

Formulation and Solution of the Stochastic Truck and Trailer Routing Problem [†]

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Abstract: In manufacturing and service industries, transportation often faces uncertain conditions. While current research on the truck and trailer routing problem (TTRP) mostly uses deterministic methods, they fall short in addressing uncertainties in travel and service times. This study aims to improve TTRP models by incorporating randomness in travel and service durations and specific time windows, better mirroring real-world scenarios. The enhanced model uses the multipoint simulated annealing (M-SA) method for practical application. The study involves 144 benchmark instances across six levels, starting with generating feasible solutions, then refining them using M-SA. A stochastic programming model with recourse (SPR) was used for problem formulation. Sensitivity analysis assessed the impact of various parameters and compared solutions obtained from M-SA and the analysis, showing minimal differences and thus the effectiveness of the proposed algorithm in solving the stochastic TTRP. The paper concludes with suggestions for future research.

Keywords: truck and trailer routing; meta-heuristic; multi-point simulated annealing; time windows; optimization

1. Introduction

Truck and trailer routing problems (TTRP) are crucial for transporting goods within factories or to markets and end users, evolving from the conventional vehicle routing problem (VRP) [1,2]. VRP, a well-studied combinatorial optimization problem, manages real-world complexities [3,4]. This paper introduces a solution for TTRP under stochastic travel and service times with time window constraints (STTRP). Unlike VRP, TTRP considers the use of single trucks or complete vehicles (trucks with trailers), acknowledging real-life challenges like road conditions and space limitations at customer sites [5–9]. Solving STTRP is more complex than VRP with stochastic parameters, a challenging combinatorial optimization problem tackled through heuristic approaches. STTRP, reduced to VRPSTTW, also relies on heuristics for solutions [10–12]. The goal is to optimize routes and total costs while satisfying all constraints. Several studies have contributed to the truck and trailer routing problem (TTRP) with stochastic parameters.

In practical scenarios, operational constraints like specific customer service times within set intervals are essential, leading to the inclusion of time windows in vehicle routing problem (VRP) models. This adaptation is mirrored in truck and trailer routing problem (TTRP) applications as TTRP with time windows. Furthermore, variables like traffic congestion, weather conditions, driver skill levels, and distribution technology impact travel and service times, often making them stochastic rather than deterministic. Recognizing these real-world limitations in traditional VRP models necessitates considering TTRP with stochastic travel and service times alongside time windows (STTRP). The objective of this research is to identify the optimal TTRP route with the minimum distance when both travel and service times are stochastic and follow a normal distribution.



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2. Stochastic Truck and Trailer Routing Problem (STTRP)

STTRP is an extension of the TTRPSTT, which was proposed by Mirmohammad-sadeghi et al. [13]. In this scenario, each vertex v_i is linked with a specific, non-negative demand q_i that must be satisfied. This model also incorporates time window constraints for each customer. Furthermore, when servicing a customer, there is a variable stochastic service time involved. Additionally, the travel times between customers are subject to variability and are considered stochastic in nature. The model categorizes customers into two types, denoted by t_i . For $t_i = 1$, the customer, labeled as a truck customer (TC), requires service exclusively by a single truck. Conversely, when $t_i = 0$, the customer is classified as a vehicle customer (VC), who can be serviced either by a single truck or by a complete vehicle, which includes a truck towing a trailer.

The fleet consists of m_k trucks and m_r trailers, where m_k is assumed to be greater than or equal to m_r . Both trucks and trailers have fixed capacities Q_k and Q_r , respectively. STTRP offers three route types: (1) pure travel route (PTR), only for single trucks, (2) pure vehicle route (PVR), exclusively for a complete vehicle, and (3) complete vehicle route (CVR), involving a main tour and at least one sub-tour for single trucks. The STTRP is approached as stochastic programming with recourse, where initial routes and sub-tours are planned, followed by adjustments for stochastic travel and service times. Key constraints include each route starting and finishing at the depot, single vehicle per vertex visits, recourse actions for time delays, and an objective to minimize costs.

The Stochastic Programming with Recourse of STTRP

The model needs to account for additional costs that arise in situations like violations of time window constraints or when drivers work beyond a predetermined number of hours. To align the model more accurately with real-world scenarios, these additional costs, known as recourse costs, should be incorporated. The typical approach in STTRP involves two stages: initially, tours and sub-tours are planned, and then, in the second stage, adjustments are made in response to random variables. This research opts for soft time windows since they are more representative of real-world conditions compared to hard time windows. In a soft time window framework, the dispatcher is not allowed to begin servicing a customer before the earliest time window, necessitating potential additional waiting time on the route [14].

