OPTIMIZED TRAVELING SALESMAN PROBLEM USING ESTIMATION MAXIMIZATION TECHNIQUE

D.Nithya,
Master of Computer Science Engineering,
Department of CSE,
K.S.Rangasamy College of Technology,
Tiruchengode,
TamilNadu ,India.
637 209.
d.nithyacse@gmail.com

Dr.B.G.Geetha,
Professor and Head,
Department of CSE,
K.S.Rangasamy College of Technology,
Tiruchengode,
TamilNadu ,India.
637 209.

ABSTRACT

Traveling salesman problem (TSP) is an NP hard problem in combinatorial optimization problem and has a major thrust in real world issues such as logistics, genetics, telecommunications and neuroscience. This work presents, Highly Optimal Maximum Likelihood Estimation (HOMLE) algorithm to restrict search space on more. The dynamic traffic conditions evolved best tour travel plan. Prior knowledge of traffic scenario is used to reduce computational complexity with sub-optimal algorithm. Iterative sub-optimal prior traffic data refines optimal algorithm search space and identify multi-path tour plan with required accuracy. Experimental evaluation is made with various benchmark cited city routes for analyzing HOMLE algorithm. Performance of HOMLE is measured in terms of Total Time for tour visits, Distance of the best tour, Accuracy of Optimal MLE and Traffic congestive ratio.

Keywords: *Traveling salesman problem (TSP), Markov decision process, Optimization, Maximum Likelihood*

I.INTRODUCTION

The traveling salesman problem (TSP) has a long history of capturing the interests of researchers, in large part because of its usefulness in modeling a variety of important real-world problems (e.g., problems in logistics, genetics, manufacturing, telecommunications, and neuroscience) and because of a myriad of intellectual challenges. The definition of the TSP as follows: Given a set of cities along with the cost of travel , the TSP is to find the cheapest way of visiting all the cities and returning to the starting point, where the order of the cities to be visited is called a tour (or circuit) and the cost of travel between each pair of cities is stationary and deterministic. In reality, for pick up and delivery (PUD) in an urban environment, travel times can unpredictably change and hence are reasonably modeled as random variables. Additionally, information technologies that sense traffic conditions in real time can provide data that permit dynamic tour determination, the real-time construction of the tour as the trip progresses based on real-time traffic congestion data. We call the problem the dynamic TSP (DTSP).

The traveling salesman problem is a prototypical NP-complete problem: easy to state, difficult to solve. In this work, the traveling salesman problem is considered in which a foreigner, starting from his home city, is to visit India in a given list and then return home. The challenge of the TSP is to find the visitation order that minimizes the total distance traveled. The TSP problem has been approached by both exact and heuristic or probabilistic methods. Exact methods include cutting planes, branch and bound, and dynamic programming. However, due to the fact that TSP is NP complete, without specialized problem reduction, exact methods are able to solve only small problems. On the other hand, heuristic and probabilistic methods are able to solve large problems. Examples of the latter methods include 2-opt, Markov chain, TABU Search, neural networks, simulated annealing, and genetic algorithms. But these methods need not suitable with difficult computational challenge and issues happened in solving realistic size of traffic vehicle. Also multifold search space is increased because of congestive traffic situation.

To conquer these issues, Highly Optimal Maximum Likelihood Estimation (HOMLE) algorithm is presented to restrict search space. Prior knowledge of traffic scenario is used to decrease computational difficulty with sub-optimal algorithm. Iterative sub-optimal prior traffic data refines optimal algorithm search space and identify multi-path tour plan with required accuracy.

II.LITERATURE REVIEW

The deterministic TSP and its variants have been widely investigated [1]. But, there has been limited investigation on solving the TSP problem with stochastic travel times. Research in [2] examined the stochastic TSP with time windows (STSPTW) comprising stochastic travel and service times. To request a least-cost tour while meeting the service necessities for every customer, they proposed a technique to approximate means and variances of arrival times at every node and after that offered an approximate algorithm to decide the least-cost STSPTW tour based on an approximate of arrival time at every node.

Study in [3] proposed a heuristic method for the STSPTW having rigid time windows. For most preceding research, we examine that the travel time random variables on every arc are frequently assumed to be random variables, and it has been a general method to estimate travel times to manage the difficulty caused by the stochastic travel time assumption.

