Computational Intelligence

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Drilling of printed circuit boards [TSP Problem]

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First Paper

Background:

Transportation problems are a class of optimization problems that arise in various real-world scenarios involving the movement of goods, people, or vehicles from one location to another. These problems are commonly encountered in logistics, supply chain management, urban planning, and transportation systems optimization. The main goal of solving transportation problems is to find the most efficient way to allocate resources (such as vehicles, routes, or transportation modes) to meet specific demands or objectives while minimizing costs, time, or other constraints. Efficient transportation systems contribute to economic development by facilitating trade, enhancing accessibility to markets, and promoting regional integration. The mathematical models used to solve these problems, such as the Transportation Model and Network Flow Problems, are grounded in linear programming and have been instrumental in streamlining logistics operations across multiple industries. Consequently, modern transportation problem-solving must incorporate sustainable practices, balancing economic objectives with environmental stewardship and social responsibility. Innovations in technology, such as AI and machine learning, are increasingly being leveraged to tackle these multifaceted challenges, offering promising avenues for creating more resilient and sustainable transportation networks.

Importance of optimization in transportation

Optimization in transportation is a challenging task. The main goal is to enhance the overall efficiency of the transportation network while minimizing costs and maximizing the usage of resources. Optimization can be applied to various modes of transportation, including road, rail, air, sea and more. Efficient route planning, load optimization, and real-time tracking contribute to streamlined operations. This is how you can reduce delays and improve the overall efficiency of the transportation process.

benefits of transport optimization:

- Cost Reduction
- Resource Utilization
- Reduced Environmental Impact
- Improved Efficiency
- Data-Driven Decision Making & Flexibility and Adaptability

Overview of computational intelligence algorithms for optimization

Computational intelligence algorithms provide an adaptable and reliable framework for dealing with issues involving non-linear connections, dynamic surroundings, and noisy data. A population-based approach to searching for the best solutions is used by evolutionary algorithms, such as **genetic algorithms** and genetic programming. They have outstanding exploration and exploitation skills, which enable them to explore enormous solution areas and locate nearly optimum solutions. Another crucial element of computational intelligence is **neural networks**, which offer strong modeling and optimization tools. To approximate the objective functions and constraints of optimization problems, neural networks may be trained to capture complicated connections and learn from data. This makes it possible to effectively find the best solutions using gradient-based optimization methods like backpropagation. On the other hand, **fuzzy systems** are excellent at handling ambiguity and uncertainty in optimization tasks. Fuzzy systems may solve issues with imperfect or insufficient information by modeling and reasoning with fuzzy sets and fuzzy rules.

While computational intelligence methods offer significant benefits, they also pose challenges in terms of algorithmic design and parameter tuning. The performance of these algorithms heavily depends on appropriately selecting and configuring their parameters, such as population size, mutation rates, neural network architectures, and fuzzy rule bases. Moreover, the computational complexity associated with large-scale optimization problems can be demanding, requiring efficient implementation and parallelization strategies. Balancing exploration and exploitation is another crucial challenge, as overly exploitative strategies can lead to premature convergence, trapping the algorithm in suboptimal solutions.

Finding the optimal option from a list of workable options while considering various objective functions and restrictions is the goal of optimization issues. Traditional optimization algorithms frequently fail to locate optimum or nearly optimal solutions in a timely manner when issue complexity rises. By fusing methods drawn from both human and natural intelligence, computational intelligence presents a viable approach to solving these problems. The suggested approach seeks to use computational intelligence to address challenging optimization issues effectively and efficiently.

FIRST PAPER

The school bus routing problem: a case study

Introduction:

In Hong Kong, where there is currently no scientific method for allocating. students to buses and planning bus routes, the project seeks to create a computer. system for school bus services. The study focuses on creating methods for arranging. school bus routes, particularly early in the day. The essay offers a survey of the literature on vehicle routing and school bus routing, formulates the issue of school bus routing in Hong Kong and suggests an algorithm to resolve the issue. The algorithm's efficacy is evaluated using information from a Hong Kong kindergarten, and the results are shown in the experimental results section.