The STTRP model is distinguished by having three distinct types of routes, each carefully planned in the initial stage of the solution process. The ultimate goal function, denoted as $F(X, Y)$, represents the aggregate of two separate cost elements: $T(X, Y)$ and $R(X, Y)$. Here, $T(X, Y)$ quantifies the value of the objective function for the first-stage routes. On the other hand, $R(X, Y)$ encompasses two components: B_k and P_k . $R(X, Y)$ signifies the cost of recourse, where B_k represents the expected expense incurred due to driver remuneration, and P_k accounts for the recourse costs associated with customers whose time window commitments are not met. Therefore, the objective function can be expressed as follows:

$$F(X, Y) = T(X, Y) + B_k + P_k \quad (1)$$

Assume the vertex v_j is the last vertex in the route k , the route k is feasible if the route is terminated before l_0 . Then

$$A_{0k} = \left\{ \max(A_{jk}, e_j) + t_{j0} + \gamma_j \right\} \leq l_0 \quad (2)$$

In addition, the arrival time of all customers can be calculated by the following recursive equation when $\gamma_0 = 0$.

$$A_{ik} = \left\{ \max(A_{i-1,k}, e_{i-1}) + t_{i-1,i} + \gamma_{i-1} \right\} \quad (3)$$

Servicing customer i prior to the earliest time e_i is not feasible, necessitating that the vehicle waits until this time arrives. Consequently, this situation may lead to additional

waiting time W_i on the route may be occurred, which is a random variable for e_i and A_{ik} are random variables.

$$W_i = \max(e_i - A_{ik}, 0) \quad (4)$$

Consequently, the total waiting time is computed as

$$W = E \sum_{i=1}^{n_k} W_i \quad (5)$$

Additionally, a penalty cost is added to the objective value if a customer is serviced after the deadline l_0 . The total random variable penalty cost P_k can be computed as

$$P_k = \sum_{j=1}^{n_k} \delta_j \cdot \max(A_{jk} - l_j, 0) \quad (6)$$

where δ_j is the unit penalty cost in servicing customer j after the deadline.

The objective function value of the first stage routes can be computed by the following equation.

$$T(X, Y) = \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} C_{ij} X_{ijk} + \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} C_{ij} Y_{ijk} \quad (7)$$

where X_{ijk} is assigned a value of 1 when customer i and j are served by a complete vehicle, and 0 otherwise. Y_{ijk} is identical to X_{ijk} , except that the customers are served exclusively by a truck without a trailer.

Each driver has a standard working duration of D hours. Should the driver's work exceed D hours, additional remuneration is required for each extra hour worked. The total driving time T_k , encompassing travel, service, and waiting times, along with the total driver remuneration B_k for route k , can be calculated using specific equations.

$$T_k = \sum_{i \in V} \sum_{j \in V} t_{ij} (X_{ijk} + Y_{ijk}) + \sum_{i \in V} (\gamma_i + W_i) \sum_{j \in V} (X_{ijk} + Y_{ijk}) \quad (8)$$

$$B_k = \begin{cases} r_k \cdot (T_k - D) & \text{if } T_k \geq D \\ 0 & \text{O.W} \end{cases} \quad (9)$$

In this context, r_k represents the per-hour driver remuneration rate for any overtime work on route k . The goal is to minimize the two-stage objective function in the stochastic programming with recourse (SPR) formulation of STTRP. The initial stage involves planning each route, while the second stage takes into account the recourse costs, which include both T_k (total driving duration) and B_k (total driver remuneration) for each route.

