ISBN 978-93-5156-328-0
International Conference of Advance Research and Innovation (ICARI-2015)

Simulated Annealing for Vehicle Routing Problem

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Article Info
Article history:
Received 3 January 2015
Received in revised form
10 January 2015
Accepted 20 January 2015
Available online 31 January 2015

Keywords
Metaheuristics;
Simulated annealing;
Best Value Algorithm;
Vehicle Routing Problem

Abstract

This paper is motivated by the growing concern of companies, governments and consumers in the area of Reverse Logistics. One of the current challenges in reverse logistics optimization is the high transportation costs and the difficulty in devising an efficient route for transportation. The aim is to develop an efficient method that optimizes the route used by vehicles when serving a group of users, commonly known as Vehicle Routing Problem (VRP). The VRP is one of the most challenging combinatorial optimization problems and belongs to the category of non-polynomial (NP)-hard problems. We have implemented algorithms, namely, simulated annealing (SA) and best-value algorithm (BVA) for this purpose.

1. Introduction

Vehicle Routing Problem (VRP) is one of the most challenging problems in reverse logistics as transportation costs constitute a major portion of total costs incurred in handling returns.

Returns may include surplus goods; defective goods sent for repair (under or out of warranty);refusal to accept goods by the customer as faced by e-commerce firms; end of life products sent for proper disposal or for recapturing their value; products returned due to an inherent fault. Thus, the need for devising an efficient path to be followed in collecting returns from several nodes or collection centers that are displaced from one another cannot be over emphasized. When the number of nodes or collection centers is small, the best path may be found manually; however, in real world the number is usually large which necessitates the use of an algorithm or program to address this issue.

In this paper we describe our problem statement taken, Best Value Algorithm (BVA), meta-heuristics technique Simulated Annealing (SA) and compare the results so obtained. The codes are written in C++running on Windows 7.

2. Vehicle Routing Problem in Reverse Logistics

Logistics is defined by The Council of Logistics Management as:

"The process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of origin to the point of consumption for the purpose of conforming to customer requirements."

Reverse logistics includes all of the activities that are mentioned in the definition above. The difference is that reverse logistics encompasses all of these activities as they operate in reverse. Therefore, reverse logistics is:

"The process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal."[1]

The VRP is a combinatorial optimization and integer programming problem seeking to service a number of customers with a fleet of vehicles. It was proposed by Dantzig and Ramser in 1959 [2]. Transportation costs involve a large portion of total costs incurred in reverse logistics. This cost can however be reduced by optimizing the route vehicle takes on its journey.

3. Simulated Annealing

SA is a generic probabilistic metaheuristic, independently described by, [3]. It is used for a good approximation to the global optimum of a given function in a large search space and is mostly used when search space is discrete. Annealing, a techniques in metallurgy which involves heating and controlled cooling of a material to increase the size of its crystals and reduce their defects which depend on its thermodynamic free energy, is the source of inspiration behind it. It is the magnitude and the rate of cooling that determines the final properties. This notion of slow cooling is implemented in the SA as a slow decrease in the probability of accepting worse solutions as it explores the solution space and thereby it allows for a more extensive search for the optimal solution. [4]

Table: 1. Relationship between Physical Annealing and Simulated Annealing

Thermodynamic Simulation	Combinatorial Optimisation
Energy	Cost
Change of State	Neighbouring Solutions
Temperature	Control Parameter
Frozen State	Solution

3.1 Acceptance Criteria

Based on the analogy stated above, the equation of probability of an increase in energy of magnitude of energy for simulated annealing is used. Therefore, the probability of accepting a worse state is given as:

$$P = exp(-c/t) > r \quad (1)$$

Where

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c= the change in the evaluation function
t = the current temperature
r = a random number between 0 and 1[4]

3.2 Starting Temperature

The starting temperature must be hot enough to allow a move to almost any neighbourhood state. However, if the temperature starts at too high a value then the search can move to any neighbour and thus transform the search (at least in the early stages) into a random search. The search will be random till the temperature is low enough to start acting as a simulated annealing algorithm. However there is no specific method to find a suitable starting temperature and involves iterative attempts which may belike the maximum distance (cost function difference) between two neighbours or we can start with a very high temperature and cool it rapidly until about 60% of worst solutions are being accepted. [4]

3.3 Final Temperature

Ideally the temperature should be reduced till it reaches zero. But this can make the algorithm run for long and becomes impractical when we deal with large problems. [4]So we decide an approximate good value.