Literature review:

The school bus routing problem is a particular kind of vehicle routing problem (VRP), which deals with the effective utilization of a fleet of vehicles to pick up and deliver clients or goods while lowering overall costs and meeting limitations. The VRP has been extensively explored in operational research journals, and most of the study focuses on creating heuristic algorithms because it is impractical to always discover the best solution. In the last two decades, the issue of school bus routing has drawn attention, and there are numerous, situation-specific options. In Braca et al.13, a survey of several of these strategies is presented.

Table 1 Literature review on the school bus routing problem

Reference	Problem type	Objective	Constraint
Bennett and Gazi's [6]	Single school	Minimize total student travel time	Bus capacity
Dulac et *al*[7]	Single school	Min {total distance × number of routes}	1. Bus capacity 2. The number of stops 3. The length of a route
Chen and Kallsen [8]	Single school	1. Minimize the number of buses required 2. Minimize fleet travel time 3. Balance the bus loads	1. Bus capacity 2. Student riding time 3. School time window

Bowerm an et at	Single school	1. Minimize the number of routes (buses) 2. Minimize total bus route length 3. Balance bus loads and route lengths 4. Minimize student walking distance	1. Bus capacity 2. Travel time on each route 3. The total travel time
Newton and Thomas 10	Multi-school	1. Minimize total bus travel time 2. Minimize the number of routes requirements	1. Bus capacity 2. Student riding time
Angel et *al*11	Multi-school	1. Minimize the number of routes 2. Minimize total bus travel time	1. Bus capacity 2. Specified route time limit
Bodin and Berman 12	Multi-school	Minimize total bus travel time	1. Bus capacity 2. Allowable student travel time
Braca et *al*13	Multi-school	Minimize the number of buses needed	1. Upper and lower bounds on bus capacity 2. Student riding distance 3. School time window 4. Earliest pick-up time

Although many papers mention multiple objectives to be considered, only Bowerman et al9 claim that their method examines the school bus routing problem from a multi-objective viewpoint. As will be seen in the next section, our problem is different from those previously reported in several aspects. The objectives considered include minimizing the number of buses required, total travel time spent by pupils at all points, total bus travel time, and balancing the bus loads and travel times. The main constraint is the bus capacity.

Problem representation:

Notation K is the number of buses available for the school bus service.
Ck is the capacity of bus k, which may be the same or different for each bus.
n is the total number of pick-up points. M is the total number of pupils to be served. $p1$, $p2$, ..., pn, are the n pick-up points. These are ordered by decreasing distance from the school. pn+1 denotes the school.
tij is the travel time from pi to pj.
fi is the number of pupils to be picked up at pi.
L is the average pick-up time at pick-up points.

$$xijk = \begin{cases} 1 & \text{if bus } k \text{ travels directly from } pi \text{ to } pj \\ 0 & \text{otherwise.} \end{cases}$$

$$zik = \begin{cases} 1 & \text{if bus } k \text{ picks up pupils at } pi \\ 0 & \text{otherwise.} \end{cases}$$

yik is the number of pupils picked up by bus k at pi.

Objectives:

To evaluate school bus routes, multiple criteria need to be considered simultaneously, including efficiency, effectiveness, and equity. Each criterion has its own set of objectives to meet, but they are all interrelated when assessing service provision. The objectives for the school bus routing problem are listed and discussed, and then classified according to the relevant criteria.

(1) Minimize the total number of buses required. This is an objective related to the service cost. The minimum number of buses K (assume one bus for one route only) required to serve all points for a school can be determined by

$$K = \min(q) \text{ such that } \sum_{k=1}^{q} k \geqslant M$$

Schools usually do operate with only K buses for the service owing to the consideration of cost.