$$\min[F(X, Y)] \quad (10)$$

Subject to:

$$\sum_{j \in V} \sum_{k \in K} (X_{ijk} + Y_{ijk}) = 1 \forall i \in V \quad (11)$$

$$\sum_{j \in V} (X_{0jk} + Y_{0jk}) = 1 \forall k \in K \quad (12)$$

$$\sum_{i \in V} (X_{i0k} + Y_{i0k}) = 1 \forall k \in K \quad (13)$$

$$\sum_{i \in V} X_{ijk} - \sum_{i \in V} X_{jik} = 0 \forall j \in V, k \in K \quad (14)$$

$$\sum_{i \in V} Y_{ijk} - \sum_{i \in V} Y_{jik} = 0 \forall j \in V, k \in K \quad (15)$$

$$\sum_{i \in V} (q_i \sum_{j \in V} X_{ijk}) \leq Q_k + Q_r \forall k \in K \quad (16)$$

$$\sum_{i \in V} (q_i \sum_{j \in V} Y_{ijk}) \leq Q_k \forall k \in K \quad (17)$$

$$P_k = \sum_{j=1}^{n_k} \delta_j \cdot \max(A_{jk} - l_j, 0) \quad (18)$$

$$T_k = \sum_{i \in V} \sum_{j \in V} t_{ij} (X_{ijk} + Y_{ijk}) + \sum_{i \in V} (\gamma_i + W_i) \sum_{j \in V} (X_{ijk} + Y_{ijk}) \quad (19)$$

$$B_k = \begin{cases} r_k \cdot (T_k - D) & \text{if } T_k \geq D \\ 0 & \text{O.W} \end{cases} \quad (20)$$

$$X_{ijk} \in \{0, 1\}, Y_{ijk} \in \{0, 1\}, \forall i, j \in V, k \in K \quad (21)$$

Equation (11) specifies that each customer should be serviced exactly once, either by a single truck or a complete vehicle. Equation (12) details the commencement of each route from the depot, leading directly to a single customer's location via vehicle k . Equation (13) mirrors Equation (12) but focuses on the route's conclusion, which involves departing from a customer. Equations (14) and (15) outline the prescribed flow along the route for vehicle k . Equations (16) and (17) set capacity constraints for the vehicle and truck routes, respectively, ensuring that customer service is practically feasible.

3. Multi-Point Simulated Annealing to Solve STTRP

Simulated annealing (SA) is a local search heuristic used for various combinatorial optimization problems. An advanced SA algorithm, featuring a crossover operator, is applied to the capacitated vehicle routing problem, navigating the solution space and transitioning between solutions. This study employs a multi-point version of SA, starting with multiple predetermined solutions [15]. The solution process involves designating the first customer on each route and adding customers sequentially while respecting vehicle capacity, which varies by route type. Routes end at a depot or the root of a sub-tour, with new routes generated as needed, ensuring compliance with capacity and travel time constraints. A route combination process is included to minimize the number of vehicles, merging routes without exceeding capacity or time limits. Excess vehicles incur a penalty cost in the objective function.

The neighborhood search is fundamental to this heuristic, using a random structure that includes swapping, reversing, inserting customers, and changing service vehicle types. Each iteration generates a new solution by applying these methods randomly, with equal probability for each method. The process also involves addressing route failures and calculating associated costs. Key parameters of SA include the initial and final temperatures (T_0 and T_f), the Boltzmann constant (K), maximum iterations at a given temperature N_{non} , the number of initial solutions n_{pop} , the number of transitions to create new solutions (n_{move}), and the iteration count at each temperature ($I_{iterpertemp}$). The algorithm starts at a high temperature, gradually cools down, and concludes when the temperature falls below T_f , with the objective of enhancing cost efficiency. This solution approach for the vehicle routing problem specifies starting each route with a predetermined customer and vehicle type, then sequentially adding customers according to capacity and sequence constraints. The routes either end at a depot or start a new sub-tour. If constraints are violated, routes can be merged to reduce the number of vehicles used, applying penalties for excess vehicle use.

4. Computational Study

In this section, the performance of a multi-point simulated annealing algorithm on STTRP is evaluated. The M-SA is coded by MATLAB R2022a. Experimental trials were conducted to enhance the credibility and validity of the algorithm. Firstly, some instances with different properties have been selected from the basic test problem of Li et al. (2010) with 50 and 100 customers and three different scheduling horizons, i.e., R1, R2, and R3. The problems in R1, R2, and R3 have short, medium, and long scheduling horizons, respectively (Li et al., 2010). Then each problem is converted into three new STTRP problems by the following description. The distances between each customer and its nearest customer are calculated and symbolized as A_i . Sixty percent of the customers with the largest A_i values are put as TCs in the first problem. This is decreased to forty and twenty percent for the second and third problems, respectively. The remained customers are specified as VCs. The

vertex coordinates and demand details are consistent with those found in Li's instances. The configuration of trucks and trailers, along with their respective capacities, has been tailored specifically for this scenario. Moreover, the travel and service times between customers are modeled as stochastic variables, following normal distributions with parameters $(\mu_{ij}, \sigma_{ij}^2)$. Here, the mean value (μ_{ij}) corresponds to the deterministic travel times reported by Li et al. in 2010, while the variance σ_{ij}^2 is a random integer selected from the range [1,4]. Measurements of distances and travel times are in meters and minutes, respectively. The time window constraints are also aligned with those outlined by Li et al. in 2010. Regarding capacity, the trucks and trailers can accommodate up to 300 and 200 units, respectively.