3.4 Temperature Decrement

The temperature is decreased so that it eventually arrives at the stopping criterion.[4]The way in which we decrement our temperature is critical to the success of the algorithm. Decrement could be arithmetic or geometric as given by the equation below:

$$t = t\alpha \quad (2)$$

3.5 Iterations at Each Temperature

Now the decision that we have to make is how many iterations we make at each temperature. Although there are a number of methods [4], we have used the formula below can be used:

$$t = t/(1 + \beta t) \quad (3)$$

4. Methodology Adopted for Simulated Annealing

4.1 Problem Statement

Problem Statement involves the movement of a vehicle to collect returns from several nodes to a central depot for disposition. Given parameters include a set of nodes to be visited and the inter node distances (or cost of visiting the node) from the depot. The objectis to determine an efficient route to visit all given nodes such that the total distance travelled is minimized which will directly impact the profits of any organization.

It is assumed that vehicle capacity is sufficient to collect material from the given set of nodes. The problem statement is suitable for reverse logistics as unlike forward supply chain; the urgency to transport the materials is less in reverse logistics.

The output which the algorithm generates includes the best tour or route for the given set of nodes, the cost incurred (or distance travelled).The mathematical formulation of the problem defined above is as below:

$$\sum_{(i,j)} D_{ij} Z_{ij} \quad (4)$$

Where Dijis the distance associated with the routeZij. Also Zij = 0 or 1

$$\sum_{(i=1)} Z_{ij} = 1, \quad \forall i \neq j \quad (5)$$

$$\sum_{(j=1)} Z_{ij} = 1, \quad \forall j \neq i \quad (6)$$

4.2 Initial Solution

A random solution is chosen to be the initial solution.

4.3 Neighbourhood Generation

In order to generate neighborhood three methods are used which are as follows:

Shifting the elements between two given nodes by one place reversing the order of the elements between two nodes Swapping of two nodes In order to explore the search space more extensively, the selection of the neighbourhood generation method to be adopted is based on a random number.

4.4 Number of Iterations

The starting temperature has been taken as a high value (equal to the square of the maximum number of nodes to be travelled).So as to explore the search space extensively, temperature decrease in each successive iteration is kept small and geometric decrement is used. Also, a fixed number of iterations are carried out at each temperature. Iterations are carried out till sufficient cooling is carried out.

4.5 Stopping criterion

When the temperature is decreased to a pre-defined sufficiently low value i.e. sufficient cooling is done, the stopping criterion is met and the program returns the output.

4.6 Algorithm

1. Take the number of nodes and inter-node distances (or cost) as input
2. An initial solution is generated and initial distance (or cost) is computed
3. Fixed number of iterations are carried out at every temperature and neighbour is generated randomly so as to find a new solution. If new solution is better than current solution; it is accepted else it is accepted with a probability
4. Temperature is decreased and step 3 is carried out till temperature reaches a sufficiently low value
5. Output is displayed

5. Methodology Adopted for Best Value Algorithm

BVA is an iterative algorithm which is used in order to obtain the actual best value of the objective function. The basic algorithm is as follows:

1. An initial base route is taken.
2. Value of distance by this route is stored in variable "X".
3. Now route is edited so that we get just next possible route.
4. If the value on this edited route is less than "X", then we store this route's value in "X".
5. Steps 3, 4 are repeated till (route == end route).
6. "X" will give us best possible distance.

However the iterative process carries out all possible iterations and is thus inefficient and nearly impossible to be used after 10*10 matrix. It has been used for the purpose of comparison with algorithm based on simulated annealing so

ISBN 978-93-5156-328-0

as to gauge how near the solution given by latter is to the actual solution.

6. Input Matrices

Following are the various input matrices:

Table: 2. 5*5 Matrix

1	2	3	4	5
2	10	34	50	78
3	34	11	21	7
4	50	21	12	6
5	78	7	6	13

Table: 3. 10*10 Matrix

1	2	3	4	5	6	7	8	9	10
2	11	7	8	17	21	23	56	91	55
3	7	22	61	54	71	62	90	13	12
4	8	61	33	5	6	7	8	9	10
5	17	54	5	44	75	56	52	41	70
6	21	71	6	75	55	21	22	27	31
7	23	62	7	56	21	66	65	70	93
8	56	90	8	52	22	65	77	46	37
9	91	13	9	41	27	70	46	88	10
10	55	12	10	70	31	93	37	10	99

