# Effective computation environment for the traveling salesman problem using three-dimensional information

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Abstract—In the traveling salesman problem (TSP), we consider benchmarks such as calculation speed and computational efficiency. However, there are few examples that utilize TSP for business purposes. In order to use TSP for this purpose, we need to shorten the computation time, achieve visualization for users, and acquire effective parameter values such as transit time and distance between nodes. We can achieve these using cloud computing. In this study, a better route for the TSP can be obtained to add parameters that is the vertical interval between nodes. We propose the route of TSP that reduces the vertical interval between nodes and equalizes the difference of elevation. This research can be used for evacuation route calculation to avoid nodes with low elevation.

## 1 Introduction

T HE traveling salesman problem (TSP) originated in the 20th century and until recently was the most basic type of combinational optimization problem. When we solve the TSP, a shortest path is computed using the distance and time required to travel between nodes. When we use TSP for business purposes, the parameter between these nodes is important. Unless the values of these parameters are suitable, a good result for the TSP is not obtained. Therefore, it is very important what kind of parameter we adopt and researches are also advanced [1], [2].

We consider not only the distance and time but also elevation to obtain the parameter between nodes; we observed that the TSP uses three-dimensional information. An actual salesman's movement involves vertical interval. In order to reduce a salesman's work, it is necessary to reduce the vertical interval as much as possible, which also leads to the reduction in a transportation cost by reducing the vertical interval.

In this paper, we compare the result of the TSP for the case of two-dimensional and three-dimensional information. From some numerical examples, we conclude that the result of three-dimensional information is more realistic for TSP [3].

The TSP is given an n by n symmetric matrix of distances between n nodes. Obviously, distance is not the only variable that we can use and other notions such as time can be considered. We use both distance and time for the TSP cost metrics in this paper. We find a minimum length tour in which each node is visited exactly once using this matrix. As combinatorial optimization problems like the TSP are very difficult to solve using algorithms because of their vast

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 E-mail: mizuno.shinya@sist.ac.jp solution space, various methods for using this model have been proposed [4], [5].

## 1.1 Multiple Traveling Salesman Problem

In general, the m-TSP can be defined as follows: Given a set of nodes, let there be m salesmen located at a single depot node. The remaining nodes, such as cities to be visited, are called intermediate nodes. Then, the m-TSP consists of finding tours for all m salesmen, who start and end at the depot; making sure that each intermediate node is visited exactly once; and also ensuring that the total cost of visiting all nodes is minimized. The cost metric can be defined in terms of distance and time [6], [7].

Solution procedures proposed for the m-TSP are as follows. In the exact solution approach [8], Lagrangian relaxation + branch and bound [9] is the first attempt to solve large-scale symmetric m-TSP. In this paper, it is used to solve non-Euclidean problems of sizes up to 500 nodes and m = 2, 4, 6, 8, 10, and Euclidean problems up to 100 cities and 10 salesmen with this algorithm. Euclidean problems are known to be harder than non-Euclidean ones. For heuristic solution procedures [10], a parallel processing approach to solve the m-TSP using evolutionary programming has been proposed by Fogel [11]. Problems with 25 and 50 cities have been solved and it is noted that the evolutionary approach obtained exceedingly good near-optimal solutions. Although these results are satisfactory, the following problems exist: High computation time, no reference about the acquisition of cost parameters, and high expense of servers required for computation. We try to address these problems in this study.

Google maps was used for the TSP and m-TSP. Because the cost is calculated using Google Maps, it is automatically displayed as can be seen in Table 1.

TABLE 1 **Examples of Automatic Cost Operations** 

Terminal node	Distance[Km]	Time [minutes]	difference of
			elevation [m]
Coventry Wolverhampton	54.245	69.48	65.57
Wolverhampton Nottingham	85.613	83.63	-106.10
Nottingham Leeds	130.401	136.22	70.19
Leeds Leicester	179.576	155.15	-48.24

## 1.2 Defining the Problem

Before describing our m-TSP, we must define a few critical aspects. The m-TSP is defined on a graph G = (V, A), where V denotes a set of n nodes, (i.e. vertices) and A denotes a set of arcs (i.e. edges). Let  $C = (c_{ij})$  denote a cost, (i.e. distance, transit time) matrix associated with A. Let  $H = (h_{ij})$  be a vertical interval matrix associated with A. Matrices C and H are said to be symmetric when  $c_{ij} = c_{ji}, h_{ij} = h_{ji}, \forall (i, j) \in A$ and asymmetric otherwise. W is the coefficient of a vertical elevation. We first define the following binary variable.

