial and this may result in De Facto Red. To limit this only that much vehicles should be allowed to enter in the upstream arterial, which may sufficiently fill the space.

The equality constraints are included in the objective function by replacing the variables. For the inequality constraints, first we have to convert them into equality constraints them include them in the objective function as a penalty function.

$$
\begin{aligned}
max.\ f_c = &\sum_{k}^{K} \sum_{i,j \epsilon L} l_{i,j} D_{i,j}(k) - \sum_{k}^{K} \sum_{i,j \epsilon L_p} \mu_{i,j}(k) q_{i,j}(k) \\
&- \sum_{(i,j)\epsilon L_s} \sum_{k=1}^{K} \mu_1(i,j,k) |cf_1(i,j,k)| \\
&- \sum_{(i,j)\epsilon L_s} \sum_{k=1}^{K} \mu_2(i,j,k) |cf_2(i,j,k)| \\
&- \sum_{i=1}^{N} \sum_{k=1}^{K} \mu_3(i,k) |cf_3(i,j,k)| \\
&- \sum_{i=1}^{N} \sum_{k=1}^{K} \mu_4(i,k) |cf_4(i,j,k)|
\end{aligned}
\tag{11}
$$

$$
\begin{aligned}
&cf1(i,j,k) = gt_i(k) - gt_j(k) - \phi_{i,j}(k) - \beta_{i,j}(k) \\
&cf2(i,j,k) = q_{i,j}(k) - q_{i,j}(max) \\
&cf3(i,k) = gt_i(k) - gt_{max} \\
&cf4(i,k) = gt_{min} - gt_i(k)
\end{aligned}
\tag{12}
$$

In the traffic network model two arterials (from signal 20 to signal 5 and from signal 10 to signal 6) are assumed to carry heavy traffic with a flow rate of 2000 $vphpl$ (vehicles per hour per lane). Arterials at other coordinated paths are assumed to have a flow rate of 1800 $vphpl$ with those at non-coordinated paths are assumed to have a flow rate of 1500 $vphpl$. For coordinated paths gt_{max} is taken to be 90 sec and gt_{min} is taken to be 30 sec. Compared to this at non coordinated paths gt_{max} is taken to be 60 sec and gt_{min} as 20 sec. Effective vehicle length is 25 $feet$ with a speed limit of $40 feet/sec$ and vehicle acceleration of 4 $feet/sec^2$. q_{init} or initial queues are assumed to be 20 vpl (vehicles per lane) with each arterial having 2 lanes. Starting and stopping shock wave speeds are taken 16 and 14 $feet/sec$. Number of cycles (K) is taken to be 15.

Eq. 11 and 12 represents the overall objective function formulation including the constraints. The values of the various penalty factors($\mu_1, \mu_2, \mu_3, \mu_4$) depends on the values of the corresponding penalty functions which is represented below:

$$
\begin{aligned}
\mu_1 &= 10 \quad if \quad cf1(i,j,k) > 0, \quad else \quad 0 \\
\mu_2 &= 10 \quad if \quad cf2(i,j,k) > 0, \quad else \quad 0 \\
\mu_3 &= 100 \quad if \quad cf3(i,j,k) > 0, \quad else \quad 0 \\
\mu_4 &= 100 \quad if \quad cf4(i,j,k) > 0, \quad else \quad 0
\end{aligned}
$$

A. Flowchart

The flowchart of the implementation of the objective function is given below. The output of the precess of the fitness of the solution generated. The fitness is passed in the optimization to generate the new set of the solutions. Here two benchmark optimization algorithms, Genetic and Termite Spatial Correlation are applied and their results are being compared.

IV. Algorithms used

A. Genetic Algorithm

Genetic Algorithm is an optimization technique for global non-linear optimization[10][11]. All you need to supply is a way to represent your solutions and a "fitness function" that measures how good the solutions are. In computer science, lower fitness traditionally means better in minimization problem. A maximization problem can be converted into minimization problem by putting negative sign at the objective function. In pseudo-code the algorithm works like this:

1) Create a population of random solutions
2) Pick a few solutions and sort them according to fitness
3) Replace the worst solution with a new solution, which is either a copy of the best solution, a mutation (perturbation) of the best solution, an entirely new randomized solution or a cross between the two best solutions.
4) Check if you have a new global best fitness, if so, store the solution.
5) If too many iterations go by without improvement, the entire population might be stuck in a local minimum (a small hole, with a possible ravine somewhere else). If so, kill everyone and start over at 1.
6) Else, go to 2.