(2) Minimize the total travel time spent by pupils at all points. This objective is what the school and parents are concerned about most. To minimize this objective is to ensure higher quality service. It can be formulated as

$$\min \sum_{k=1}^{K} \left\{ \sum_{i=1}^{n} \left[\sum_{j=1}^{n+1} t_{ij} x_{ijk} \left(\sum_{l=1}^{i} z_{lk} \right) + L z_{ik} \left(\sum_{l=1}^{i} z_{lk} \right) \right] \right\}$$

Let di denote the shortest travel time from pi to the school. The school and parents will compare the actual travel times spent with di to evaluate the service quality. Therefore, is the lower bound of this objective.

$$T = \sum_{i=1}^{n} d_i$$

(3) Minimize the total bus travel time. This is another objective related to the service cost. It consists of two parts: minimizing the total bus loaded travel time (from route origins to the school) and minimizing the total bus vacant travel (deadheading) time (from parking places to the route origins). The former can be formulated as

$$\min \sum_{k=1}^{K} \left[\sum_{i=1}^{n} \left(\sum_{j=1}^{n+1} t_{ij} x_{ijk} + L z_{ik} \right) \right]$$

A solution resulting in the improvement of objective (2) usually leads to the improvement of this part of objective (3). In the case of all buses with the same capacity, the latter can be formulated as the following assignment problem.

Minimize $\sum_{i=1}^{K} \sum_{j=1}^{K} c_{ij} u_{ij}$

subject to

$$\sum_{i=1}^{K} u_{ij} = 1 \quad j = 1, \ldots, K$$

$$\sum_{j=1}^{K} u_{ij} = 1 \quad j = 1, \ldots, K$$

$$u_{ij} = 0 \text{ or } 1 \quad i, j = 1, \ldots, K$$

where c_{ij} is the travel time from parking place of bus i to the origin of route j.

$u_{ij} = \{1$ if bus i is assigned to route j

0 otherwise

Otherwise, this assignment, or part of it, is given by the route planner.

(4) Balance the loads and travel times between buses. It is very important in practice to do so. The acceptable level of load and travel time balance depends on the route planner, parents, and bus drivers.

The priority of objectives is the same order as above, i.e. giving priority to objective (1), second to objective (2), then objective (3), and finally objective (4). The classification of the objectives considered is given below.

A measure of efficiency is the ratio of the level of a service compared to the cost of the resources required to provide the service. Objectives (1) and (3) belong to the efficiency criterion.