Computational Results

The performance of the M-SA is evaluated for solving SPR versions of STTRP. The quality of computational outcomes may be influenced by the parameters selected for the model. To achieve improved solutions, various parameter values were experimented with in the initial trials. The M-SA is then applied for solving the SPR version of STTRP. Each set was executed 10 times, and the best result ($F(X, Y)$) along with the average results for each problem are presented in Tables 1 and 2. Additionally, the problems have been analyzed through sensitivity parameter analysis to understand the impact of various parameters and data elements.

Table 1. Results for STTRP with 50 customers and R1, R2, and R3 scheduling horizons.

Problem ID	R1 Best Solution	R1 Average Solution	R1 Sensitivity Analysis	R2 Best Solution	R2 Average Solution	R2 Sensitivity Analysis	R3 Best Solution	R3 Average Solution	R3 Sensitivity Analysis
1	5047.45	5073.63	5036.90	4584.96	4601.43	4567.75	2968.75	2983.83	2939.73
2	4960.84	5024.88	4947.71	4621.35	4642.24	4601.56	3060.14	3084.74	3052.00
3	5194.44	5217.31	5169.65	4441.93	4456.23	4426.98	3194.60	3217.90	3186.86
4	4529.11	4542.56	4512.05	5101.11	5112.86	5093.17	2522.15	2542.56	2508.49
5	3487.01	3503.11	3472.73	5009.47	5120.55	4957.85	2407.71	2423.41	2394.72
6	3801.90	3821.86	3792.31	5222.54	5231.54	5189.09	2081.75	2101.96	2067.69
7	2812.34	2819.09	2795.52	2724.47	2731.84	2704.68	2112.34	2119.19	2112.34
8	2833.20	2845.23	2824.86	2841.43	2850.73	2823.11	2133.20	2145.23	2124.62
9	2878.87	2890.76	2861.33	2821.63	2834.56	2800.60	2474.67	2490.36	2453.38
10	2607.32	2615.12	2599.29	2562.53	2572.88	2547.30	2527.82	2535.17	2513.47
11	2720.02	2732.60	2689.03	2611.21	2630.42	2587.62	2633.82	2662.43	2621.47
12	2891.29	2908.34	2880.74	2579.09	2583.86	2564.42	2991.54	3008.54	2980.02
13	5232.69	5241.77	5210.37	4023.37	4035.54	4011.56	4232.39	4351.37	4216.48
14	5300.32	5308.56	5279.65	4165.54	4173.03	4146.99	4324.21	4340.67	4321.15
15	5392.65	5401.53	5378.12	4089.90	4101.86	4066.42	4412.45	4431.13	4400.03
16	3592.37	3610.09	3588.73	3835.71	3849.09	3817.58	2743.17	2770.02	2737.31
17	3359.52	3367.73	3342.68	3495.47	3511.81	3487.92	2384.92	2407.23	2367.62
18	3478.93	3485.82	3464.38	3684.76	3699.22	3672.01	2975.33	3005.05	2968.21
19	3769.00	3777.83	3746.00	2947.48	2958.73	2931.91	3024.37	3037.81	3011.92
20	3783.72	3790.70	3759.93	3163.52	3181.85	3143.40	3283.28	3299.70	3278.54
21	3844.62	3853.52	3835.59	3215.96	3242.95	3200.76	3731.85	3753.02	3719.11

Table 1. Cont.

