

**SIMULATED ANNEALING BASED OPTIMIZED  
DRIVER SCHEDULING FOR VEHICLE DELIVERY**

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Degree of Master of Science

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Thesis submitted in partial fulfillment of the requirements for the degree Master of  
Science in Computer Science and Engineering

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Dr. HMN Dilum Bandara

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Eng. Nishal Samarasekara

Signature of the supervisor:

Date:

## **Abstract**

### **Simulated annealing based optimized driver scheduling for vehicle delivery**

Vehicle delivery is a major business where third-party drivers are hired to deliver vehicles when they are relocated, sold, or while returning rental cars. This is motivated due to the busy schedule of individuals and companies, convince, and cost saving. A vehicle delivery company typically operates in a chosen geography varying from a region of a country to a set of countries that are nearby. Hence, the drivers are also geographically dispersed. This is a complicated process due to the wide variation in collection/delivery locations, driver availability, time bounds, types of vehicles, special skills required by drivers, and impact due to traffic and weather. Currently the process is manipulated manually by a scheduling manager who creates next day's schedule at the end of the working day based on the jobs received. However, as the number of jobs and drivers increase, it is hard to decide on the most appropriate driver for the job such that both the customer and company goals are optimally satisfied. We propose an automated driver scheduling solution to maximize the number of vehicle deliveries and customer satisfaction while minimizing the delivery cost and distributing driver income based on their availability. Proposed solution consists of a rule checker and a scheduler. Rule checker enforces constraints such as deadlines, vehicle types, license types, skills, and working hours. Scheduler uses simulated annealing to assign as many jobs as possible while minimizing the overall cost. Using a workload derived from an actual vehicle delivery company, we demonstrate that the proposed solution has good coverage of jobs while minimizing the cost and equitably distributing the income among drivers based on their availability. Moreover, the proposed solution has the flexibility to tolerate exceptions due to breakdowns, excessive traffic, and bad weather without a considerable impact on the majority of the already scheduled jobs.

**Keywords:** Optimization, Scheduling, Simulated Annealing, Vehicle Delivery

## **Dedication**

I dedicate my thesis work to my family and many friends. A special feeling of gratitude to my loving parents, Sarathchandra and Aruna Muramudalige whose words of encouragement and push for tenacity ring in my ears. My sister Dulari Muramudalige and my wife Sonali Muthukumarana have never left my side and are very special.

I also dedicate this thesis to my many friends and colleagues who have supported me throughout the process. I will always appreciate all they have done, especially for helping me develop my technology skills.

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## List of Abbreviations

ANN	Artificial neural network
ANS	Artificial Neural Systems
BDSP	Bus Driver Scheduling Problem
DA	Dispatch Area
GPS	Global Positioning System
HC	Hill Climbing
IBK	Naive Bayes classifier
ILP	Integer Linear Programming
J48	Decision tree
ML	Machine Learning
NB	K nearest neighbor
PART	Rule based algorithm
RMC	Ready Mix Concrete
RMP	Restricted Master Problem
SA	Simulated Annealing
SMO	Support vector machine
TDSP	Truck Driver Scheduling Problem
VD	Vehicle Delivery