$$X_{ij} = \begin{cases} 1 & if \ arc(i,j) \ is \ used \ on \ the \ tour, \\ 0 & otherwise. \end{cases}$$
 (1)

Then, the general scheme of the assignment-noded directed integer linear programming formulation of the m-TSP is as follows.

$$Minimize \qquad \sum_{i=1}^{n} \sum_{j=1}^{n} (c_{ij}x_{ij} + W \cdot h_{ij}x_{ij}) \tag{2}$$

s.t.

$$\sum_{j=2}^{n} x_{1j} = m \tag{3}$$

$$\sum_{j=2}^{n} x_{j1} = m \tag{4}$$

$$\sum_{i=1}^{n} x_{ij} = 1 j = 2, \dots, n, (5)$$

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$$\sum_{i \in S} \sum_{i \in S} x_{ij} \le |S| - 1, \quad \forall \subseteq V \setminus \{1\}$$
 (7)

Constraints in Eq. (7) impose connectivity requirements for the solution, i.e. prevent the formation of subtours of cardinality S, not including the depot. For details, please refer to Ref. [16].

We have some problems with the m-TSP. Specifically, both the TSP and the allotment of nodes are NP-complete; therefore, completion of calculation requires a large amount of time. We decide the allotment of the nodes by using the following methods [12].

## 1.2.1 [Step1]

For all nodes, we obtain a route using a suitable optimization technique. For this study, we use a genetic algorithm. The route length is referred to as T. The distance between a departure node and the node that is furthest from it is referred to as CMax.

# 1.2.2 [Step2]

For  $1 \le j < m$ , the subtour of salesman j cannot exceed the maximum subtour length

$$(j/m)(T - 2C_{max}) + C_{max} \tag{8}$$

from the departure node. Using the route calculated in Step 1, salesman j goes to the node next to the end node of salesman j-1. Next, he circulates the route up to the limit that does not exceed Eq. (8).

We have adopted this method for the following reason. When solving the m-TSP, the computational complexity will increase enormously as the number of salesmen increase. This method distributes a route to each salesman after computing the optimal route of all nodes first. Therefore, the computation time depends on the number of nodes and not on the number of salesmen. This method has a partially inefficient field when the salesman returns to the depot node. We may end up with a longer route for a specific salesman. However, this method can also be improved easily if similar methods [13], [14] are used. Moreover, this method is extensible to the problem of multiple depot nodes [15].

## 1.3 System configuration.

Next, we describe the TSP system configuration. The system does not depend on any specific optimized algorithm.

Fig. 1. Flow of the m-TSP system

#### 1. Input nodes information

We obtain node information such as latitude, longitude, and elevation using Google Map API.

#### 2. Acquisition of parameters

We use the GDirections function of Google Maps API Ver3 to obtain the distance and transit time between nodes easily, in approximately 1 second for one combination of nodes.

# 3. Specification of an optimization option

We set the optimization options, which include: only distance, only transit time, distance and elevation, and transit time and elevation. We set the number of salesman and the coefficient W.

### 4. Computation of m-TSP

Here, we use cloud computing technology. Therefore, the server's capacity can be increased easily. We scale up the server capacity, for example, by increasing the number of cores of the CPU. Then, we can set the number of threads for programming and the computation time becomes shorter.

#### 5. Visualization of a result

We visualize the result of the m-TSP using Google Maps. We propose the optimization route and route navigation easily.

# 1.4 Numerical examples

In this study, we use a genetic algorithm (GA) for the optimized algorithm. The setting of the GA is shown in Table 2. We have adopted master-slave parallelization for parallel computation. Many parallel computing techniques for GA have been proposed [15]. For Google Maps programming, the PHP language is usually used. We choose this parallel method as can be easily programmed by using PHP.

TABLE 2 Setting of GA

Gene	Value
Number of genes	100
Number of generations	50000
Intersection	partially matched crossover
Selection pressure	0.7
Sudden generation	insertion mutation
Sudden incidence	0.03
Parallelization method	master-slave parallelization

We first calculate the TSP using only two-dimensional information, e.g., distance or transit time. We set the value of W to 0. Tables 3-5 show an optimal route with three salesmen and the vertical interval between the nodes. We obtain the total distance and difference of elevation for each salesman from Tables 3-5. Fig. 2 shows an optimal route for each salesman.