Problem ID	R1 Best Solution	R1 Average Solution	R1 Sensitivity Analysis	R2 Best Solution	R2 Average Solution	R2 Sensitivity Analysis	R3 Best Solution	R3 Average Solution	R3 Sensitivity Analysis
22	2932.74	2941.94	2916.48	2932.28	2950.01	2930.23	3072.54	3101.94	3058.53
23	2777.93	2790.45	2759.75	3010.83	3025.53	2992.02	2977.73	2990.95	2968.27
24	2894.23	2910.11	2879.53	3454.48	3479.88	3448.35	3194.13	3210.11	3180.37
Avg.	3755.11	3769.77	3739.31	3630.89	3649.10	3613.05	2977.70	3000.14	2966.06

Table 2. Results for STTRP with 100 customers and R1, R2, and R3 scheduling horizons.

Problem ID	R1 Best Solution	R1 Average Solution	R1 Sensitivity Analysis	R2 Best Solution	R2 Average Solution	R2 Sensitivity Analysis	R3 Best Solution	R3 Average Solution	R3 Sensitivity Analysis
1	8963.53	9013.63	8927.07	11,528.15	11,563.83	11,502.26	9568.35	9583.22	9559.43
2	6599.54	6634.35	6589.52	10,960.67	11,004.08	10,954.72	9065.13	9084.34	9065.13
3	7294.43	7317.30	7285.72	10,074.90	10,117.49	10,074.90	9194.60	9217.90	9190.92
4	10,562.85	10,642.56	10,555.98	9572.45	9602.56	9561.55	8532.15	8574.36	8521.04
5	9407.71	9443.41	9389.32	8727.71	8743.21	8720.21	8807.71	8843.41	8793.63
6	8081.42	8101.56	8077.22	8081.93	8101.32	8064.78	8081.65	8101.06	8076.57
7	6115.42	6129.59	6115.42	6102.34	6119.59	6081.16	7612.14	7639.13	7603.85
8	5432.04	5445.93	5424.58	6734.27	6815.43	6722.54	7103.25	7145.03	7100.88
9	6271.78	6310.06	6260.05	6474.32	6490.66	6465.80	7436.17	7490.26	7427.54
10	4527.42	4552.26	4493.85	5323.94	5405.37	5214.57	6517.82	6538.87	6508.01
11	4682.03	4698.43	4674.93	5661.12	5682.43	5656.38	6634.22	6675.93	6624.36
12	5011.54	5018.27	5002.24	5291.34	5308.04	5283.46	7091.54	7108.54	7091.54
13	6032.99	6051.11	6021.31	8282.69	8301.37	8276.24	8272.42	8301.39	8270.22
14	5324.43	5344.32	5312.90	8994.51	8040.67	8988.56	8358.23	8380.27	8351.46
15	5712.46	5731.17	5700.18	8012.05	8063.13	7993.31	8415.35	8440.19	8410.14
16	8753.66	8770.82	8753.66	10,743.17	10,810.02	10,741.04	9703.17	9740.42	9689.42
17	8374.72	8400.23	8353.60	9374.93	9407.23	9363.85	8704.92	8767.34	8701.82
18	9275.23	9288.62	9265.41	9975.53	10,005.05	9971.92	8975.33	9015.05	8970.57
19	7024.69	7041.81	7016.79	7424.38	7437.41	7424.38	6724.75	6757.85	6716.67
20	6783.78	6799.74	6769.04	6887.68	6909.30	6879.73	7083.26	7109.70	7076.74
21	5991.95	6053.04	5988.56	7031.85	7053.02	7025.92	6931.53	6953.02	6931.53
22	4672.54	4701.24	4666.83	6076.74	6101.04	6096.54	6072.43	6101.98	6066.82
23	4957.43	4990.44	4954.97	5977.73	6990.95	5969.60	6977.73	7030.95	6967.49
24	4094.14	4210.72	4094.14	5197.13	5213.91	5192.27	6194.13	6217.11	6183.34
Avg.	6664.49	6695.42	6653.86	7854.65	7887.09	7842.74	7835.75	7867.35	7829.13

The study demonstrated that the multi-point simulated annealing algorithm effectively optimized the stochastic truck and trailer routing problem (STTRP), minimizing vehicle use without exceeding capacity and adhering to time constraints. The consistency of the algorithm's performance was confirmed by the minimal differences between the best, average, and sensitivity-analyzed solutions across various test scenarios.