Research in [4] introduced a VRP with time-dependent travel speed that convinces the first-in–first-out property. In [5] developed a genetic algorithm for the VRP having a incessant travel time function and proposed a approach to adjust the vehicle route at certain times in the planning horizon based on recently available traffic or demand information.

Research in [6] concentrates on seeking an optimal policy (not an a priori tour) that is dependent on presently observed network status in a stochastically developing network. To the best of our knowledge, there have been only a few studies regarding tours that dynamically alter depending on network status. Research in [7] observed that the dynamic adjustment of a tour in transit based on up-to-date travel time information can decrease the expected travel time and, hence, can reduce total costs.

Recently, authors in [8] have performed a case study whose objective is to determine the subset of fixed routes in a highway network based on real-time traffic information to bring maximal benefits of traveler information systems and modeled the problem with a nonlinear integer programming technique. Stochastic routing problems and their variants have been studied in [9] and [10]; however, this research does not address dynamic tour determination in a stochastic network.

In [12] assumes that traffic congestion dynamics are governed by a discrete-time Markov chain. Research in [11] investigated the application of graph heuristic search algorithm, AO*, to a stochastic shortest path problem with random and time-dependent travel times.

III. OPTIMIZED TRAVELING SALESMAN PROBLEM USING ESTIMATION MAXIMIZATION TECHNIQUE

In this section, present Highly Optimal Maximum Likelihood Estimation (HOMLE) algorithm. HOMLE algorithm provides better solution for Dynamic Traveling Salesman Problem. Dynamic traffic prior knowledge is utilized to arrive sub-optimal algorithm. The main purpose of HOMLE (fig. 1.1) is to evaluate value and variance of real-time traffic data and to design dynamic tours and management capability of DTSP. It reduces computational complexity. The iterative sub-optimal prior traffic data refines optimal algorithm search space and identify multi-path tour plan with required accuracy. HOMLE improves the search space to realistic traffic vehicle sizes and minimizes computational time of tour plan derivatives. It increases more optimal tour (foreigner visit India with low search cost) on high varying traffic conditions and avoid congested traffic data with prior knowledge on trained traffic tour plans.

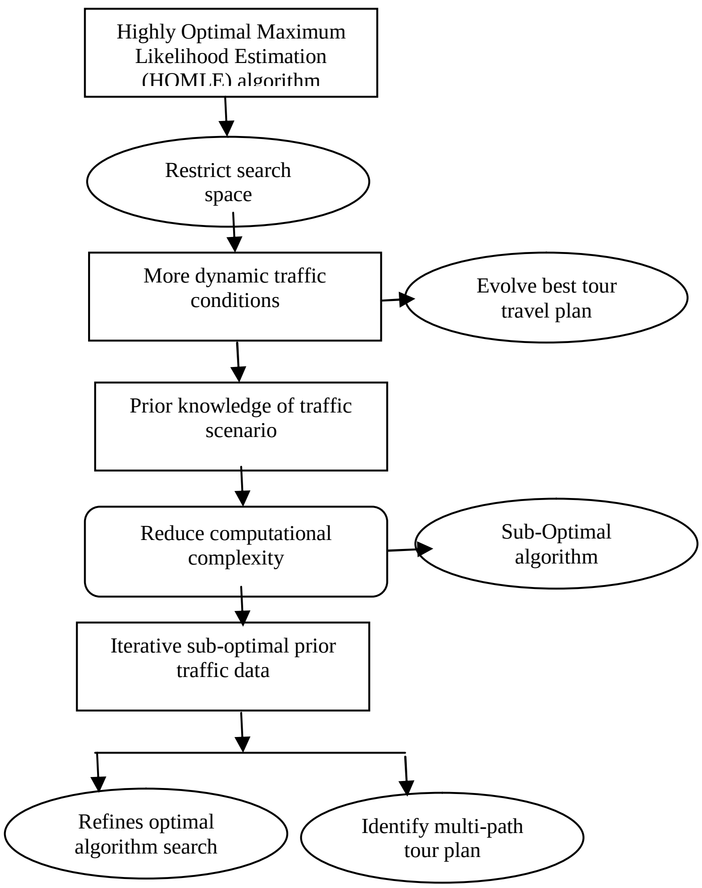

Fig. 1.1 Highly Optimized Maximum Likelihood Estimation Technique

Highly Optimized Maximum Likelihood Estimation (HOMLE) Technique involves five important concerns to control search space for foreigner to visit India with minimal search cost.