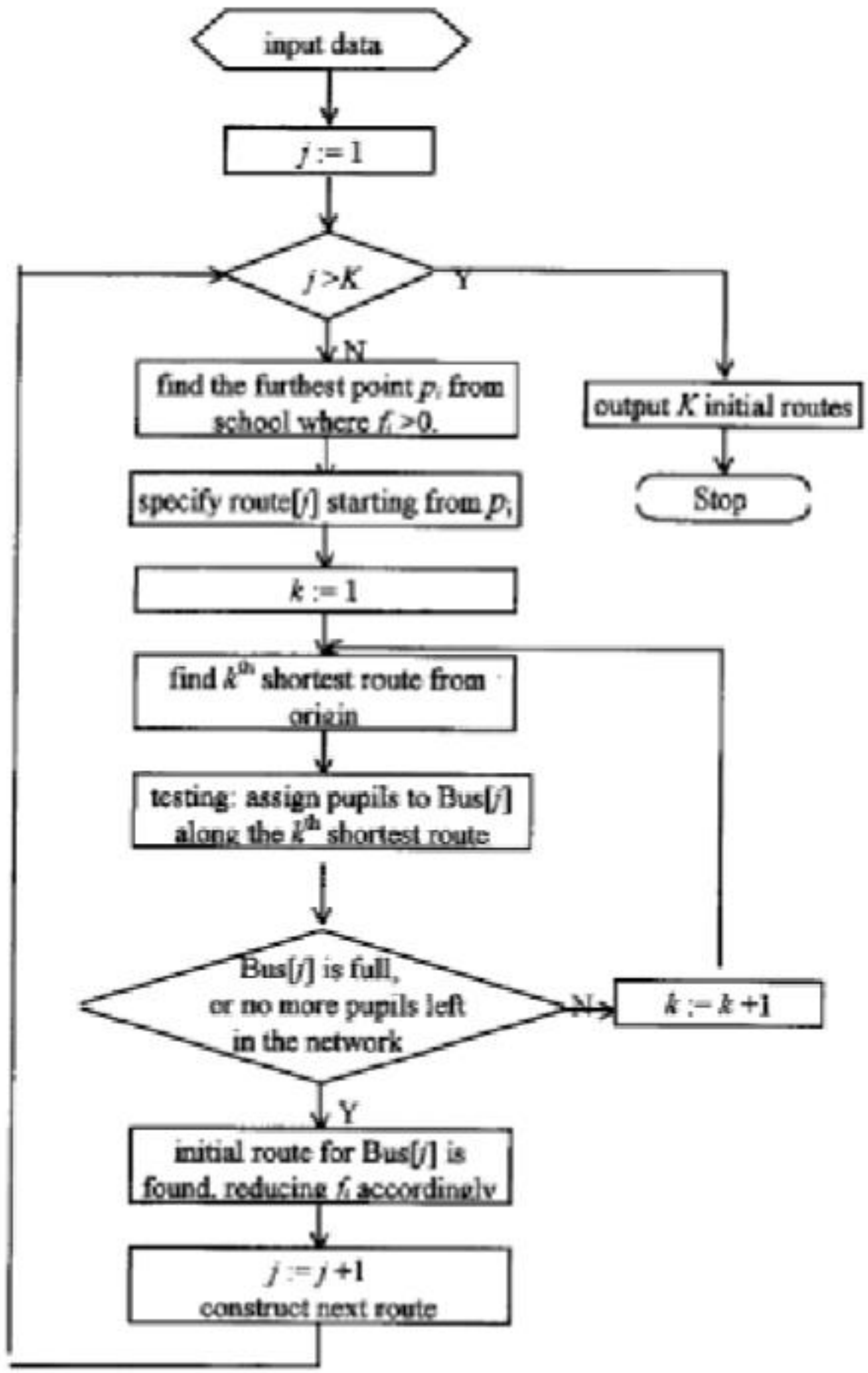
Solution algorithm:

Stage 1. Find the optimal solution K for objective (1), where.

$$K = \min(q) \text{ such that } \sum_{k=1}^{q} C_k \geqslant M$$

Stage 2. At this stage the solution building strategy is applied to find an initial feasible solution by constructing the routes one by one. The flowchart of stage 2 is shown in Figure 1. If the bus capacities in the fleet are different, the route planner may determine randomly or according to own preference which bus to serve this route interactively and hence its capacity is known.

Stage 3. The improvement strategy is adopted at this stage. to improve the initial solution.