TABLE 3
Route for salesman1(Distance priority)

Order	From	То	Distance	difference of
			[Km]	elevation [m]
1	London (the Palace of	Southampton (Tudor	131.319	-7
	Westminster)	House & Garden)		
2	Southampton (Tudor	Nottingham	273.113	41
	House & Garden)	(nottingham old		
		market square)		
3	Nottingham	Leeds (University of	123.489	70
	(nottingham old	Leeds)		
	market square)			
4	Leeds (University of	Belfast (Titanic	467.501	-114
	Leeds)	Belfast)		
5	Belfast (Titanic	Glasgow (University	203.742	21
	Belfast)	of Glasgow)		
6	Glasgow (University	Edinburgh	84.112	62
	of Glasgow)	(Edinburgh Castle)		
7	Edinburgh	London (the Palace of	651.246	74
	(Edinburgh Castle)	Westminster)		
The total value of distance 1934.522				
The absolute total value of difference of elevation			390	

TABLE 4
Route for salesman2(Distance priority)

Order	From	То	Distance	difference of
			[Km]	elevation [m]
1	London (the Palace of	Liverpool (Tate Liver-	341.407	-5
	Westminster)	pool)		
2	Liverpool (Tate Liver-	Manchester (Artzu	54.832	28
	pool)	Gallery - Art Gallery		
		Manchester)		
3	Manchester (Artzu	Bradford (bradford	63.614	74
	Gallery - Art Gallery	cathedral)		
	Manchester)			
4	Bradford (bradford	London (the Palace of	323.836	97
	cathedral)	Westminster)		
The total value of distance 783.689				
The absolute total value of difference of elevation			205	

TABLE 5
Route for salesman3(Distance priority)

Order	From	То	Distance	difference of
			[Km]	elevation [m]
1	London (the Palace of	Plymouth (smeaton	384.268	-5
	Westminster)	tower)		
2	Plymouth (smeaton	Cardiff (Cardiff Cas-	244.629	5
	tower)	tle)		
3	Cardiff (Cardiff Cas-	Wolverhampton	200.825	140
	tle)	(Saint John's Church)		
4	Wolverhampton	Leicester (St. Martin's	88.939	-84
	(Saint John's Church)	Cathedral)		
5	Leicester (St. Martin's	Birmingham	70.176	77
	Cathedral)	(Birmingham		
		Museum & Art		
		Gallery)		
6	Birmingham	Coventry (Coventry	36.961	-59
	(Birmingham	Cathedral)		
	Museum & Art			
	Gallery)			
7	Coventry (Coventry	Stoke-on-Trent	107.318	32
	Cathedral)	(Staffordshire		
		University)		
8	Stoke-on-Trent	Sheffield (The Uni-	80.528	-23
	(Staffordshire	versity of Sheffield)		
	University)			
9	Sheffield (The Uni-	Kingston upon	107.921	-91
	versity of Sheffield)	Hull(Streetlife		
		Museum of		
		Transport)		
10	Kingston upon Hull	Bristol(Bristol	365.152	50
	(Streetlife Museum of	Museum and Art		
	Transport)	Gallery)		
11	Bristol(Bristol	London(the Palace of	192.578	43
	Museum and Art	Westminster)		
	Gallery)			
	The total value of distance			_
	The absolute total value of difference of elevation			609





Fig. 2. A optimal route for each salesman with two-dimensional information

We solve the TSP using three-dimensional information again. We set the value of W to 5. Similarly, Tables 6-8 show an optimal route with three salesmen and the vertical interval between nodes. Fig. 3 shows an optimal route for each salesman.

