

AN INTEGRATED AND INTELLIGENT METAHEURISTIC FOR CONSTRAINED VEHICLE ROUTING

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Summary

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South African metropolitan areas are experiencing rapid growth and requires an increase in network infrastructure. Increased congestion negatively impacts both public and freight transport costs. The concept of *City Logistics* is concerned with the mobility of cities, and entails the process of optimizing urban logistics activities by concerning the social, environmental, economic, financial, and energy impacts of urban freight movement. In a cost-competitive environment, freight transporters often use sophisticated vehicle routing and scheduling applications to improve fleet utilization and reduce the cost of meeting customer demands.

In this thesis, the candidate builds on the observation that vehicle routing and scheduling algorithms are inherent problem specific, with no single algorithm providing a dominant solution to all problem environments. Commercial applications mostly deploy a single algorithm in a multitude of environments which would often be better serviced by various different algorithms.

This thesis algorithmically implements the ability of human decision makers to choose an appropriate solution algorithm when solving scheduling problems. The intent of the routing agent is to classify the problem as representative of a traditional problem set, based on its characteristics, and then to solve the problem with the most appropriate solution algorithm known for the traditional problem set. A *not-so-artificially-intelligent-vehicle-routing-agentTM* is proposed and developed in this thesis. To be considered *intelligent*, an agent is firstly required to be able to recognize its environment. Fuzzy *c*-means clustering is employed to analyze the geographic dispersion of the customers (nodes) from an unknown routing problem to determine to which traditional problem set it relates best. Cluster validation is used to classify the routing problem into a traditional problem set.

Once the routing environment is classified, the agent selects an appropriate metaheuristic to solve the complex variant of the Vehicle Routing Problem. Multiple soft time windows, a

heterogeneous fleet, and multiple scheduling are addressed in the presence of time-dependent travel times. A new initial solution heuristic is proposed that exploits the inherent configuration of customer service times through a concept referred to as *time window compatibility*. A high-quality initial solution is subsequently improved by the Tabu Search metaheuristic through both an adaptive memory, and a self-selection structure.

As an alternative to Tabu Search, a Genetic Algorithm is developed in this thesis. Two new crossover mechanisms are proposed that outperform a number of existing crossover mechanisms. The first proposed mechanism successfully uses the concept of time window compatibility, while the second builds on an idea used from a different sweeping-arc heuristic.

A neural network is employed to assist the intelligent routing agent to choose, based on its knowledge base, between the two metaheuristic algorithms available to solve the unknown problem at hand. The routing agent then not only solves the complex variant of the problem, but adapts to the problem environment by evaluating its decisions, and updating, or reaffirming its knowledge base to ensure improved decisions are made in future.

Keywords: Vehicle routing; fuzzy clustering, time-dependent travel time; metaheuristics

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Acronyms

ACO	Ant Colony Optimization
ACS	Adapted Combined Savings
AI	Artificial Intelligence
AMD	Absolute Mean Deviation
AMP	Adaptive Memory Procedure
ANN	Artificial Neural Network
ANNs	Artificial Neural Networks
AOOS	Adapted Optimistic Opportunity Savings
AROS	Adapted Realistic Opportunity Savings
CMTSP	Capacitated Multiple Traveling Salesman Problem
CS	Combined Savings
CVRP	Capacitated Vehicle Routing Problem
CW	Clarke-Wright
DP	Dynamic Programming
EER	Enhanced Edge Recombination
ER	Edge Recombination
FIFO	First-In-First-Out

FSMVRP	Fleet Size and Mix Vehicle Routing Problem
FSMVRPTW	Fleet Size and Mix Vehicle Routing Problem with Time Windows
GA	Genetic Algorithm
GIS	Geographical Information System
HVRP	Heterogeneous Fleet Vehicle Routing Problem
ILP	Integer Linear Program
ITS	Intelligent Transportation System
LP	Linear Programming Problem
MPVRP	Multi Period Vehicle Routing Problem
MSE	Mean Square Error
MTMCP	Multiple Tour Maximum Collection Problem
MTSP	Multiple Traveling Salesman Problem
MTVRP	Multi-Trip Vehicle Routing Problem
MVRPSP	Multi-Vehicle Routing Problem with Split Pick-ups
MX	Merged Crossover
OOS	Optimistic Opportunity Savings
PFIH	Push Forward Insertion Heuristic
PMX	Partially Matched Crossover
ROS	Realistic Opportunity Savings
SA	Simulated Annealing
SEC	Subtour Elimination Constraints
SIH	Sequential Insertion Heuristic
TDTSP	Time Dependent Traveling Salesman Problem
TDVRP	Time Dependent Vehicle Routing Problem

TP	Thesis Problem
TS	Tabu Search
TSP	Traveling Salesman Problem
TWC	Time Window Compatibility
TWCM	Time Window Compatibility Matrix
VFM	Vehicle Fleet Mix problem
VRP	Vehicle Routing Problem
VRPHE	Vehicle Routing Problem with a Heterogeneous fleet of vehicles
VRPM	Vehicle Routing Problem with Multiple use of vehicles
VRPMVTTW	Vehicle Routing Problem with Multiple Vehicle Types and Time Windows
VRPPD	Vehicle Routing Problem with Pickups and Deliveries
VRPTW	Vehicle Routing Problem with Time Windows