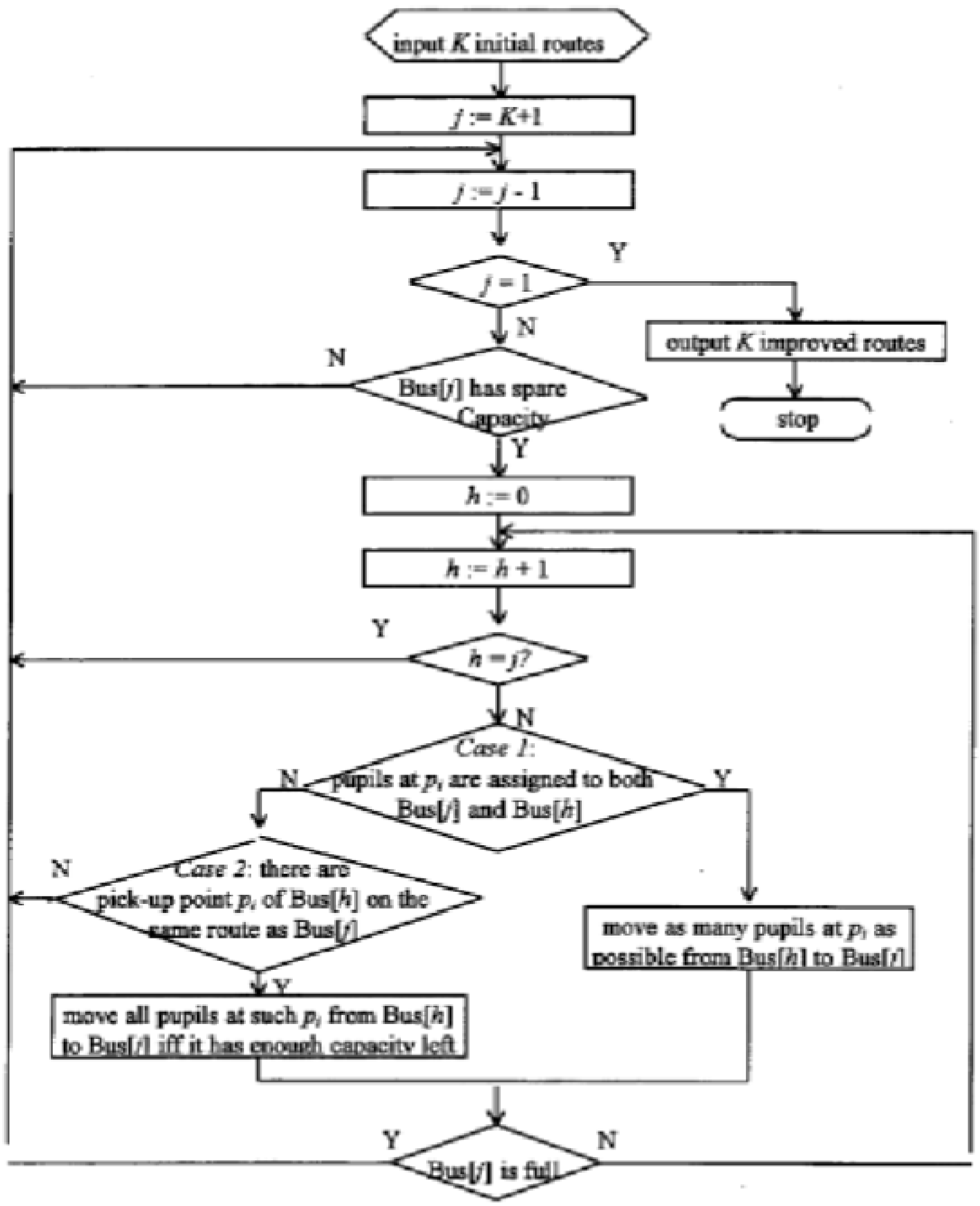


input data
j := 1
j > K
Y
N
find the furthest point p_i from school where f_i > 0.
output K initial routes
Stop
specify route[j] starting from p_i
k := 1
find k^th shortest route from origin
testing: assign pupils to Bus[j] along the k^th shortest route
Bus[j] is full, or no more pupils left in the network
N
k := k + 1
Y
initial route for Bus[j] is found, reducing f_i accordingly
j := j + 1
construct next route

Experimental results:

The algorithm is applied to a kindergarten in Hong Kong to test its effectiveness. The existing school bus routes of the kindergarten are planned manually.

Data input the following (see Table 2) are the data used to find the solution. The total number of pupils to be served is 86. All buses have the same capacity, 36. Then K = 3. Average pick-up time *L* = 25



(s). There are 54 pick-up points, where each has 1-8 pupils. The shortest distances from every pick-up point to the school are found by using the program codes of Dijkstra's algorithm in Syslo et al. 18 All pick-up points pi are ordered by decreasing distance to the school. There are both one-way streets and two-way streets on the street network.