Table: 4. 15*15 Matrix

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2	11	5	7	8	9	11	12	16	21	70	86	90	100	86
3	5	22	14	21	27	63	81	9	17	21	33	42	50	70
4	7	14	33	16	17	18	19	51	71	100	61	17	18	92
5	8	21	16	44	33	44	55	70	90	21	74	61	50	41
6	9	27	17	33	55	22	23	27	31	41	42	43	49	52
7	11	63	18	44	22	66	20	15	71	66	70	81	90	21
8	12	81	19	55	23	20	77	50	41	52	37	14	17	93
9	16	9	51	70	27	15	50	88	98	97	21	26	25	20
10	21	17	71	90	31	71	41	98	99	14	17	18	12	11
11	70	21	100	21	41	66	52	97	14	110	200	210	220	211
12	86	33	61	74	42	70	37	21	14	200	121	300	400	500
13	90	42	17	61	43	81	14	26	18	210	300	130	60	70
14	100	50	18	50	49	90	17	25	12	220	400	60	140	80
15	86	70	92	41	52	21	93	20	11	211	500	70	80	150

Table: 5. 20*20 Matrix

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
2	11	5	7	10	11	26	27	28	29	30	31	32	33	34	35	36	37	38	39
3	5	22	19	20	16	15	14	13	12	11	10	9	21	22	23	24	25	26	27
4	7	19	33	17	18	19	20	21	22	51	52	53	54	57	59	60	71	30	81
5	10	20	17	44	91	100	41	32	42	30	71	19	18	7	93	100	21	16	15
6	11	16	18	91	55	41	59	60	61	62	63	64	65	66	67	68	69	70	71
7	26	15	19	100	41	66	89	90	91	92	93	94	95	96	97	98	99	100	101
8	27	14	20	41	59	89	77	50	51	52	53	54	55	56	57	58	59	60	61
9	28	13	21	32	60	90	50	88	71	72	77	61	62	63	64	65	66	67	68
10	29	12	22	42	61	91	51	71	99	41	42	43	44	45	46	47	48	49	50
11	30	11	51	30	62	92	52	72	41	100	7	8	9	10	11	12	13	14	15
12	31	10	52	71	63	93	53	77	42	7	80	21	22	23	24	25	16	17	18
13	32	9	53	19	64	94	54	61	43	8	21	90	19	93	10	11	12	13	14
14	33	21	54	18	65	95	55	62	44	9	22	19	71	62	63	64	65	66	67
15	34	22	57	7	66	96	56	63	45	10	23	93	62	64	12	13	14	15	16
16	35	23	59	93	67	97	57	64	46	11	24	10	63	12	27	9	8	7	6
17	36	24	60	100	68	98	58	65	47	12	25	11	64	13	9	28	21	22	23
18	37	25	71	21	69	99	59	66	48	13	16	12	65	14	8	21	29	14	17
19	38	26	80	16	70	100	60	67	49	14	17	13	66	15	7	22	14	56	18
20	39	27	81	15	71	101	61	68	50	15	18	14	67	16	6	23	17	18	71

ISBN 978-93-5156-328-0

7. Solution and Results

Thesolutions obtained when the square matrices of size 5 and 10 are fed to the programs are same forboth SA and BVA and the result is shown below:
Optimized Distance = 53

Table: 6. Best Tour for 5*5 Matrix

1	**2**	**3**	**5**	**4**

Optimized Distance for 10*10 matrix = 118

Table: 7. Best Tour for 10*10 Matrix

1	9	10	3	2	5	4	7	6	8

The computer however fails when square matrices of size equal to and above 15 are fed into BVA program. But SA provides the following results:
Optimized Distance for 15*15 matrix = 217

Table 8: Best Tour for 15*15 Matrix

1	7	15	10	14	8	13	4	6	2	5	11	3	9	12

Optimized Distance for 20*20 matrix = 291

Table: 9. Best Tour for 20*20 Matrix

1	7	6	2	5	15	17	13	18	19	16	20	12	11	14	10	3	9	4	8

8. Conclusions

The deliverable of this paper is a metaheuristic search algorithm to optimize the VRP. The algorithm will receive distance (or cost) matrix for a given set of nodes to be visited. The output which the algorithm generates includes the best tour or route for the given set of nodes and the total distance travelled (or cost incurred).The developed solution algorithm is capable of achieving the targets which were initially set for it and is capable of solving a considerable array of problem instances.

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