5. Conclusions and Recommendation

This paper introduces and addresses the stochastic truck and trailer routing problem (STTRP). Unlike typical research focusing on deterministic TTRP, this study incorporates stochastic travel and service times to reflect real-world conditions like traffic and varying driver skills. The problem is formulated using a stochastic programming model with recourse (SPR) and solved with a multi-point simulated annealing algorithm (M-SA) that utilizes a random neighborhood structure with four types of moves. To evaluate the algorithm, 144 benchmark problems for STTRP are created, divided into six sets, and each set is run ten times. The consistency of the algorithm is demonstrated by the minimal differences between the best, average, and sensitivity analysis-derived solutions. The study's limitations include a fixed number of vehicles and the lack of consideration for multiple depots. The paper suggests future research could improve the model by adding elements like multiple time windows and depots, and varying travel times, and calls for new benchmark problems to better simulate these complex scenarios.

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References

- Oyola, J.; Arntzen, H.; Woodruff, D.L. The stochastic vehicle routing problem, a literature review, part I: Models. *EURO J. Transp. Logist.* **2018**, *7*, 193–221. [\[CrossRef\]](#)
- Lei, H.; Laporte, G.; Guo, B. The capacitated vehicle routing problem with stochastic demands and time windows. *Comput. Oper. Res.* **2011**, *38*, 1775–1783. [\[CrossRef\]](#)
- Kumari, M.; De, P.K.; Chaudhuri, K.; Narang, P. Utilizing a hybrid metaheuristic algorithm to solve capacitated vehicle routing problem. *Results Control Optim.* **2023**, *13*, 100292. [\[CrossRef\]](#)
- Miranda, D.M.; Branke, J.; Conceição, S.V. Algorithms for the multi-objective vehicle routing problem with hard time windows and stochastic travel time and service time. *Appl. Soft Comput.* **2018**, *70*, 66–79. [\[CrossRef\]](#)
- Alves da Cruz, H.F.; Salles da Cunha, A. The Profitable Single Truck and Trailer Routing Problem with Time Windows: Formulation valid inequalities and branch-and-cut algorithms. *Comput. Ind. Eng.* **2023**, *180*, 109238. [\[CrossRef\]](#)
- Mirmohammadsadeghi, S.; Ahmed, S.; Nadirah, E. Application of memetic algorithm to solve truck and trailer routing problems. In Proceedings of the 2014 International Conference on Industrial Engineering and Operations Management, Bali, Indonesia, 7–9 January 2014; pp. 747–757.
- Derigs, U.; Pullmann, M.; Vogel, U. Truck and trailer routing—Problems, heuristics and computational experience. *Comput. Oper. Res.* **2013**, *40*, 536–546. [\[CrossRef\]](#)
- Villegas, J.G.; Prins, C.; Prodhon, C.; Medaglia, A.L.; Velasco, N. A matheuristic for the truck and trailer routing problem. *Eur. J. Oper. Res.* **2013**, *230*, 231–244. [\[CrossRef\]](#)
- Chao, I.M. A tabu search method for the truck and trailer routing problem. *Comput. Oper. Res.* **2002**, *29*, 33–51. [\[CrossRef\]](#)
- Alkaabneh, F. Matheuristic for synchronized vehicle routing problem with multiple constraints and variable service time: Managing a fleet of sprayers and a tender tanker. *Comput. Oper. Res.* **2024**, *162*, 106454. [\[CrossRef\]](#)
- Jie, K.W.; Liu, S.Y.; Sun, X.J. A hybrid algorithm for time-dependent vehicle routing problem with soft time windows and stochastic factors. *Eng. Appl. Artif. Intell.* **2022**, *109*, 104606. [\[CrossRef\]](#)
- Labadie, N.; Gutierrez, A. A multi population memetic algorithm for the vehicle routing problem with stochastic travel and service times. *IFAC-PapersOnLine* **2016**, *49*, 1204–1209.
- Mirmohammadsadeghi, S.; Masoumik, S.M.; Alavi, S. Multi-Point Simulated Annealing Algorithm for Solving Truck and Trailer Routing Problem with Stochastic Travel and Service Time. *J. Soft Comput. Decis. Support Syst.* **2020**, *7*, 14.

14. Li, X.; Tian, P.; Leung, S.C. Vehicle routing problems with time windows and stochastic travel and service times: Models and algorithm. *Int. J. Prod. Econ.* **2010**, *125*, 137–145. [[CrossRef](#)]
15. İlhan, İ. An improved simulated annealing algorithm with crossover operator for capacitated vehicle routing problem. *Swarm Evol. Comput.* **2021**, *64*, 100911. [[CrossRef](#)]

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