Result analysis:

The algorithm has been programmed using Turbo Pascal. After inputting the above data, the algorithm requires only a few seconds on a PC to output the results. The results are shown in Table 3. In this example the load of bus 3 is much less than that of buses 1 and 2. The reason is that the improvement of load balance in Stage 3 is limited owing to priorities been given to objectives (2) and (3). However, one may obtain the desirable level of load balance simply by decreasing the bus capacity to a suitable level interactively and forcing the algorithm to get a result with desirable balance loads. The closer to the average bus load the bus capacity, the more balanced the actual bus loads are. In this case, however, the values for objectives (2) and (3) will possibly increase, resulting in lower service quality. This is a trade-off to be made. A comparison of objective (2) (excluding pick-up time) is shown in Table 4. The result is just 17.4% above the lower bound $T = \sum i=1\ n\ di$. Notice that the lower bound is just a very loose one. The actual gap between the optimum and the solution found by the algorithm should be much narrower. The new routes produced by the algorithm save 29% of total pupil travel time in comparison with that of the existing routes. A comparison of the bus loaded-travel times (objective (3)) (including pick-up times) is shown in Table 5. 13.2%, 32.5% and 23.4% are shortened respectively for each route.

Conclusion:

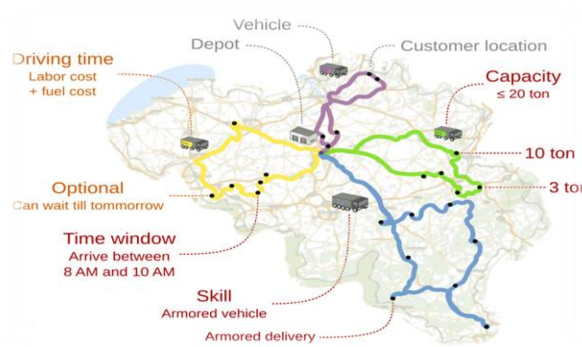
The paper presents a case study of the school bus routing problem, which is formulated as a multi-objective combinatorial optimization problem. An efficient heuristic algorithm, combining various optimization methods, is proposed for its solution. The objectives of the problem include minimizing the total number of buses required and the total travel time spent by pupils at all pick-up points, which are important concerns for the school and parents. The algorithm runs efficiently on a personal computer.

SECOND PAPER

Vehicle routing problem

Description of the problem:

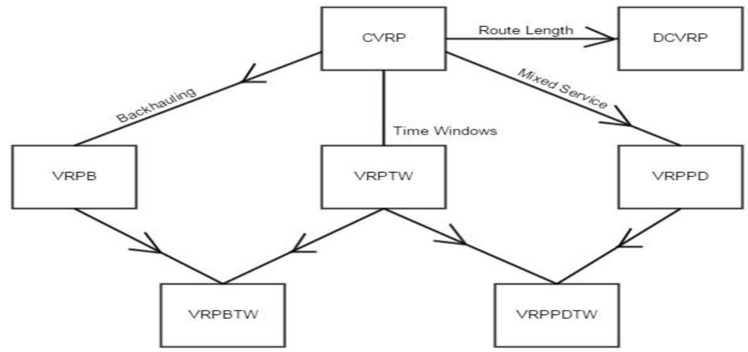
The vehicle routing problem (VRP) is a combinatorial optimization and integer programming problem which asks, "What is the optimal set of routes for a fleet of vehicles to traverse in order to deliver to a given set of customers?" It generalizes the travelling salesman problem (TSP). It first appeared in a paper by George Dantzig and John Ramser in 1959,[1] in which the first algorithmic approach was written and was applied to petrol deliveries. Often, the context is that of delivering goods located at a central depot to customers who have placed orders for such goods. The objective of the VRP is to minimize the total route cost. In 1964, Clarke and Wright improved Dantzig and Ramser's approach using an effective greedy algorithm called the savings algorithm.



Objectives:

the objective of a VRP changes depending on the application of the result:

- Minimize the global transportation cost based on the global distance travelled as well as the fixed costs associated with the used vehicles and drivers.
- Minimize the number of vehicles needed to serve all customers.
- Least variation in travel time and vehicle load.
- Minimize penalties for low quality service.
- Maximize a collected profit/score.