TABLE 6
Route for salesman1(Distance and Elevation priority)

Order	From	То	Distance [Km]	difference of elevation [m]
1	London (the Palace of Westminster)	Plymouth (smeaton tower)	384.276	-4
2	Plymouth (smeaton tower)	Bradford (bradford cathedral)	521.413	102
3	Bradford (bradford cathedral)	Leeds (University of Leeds)	14.763	7
4	Leeds (University of Leeds)	Stoke-on-Trent (Staffordshire University)	152.223	3
5	Stoke-on-Trent (Staffordshire University)	Wolverhampton(Saint John's Church)	53.329	33
6	Wolverhampton (Saint John's Church)	Birmingham (Birmingham Museum & Art Gallery)	27.805	-7
7	Birmingham (Birmingham Museum & Art Gallery)	Coventry (Coventry Cathedral)	36.961	-59
8	Coventry (Coventry Cathedral)	Leicester (St. Martin's Cathedral)	39.954	-19
9	Leicester (St. Martin's Cathedral)	Bristol (Bristol Museum and Art Gallery)	207.822	-13
10	Bristol (Bristol Museum and Art Gallery)	Southampton (Tudor House & Garden)	169.835	-50
11	Southampton (Tudor House & Garden)	London (the Palace of Westminster)	131.327	-6
	The total value of	distance	1739.708	
	The absolute total value of difference of elevation			303

TABLE 7
Route for salesman2(Distance and Elevation priority)

Order	From	То	Distance	difference of
			[Km]	elevation [m]
1	London (the Palace of	Manchester (Artzu	334.839	23
	Westminster)	Gallery - Art Gallery		
		Manchester)		
2	Manchester (Artzu	Kingston upon Hull	156.831	-29
	Gallery - Art Gallery	(Streetlife Museum of		
	Manchester)	Transport)		
3	Kingston upon Hull	Sheffield (The Uni-	107.921	91
	(Streetlife Museum of	versity of Sheffield)		
	Transport)			
4	Sheffield (The Uni-	Nottingham	73.312	-50
	versity of Sheffield)	(nottingham old		
		market square)		
5	Nottingham	London (the Palace of	205.356	35
	(nottingham old	Westminster)		
	market square)			
	The total value of distance 878.259			
The absolute total value of difference of elevation			228	

TABLE 8
Route for salesman3(Distance and Elevation priority)

Order	F	т-	Distance	difference of
Order	From	То		
			[Km]	elevation [m]
1	London (the Palace of	Edinburgh	651.253	75
	Westminster)	(Edinburgh Castle)		
2	Edinburgh	Glasgow (University	84.112	-62
	(Edinburgh Castle)	of Glasgow)		
3	Glasgow (University	Belfast(Titanic	203.742	-21
	of Glasgow)	Belfast)		
4	Belfast (Titanic	Liverpool (Tate Liver-	442.179	4
	Belfast)	pool)		
5	Liverpool (Tate Liver-	Cardiff (Cardiff Cas-	334.391	6
	pool)	tle)		
6	Cardiff (Cardiff Cas-	London (the Palace of	244.394	1
	tle)	Westminster)		
	The total value of distance 1960.071			
	The absolute total value of difference of elevation			169





Fig. 3. An optimal route for each salesman with three-dimensional information

We obtain the result of the comparison of twodimensional and three-dimensional information in Table 9. This table shows that the salesman's work is reduced when three-dimensional information is used, such as vertical interval for optimization. Therefore, we should use threedimensional information for the TSP to obtain more realistic solution for the TSP.

TABLE 9
Route for salesman3(Distance and Elevation priority)

	Distance		Distance and Elevation	
	The total	The absolute to-	The total	The absolute total
	value of	tal value of dif-	value of	value of difference
	distance	ference of eleva-	distance	of elevation [m]
	[Km]	tion [m]	[Km]	
Salesman1	1934.522	390	1739.708	303
Salesman2	783.689	205	878.259	228
Salesman3	1879.295	609	1960.071	169
Total	4597.506	1204	4578.038	700

# 2 CONCLUSION

When considering the TSP, we enabled automatic calculation and proposed a simple method for deciding the criterion of the cost of three-dimensional information. Our calculations can be easily visualized through Google Maps and can be performed at a realistically usable speed using cloud computing. One of the purposes of this research was to construct a TSP system for business purposes. In previous research, we used only two-dimensional information. Therefore, we adopted no elevation. It is very important to reduce the vertical interval between nodes. Because we need to reduce carbon dioxide gas emissions and gasoline consumption for environment and cost, we think that this system is effective. Because we adopt the elevation of a node, we think that this system is also useful in disaster scenarios. During tsunamis, refuge is required in elevated places. We can obtain the optimal route using only the nodes that have high elevation using this system. Therefore, this system can have many applications.

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