- Dynamic Touring Requirements
- Congestive Traffic Scenario
- Markov decision process for DTSP
- Maximum Likelihood Estimation (MLE)
- Optimization of Touring Plan
- Optimized MLE Performance of Touring

The process initially starts with Dynamic Touring Requirements. In this process, Traveling salesman initially has expected places to visit for client meetings. On course of few meeting the tour plans may change. So, they need to address various dynamic tour plans. Initial route plan as per preliminary need unable to suit the varying demands of time schedule and client call postpone or prepone. Once Dynamic Touring Requirements are specified, Congestive Traffic Scenario is initialized. In this scenario, Commercial tour schedule did not include the traffic congestion delay time.

In different areas tour time varies based on the peak congestive time slot travel. Time modeling approach function must satisfy destination reaching condition. The travel time data is derived from modern traffic information systems and implemented time-varying travel times in various vehicle-routing models. Computational tests with travel time data are made from traffic information system.

The time-minimizing vehicular movements are estimated and analyzed in road network where link speeds vary over time. Traffic network conditions recognize intrinsic relationship between speed and travel duration and arrival substantiated by elementary methods to obtain link travel duration.

A. Dynamic Touring Requirements

Traveling salesmen initially have expected places to visit for client meetings. On course of few meeting the tour plans may change. Needs to Address various dynamic tour plans. Initial route plan as per preliminary need unable to suit the varying demands of time schedule and client call the varying demands

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B. Congestive Traffic Scenario

Commercial tour schedule did not include the traffic congestion delay time. In different areas tour time varies based on the peak congestive time slot travel. Time modeling approach function must satisfy destination reaching condition .Derivation of travel time data from modern traffic information systems. Implement time-varying travel times in various vehicle-routing models. Computational tests with travel time data are made from traffic information system. Analyze estimated time-minimizing vehicular movements in road network where link speeds vary over time.

C. Markov decision process for DTSP

The markov decision process (MDP) is described by Graph with number of nodes and distance matrix is formed between any two nodes. Two node indicates starting point (home city of foreigner) to end point (India). It determines circuit of minimum total distance passing each node once. Shortest path is calculated by passing once at each node. MDP is based on time at which decision is made. Set of decisions epochs at which decision is made. Set of decisions epochs are initialized either discrete or continuum. Set is finite or infinite (horizons).At each decision epoch DTSP occupies a state. The set of all possible system states is represented by S. The set of allowable actions in state S is represented by As.

$A = \cup_{s \in S} As$: set of all possible actions

S and As can be finite sets, countable infinite sets and compact sets.

D. Maximum Likelihood Estimation (MLE)

In Maximum Likelihood Estimation (MLE), a tree is chosen which maximizes the probability that observed data would have occurred. All possible topologies are generated by MLE. MLE uses the lengths of the edges that maximize the likelihood. It conditions. MLE evolves best tour travel plan and reduce computational complexity with sub-optimal algorithm. Iterations of sub-optimal traffic data analysis arrive MLE and arrives optimal search space. It identifies best tour plan with minimum one visit off all the required location to be visited. In Maximum Likelihood Estimation input is taken as, a set of unaligned tour visit cities sequences and output is produced as a tree with a minimum score. The Error checking is performed by MLE. The tree is correct if each distance is no greater than x/2,where x is the length of the shortest edge in the tree.

E. Optimization of Touring Plan

Let p* = {m*0, ..., m*N-1} be an optimal policy for the basic problem for the N time periods. Then truncated policy {m*i, ..., m*N-1} is optimal for the sub-problem minimization of the cost from time i to time N by starting with state xi at time i. Assume S is finite or countable, and that As is finite for each $s \in S$. Then there exists a deterministic Markovian policy which is optimal. By using HOMLE technique Optimal value is determined for the touring plan.

F. Optimized MLE Performance of Touring

Performance of optimized MLE are measured in terms of Number of cities,Tour visits,Total Time for tour visits, Distance of the best tour, Accuracy of Optimal MLE, Error variance of Optimal MLE, Traffic congestive ratio, Delay time on congestive routes.