CVRP
Route Length
DCVRP
Backhauling
Time Windows
Mixed Service
VRPB
VRPTW
VRPPD
VRPBTW
VRPPDTW

Vehicle flow formulations:

The formulation of the TSP by Dantzig, Fulkerson and Johnson was extended to create the two index vehicle flow formulations for the VRP :

$$\min \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij}$$

subject to

$$\sum_{i \in V} x_{ij} = 1 \quad \forall j \in V \setminus \{0\} \tag{1}$$

$$\sum_{j \in V} x_{ij} = 1 \quad \forall i \in V \setminus \{0\} \tag{2}$$

$$\sum_{i \in V \setminus \{0\}} x_{i0} = K \tag{3}$$

$$\sum_{j \in V \setminus \{0\}} x_{0j} = K \tag{4}$$

$$\sum_{i \notin S} \sum_{j \in S} x_{ij} \geq r(S), \ \ \forall S \subseteq V \setminus \{0\}, S \neq \emptyset \tag{5}$$

$$x_{ij} \in \{0,1\} \quad \forall i,j \in V \tag{6}$$

In this formulation represents the cost of going from node to node , is a binary variable that has value if the arc going from to is considered as part of the solution and otherwise, is the number of available vehicles and corresponds to the min number of vehicles needed to serve set . We are also assuming that is the depot node.

Application of Computational Intelligence Algorithms:

Simulated Annealing (SA) is a probabilistic technique for approximating the global optimum of a given function. Specifically, it’s a metaheuristic to approximate global optimization in a large search space. It’s particularly useful for solving the Vehicle Routing Problem (VRP) due to its ability to escape local optima and explore the search space extensively.

Algorithm 2. Simulated Annealing

```
procedure SA()
  T := InitialTemperature()
  init := SolomonI1()
  s := LocalSearch(init)
best := s
  while not Terminate() do
    s' := Escape(s)
    s" := LocalSearch(s')
  if (f (s'') <f (s)) then
   s := s''
  else
      j := rnd(0, 1)
   k := -((f(s'')-f(best))/T
   if j <exp(k) then
    s := s"
   endif
  endif
  if (f(s) <f(best)) then
    best := s
  endif
    T := CoolingSchedule (T)
 endwhile
 return best
end
```

Results and Findings

Recent studies have shown that CI algorithms can effectively reduce travel times and operational costs. For instance, evolutionary algorithms have been used to optimize routes with time windows under uncertainty, providing robust solutions that can adapt to changes in real-time5.

Conclusion

The VRP is a critical problem in logistics and transportation, with significant implications for efficiency and customer satisfaction. Advances in computational intelligence have opened new avenues for solving complex VRPs, leading to more effective and adaptable routing solutions. As e-commerce and urbanization continue to grow, the importance of optimizing vehicle routing will only increase.

Literature Review

Review of existing literature on transportation problems And optimization techniques:

Transportation problems, a subclass of linear programming problems, focus on efficiently distributing goods from multiple sources to multiple destinations while minimizing transportation costs and satisfying supply and demand constraints. First formulated by Gaspard Monge in 1781, these problems have evolved over time, now including various extensions and applications. Optimization techniques in transportation span from exact methods like the Simplex algorithm to approximate methods such as heuristics and metaheuristics, addressing not only traditional cost-minimization problems but also multi-objective, dynamic, and stochastic scenarios. With advancements in computational capabilities, there's been a significant shift towards intelligent algorithms that combine metaheuristics with simulation and machine learning, aiming to enhance the efficiency of transportation systems. Moreover, recent transportation research emphasizes sustainability, leading to the development of optimization models that integrate environmental and social criteria alongside economic objectives, reflecting the complexity and importance of transportation systems in modern society.

In summary, the literature on transportation problems and optimization techniques is extensive and diverse, showcasing ongoing efforts to address the evolving challenges in transportation systems. Researchers continually explore new methodologies and technologies, driven by the need to optimize economic objectives while also considering environmental sustainability and social equity.