In step 2 the method of selection used is tournament selection. In this process, a group of individuals are selected randomly from the population and they are allowed to compete against each other. The most fit solution is allowed to

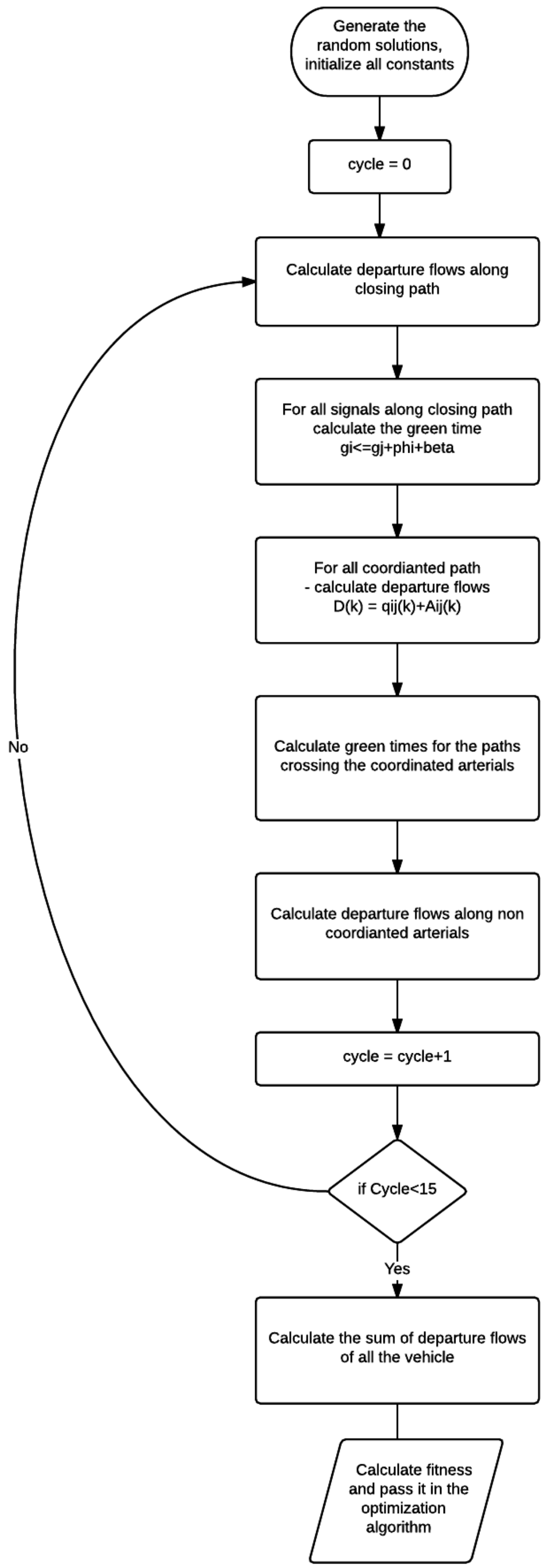

Fig. 2. Flowchart for implementation of objective function

reproduce. The population size selected here was 1000. The tourney size selected here is 10. The number of solutions that compete for the privilege of getting an offspring. A lower value means slower convergence, but lower than 3 would be silly. The function was evaluated for 20000 iterations.[9]

B. *Termite spatial correlation optimization (TSCO) algorithm*

TSCO algorithm is a recently proposed heuristic optimization technique inspired by step/spatially correlated movement exhibited by individuals of a termite colony. Implementation of this algorithm is similar to that of GA as this algorithm also requires a fitness function similar to that required by the GA algorithm. The algorithm can be implemented as follows:-

1) Initialize termite population randomly within the solution space.
2) **Attribute update phase**: This phase involves updating various attributes like fitness, past velocities, correlation coefficients, best position and best fitness of each agent in the swarm such that these attributes can be used in the later phases of the algorithm.
3) **Replacement and mutation phase**: For this phase bad performing agents are killed and replaced with new agents by initializing them according to attributes of surviving agents in the swarm and mutating them.
4) **Swarm update phase**: This phase involves updating each agent's velocity and position in the search space so as to be used in the next iteration.
5) If desired solution not found go to step 2.

Size of the population was taken to be 40 and the function was evaluated for 1000 iterations. The number of killings is taken to be 10% (4). For each killed termite 5 other termites have been randomly chosen from remaining population as parent termites to initialize the replacement termite.

V. Results and Discussion

The cycle times of the different signals were calculated according to different optimization algorithms, namely Genetic and Termite spatial correlation algorithm. It can be clearly seen that the cycle lengths along all the arterials follow the reference signal i.e. signal 20, along the northbound and the eastbound signals. Fig 3 and Fig 4 shows the cycle times calculated by GA and TSCO along the closing path of the signals 5,10,15 and 20 respectively. It can be easily inferred that the offset in the cycle times calculated by GA is more than TSCO. This means the vehicles have to wait more at the intersection in the green time calculated by GA than TSCO. Fig 5 and Fig 6 are the plots of the cycle times of signals along eastbound arterial 20,19,18,17 and northbound arterial 2,7,13,17 respectively calculated by TSCO. Fig 7 and Fig 8 compare the convergence plots of GA and TSCO. It can be easily seen that TSCO has better convergence than GA. As depicted by fig 7 and 8 the total function evaluations taken by GA are much higher in comparison to TSCO as each iteration of GA takes 1000 function evaluations in comparison to 40 as taken by TSCO. Further TSCO has been evaluated for just 1000 iterations as compared to 20000 iterations as taken by GA algorithm. This clearly proves the efficiency of TSCO algorithm in solving oversaturated signal coordination problem.