IV.PERFORMANCE RESULTS AND DISCUSSION

In this section experimentation is conduced and the performance of HOMLE is evaluated. Here, we now analyze the reduction of the expected total cost due to dynamic tour determination (Foreigner visit India from his/her home city), relative to the expected cost accrued by fixed tours. The value of using real-time network information is the difference between the expected cost generated by the fixed tour and the expected cost generated by an optimal dynamic tour. Performance of optimized MLE are measured in terms of Number of cities, Accuracy of Optimal MLE, Error variance of Optimal MLE, and Delay time on congestive routes.

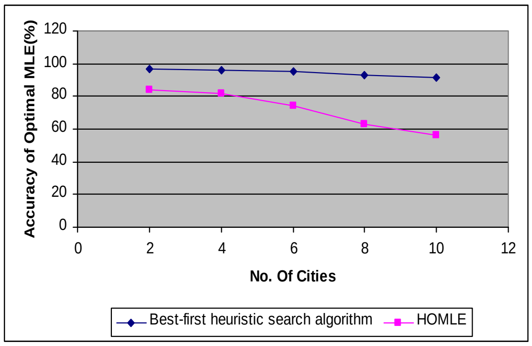

Figure 4.1 Accuracy of Optimal MLE

Figure 4.1 shows the comparison result of Accuracy of Optimal MLE. HOMLE indicates the best performance possible on this metric, because it used efficient mechanism when searching its route, effectively accelerating the route discovery process. Existing method has moderate accuracy. All the curves show a more or less yet steady descendant when number of visited cities increases. Figure 4.1 shows better Accuracy of Optimal MLE performance of HOMLE than existing method. HOMLE achieves 10% to 28% higher accuracy.

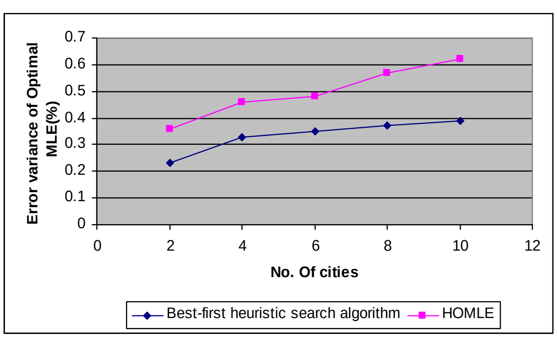

Figure 4.2 Error variance of Optimal MLE

Figure 4.2 shows the comparison result of Error variance of Optimal MLE. HOMLE indicates the best performance possible on this metric, because it used Maximum Likelihood Estimation while the route discovery process. Existing method has more error variance. Figure 4.2 shows Error variance of Optimal MLE of HOMLE than existing method. HOMLE achieves 12% to 21% less error rate.

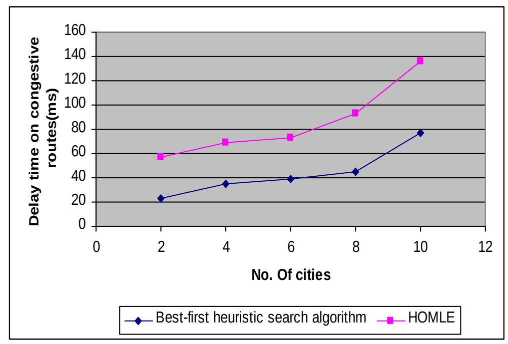

Figure 4.3 Delay time on congestive routes

Figure 4.3 compares the Delay time on congestive routes. Existing method is having higher delay time, HOMLE less. When there is less number of cities visited, both methods display small delay time, because once a route is established, a stable network allows a longer average route lifetime. When number of cities increased, delay increases accordingly. Figure 4.3 shows better performance of HOMLE in terms of Delay time on congestive routes than existing method. HOMLE achieves 12% to 35% less end Delay time on congestive routes when compared with existing schemes.

V. CONCLUSION

This paper implements Highly Optimal Maximum Likelihood Estimation (HOMLE) technique to restrict search space on more. We have investigated the value of dynamically determining a tour for the TSP based on current network conditions and assuming network arc costs are random variables. The dynamic traffic conditions evolved best tour travel plan. Prior knowledge of traffic scenario is used to reduce computational complexity with sub-optimal algorithm. Experimental evaluation is made with various benchmark cited city routes for analyzing HOMLE algorithm. A numerical study has shown the potential for a significant reduction in the expected total travel costs due to dynamic tour determination, relative to two benchmarks. HOMLE achieves 12% to 21% less error rate and 10% to 28% higher accuracy.

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