Identification of gaps or areas where computational intelligence algorithms can be applied:

The application of computational intelligence (CI) algorithms spans numerous fields, yet there remain gaps and areas ripe for exploration. Here are some identified gaps where CI algorithms can be further applied:

- *Integration with IoT and Edge Computing*: The Internet of Things (IoT) generates vast amounts of data that CI algorithms can analyze. However, there's a gap in deploying these algorithms efficiently at the edge of the network, closer to where data is collected.
- *Adaptation to Climate Change*: CI algorithms can play a significant role in modeling and adapting to climate change effects. There's a gap in applying CI to predict climate

patterns, optimize resource use, and develop sustainable practices.

- *Healthcare Personalization*: Personalized medicine is an emerging field where CI can make a significant impact. There’s a gap in developing algorithms that can analyze complex biological data to provide personalized treatment plans.
- *Vehicle Efficiency and Low-Carbon Technologies*: There is a need for innovation in efficiency technologies and low-carbon vehicles and fuels, especially in harder-to-abate modes like heavy-duty vehicles, maritime, and aviation. CI algorithms can help optimize vehicle design and operations for better fuel efficiency and lower emissions.

Future Directions and Challenges

Potential areas for future research in transportation optimization:

Future research in transportation optimization holds significant promise for addressing emerging challenges and improving efficiency across various domains.

- **Deep Learning for Recyclable Material Transportation**: Utilizing deep learning algorithms to optimize the transportation of recyclable materials, improving recycling rates and reducing costs.
- **Smart Transportation Route Optimization**: Leveraging smart technologies to optimize transportation routes, considering factors like traffic, weather, and infrastructure conditions.
- **Green Logistics and Environmental Sustainability:** Developing optimization models that prioritize environmental sustainability by minimizing carbon emissions, promoting energy-efficient transportation modes, and optimizing vehicle loading to reduce fuel consumption and environmental impact.
- **Crowdsourced and Peer-to-Peer Transportation Networks:** Investigating the potential of crowdsourced transportation platforms and peer-to-peer sharing economy models to optimize resource utilization, reduce congestion, and enhance transportation accessibility in urban and rural areas.
- **Last-Mile Delivery Optimization:** Addressing the challenges associated with last-mile delivery, including congestion, accessibility, and environmental impact, by designing innovative optimization algorithms tailored to urban environments and emerging delivery methods such as drones and autonomous robots.

Challenges and considerations for implementing CI algorithms in practice:

Implementing Computational Intelligence (CI) algorithms in practice presents several challenges and considerations that need to be carefully addressed to ensure their effective deployment and integration into real-world applications. Some of these challenges include:

- **Computational Complexity:** Many CI algorithms, such as genetic algorithms (GA) and particle swarm optimization (PSO), involve complex optimization processes that require significant computational resources and time to converge to optimal solutions. Implementers need to consider computational scalability and efficiency, especially when dealing with large-scale optimization problems or real-time applications.
- **Integration with Existing Systems:** Integrating CI algorithms into existing software systems or workflows can be complex, particularly in domains with legacy infrastructure or proprietary technologies. Implementers need to consider

compatibility, interoperability, and data exchange mechanisms to ensure seamless integration with existing systems and processes while minimizing disruption and adaptation costs.

- **Data Quality and Preprocessing:** The effectiveness of CI algorithms often depends on the quality, relevance, and availability of input data. Implementers need to carefully preprocess and validate data to address issues such as noise, missing values, outliers, and bias, which can adversely affect algorithm performance and reliability. Moreover, collecting and maintaining high-quality data can be resource-intensive and may require collaboration with domain experts and data providers.
- **Ethical and Legal Considerations:** Implementers must be aware of ethical and legal considerations related to the use of CI algorithms, particularly in sensitive domains such as healthcare, finance, and criminal justice. Issues such as algorithmic bias, fairness, privacy, accountability, and regulatory compliance need to be carefully addressed to mitigate potential risks and ensure responsible and ethical deployment of CI solutions.
- **Parameter Tuning and Sensitivity:** CI algorithms often rely on a set of parameters that control their behavior and performance. Finding appropriate parameter settings can be challenging and may require extensive experimentation and fine-tuning. Moreover, CI algorithms can be sensitive to changes in parameter values, requiring careful adjustment to ensure robust and reliable performance across different problem instances.

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