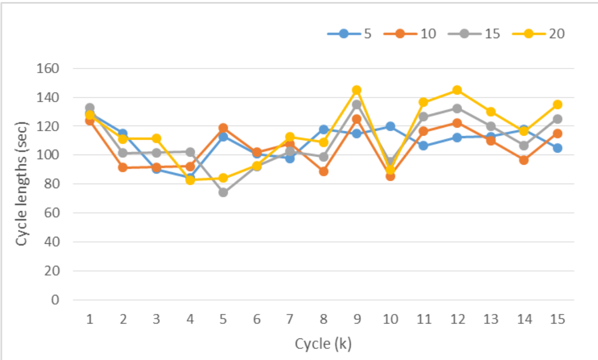

Fig. 3. Cycle times obtained by GA for signal 5 to 20

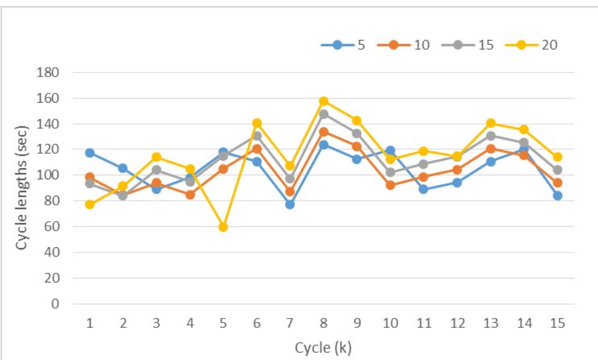

Fig. 4. Cycle times obtained by TSCO for signal 5 to 20

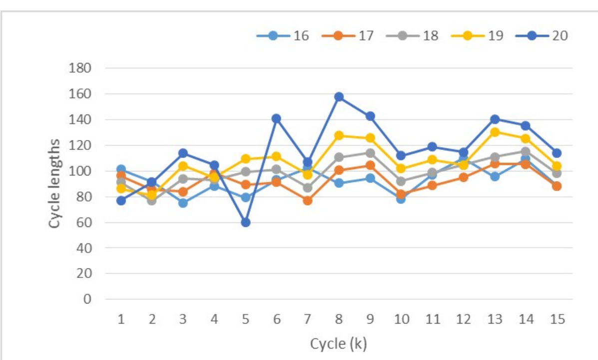

Fig. 5. Cycle times obtained by TSCO for signal 16 to 20

VI. Conclusion and Future Work

Traffic congestion occurs when the queue length at the intersection exceeds the capacity of the street. This blocks the traffic coming from the upstream signals. There is utmost need of developing an efficient algorithm for handling this situation

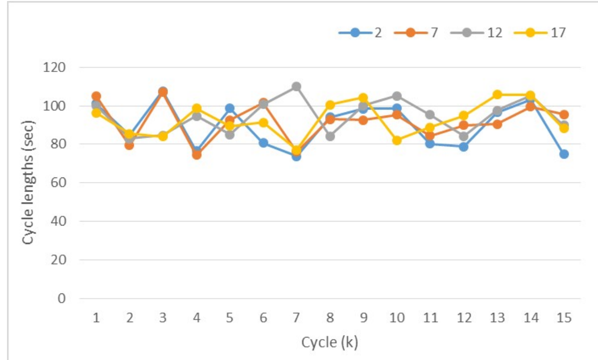

Fig. 6. Cycle times obtained by TSCO for signal 2 to 17

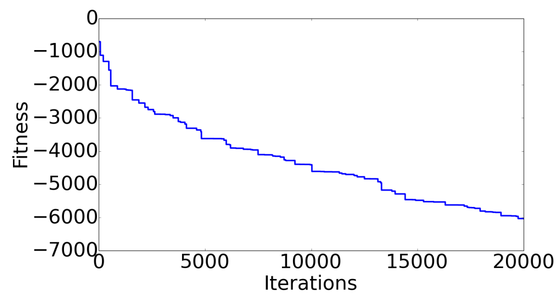

Fig. 7. GA convergence curve

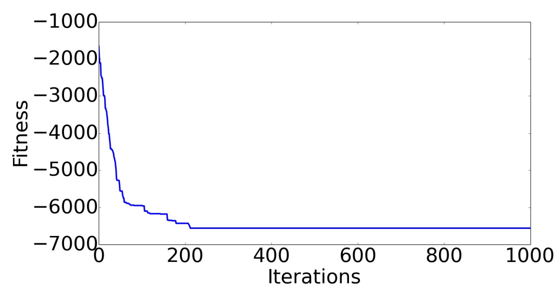

Fig. 8. TSCO convergence curve

with increase in urban development. This paper compares the two algorithms on a benchmark optimization problem of traffic signal coordination under over-saturated conditions. In this paper it was easily found that TSCO algorithm performance is better than the traditional GA with tournament selection as it requires less number of function evaluation than GA. This problem can be further be analysed by application more number of different optimization algorithms. A real time traffic model can be included which can have all the arterials as coordinated arterials. For decreasing the time complexity parallel computing for function evaluation can also be done. Many similar type of problems also exists like data routing in communication and air traffic control etc. These techniques can also be applied to such problems also.

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