Design of Next Generation Smart Surface Transportation System

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Abstract: Transportation systems of the future need to be adaptive, adoptive, and responsive in order to meet the diverse challenges and ever-evolving demands. Conventional method of adding more resources on the road does not enhance its utility, rather it creates traffic congestion. Optimization of the usage of existing resources has been found to be one of the most effective solution to manage traffic congestion. The method we propose consists in increasing the occupancy rate of each vehicle and utilize other untapped resources in existing infrastructure. The resource optimization problem studied in this paper is NP hard, due to the vehicle routing and resource matching problem. In this paper, we are focused on developing a Multi-Objective Evolutionary Algorithm to optimize the use of taxi service not just as a carrier for people but also as a transport system for parcel delivery. Preliminary experiment with real-world data shows that our approach is able to quickly produce satisfactory solutions and the algorithm is able to provide an average of 17.7% improvement over conventional methods.

1 INTRODUCTION

Over the past decade or so, the transportation systems in major cities round the world have rapidly evolved to meet multiple challenges and demands they have faced. In the public transportation domain, taxies provide flexibility and comfort of door-to-door rides, use existing road infrastructure, and provide travel freedom that is comparable to travel in a personal vehicle. However, this form of vehicular transportation usually carries one or two individuals, resulting in many empty seats and hence a significant underutilization of the overall capacity. Statistics reported by Nokia Research (Hartwig, 1997) show that vehicles in United Kindom have an average occupancy of 1.5. The result of underutilized transportation resources may lead to detrimental effects such as traffic congestion, air pollution, and increase in fuel consumption (Huang, 2015). Uber hired service allow passengers to submit their trip request ahead of time. Uber successfully demonstrated the concept of matching demand to supply through technology. This is unlike traditional taxi services that result in excessive and unnecessary cruising and waiting in the hunt for passengers (Takayama, 2011).

In recent years, we have seen an exponential increase in e-commence (Jones, 2013). Consumers are shifting away from physical high street brick-and-mortar shopping to the comfort of purchasing through online stores. Hence, products in warehouses are no longer needed to be delivered to retail stores, but directly to the customer's premises. Conventional parcel delivery method may take days to complete. However online giant Amazon noticed that faster delivery time boost sales. Coupled with perishable products (such as groceries) being sold online, there has been a significant increase for on-demand parcel delivery services.

In people transportation, carpooling (ride-sharing of a vehicle) is known to resolve resource crunch and increase occupancy rate. Overall, it has been found to be one of the best solutions to manage traffic congestions (Fagin, 1983) (Megalingam, 2011). However, passenger of the future may come with diverse needs beyond the requirement for physical transportation space. They may want to charge their mobile device or stay connected through alternative connectivity services such as WiFi. When it comes to parcel delivery, fast and efficient delivery requires the flexibility of on-demand door-to-door rides like a taxi service. The taxies today, in most instances, offer one or more

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empty seats. In future, other form of resources may also be offered. This includes trunk space, power for mobile devices, and even connectivity services (such as WiFi). The future of transportation will need to be adaptive to meet the diverse demands and needs.

In this study of transportation systems, we analyze potential untapped resources and opportunity that can be used in the future transportation systems. It is critical to develop an algorithmic approach for optimizing the matching of driver, passenger, and delivery of parcels. In this work, we carry out a theoretical study of Single Driver to Multiple Passenger/Parcel (SDMP). The SDMP arrangement means that each driver may pick up and deliver one or more passengers and parcels during their trip, in which the seat occupancy can be increased while opening the available trunk space for parcel delivery.

The organization of the paper is as follows. Section 2 describes related intelligent transportation system approaches. The problem formulation is highlighted in Section 3. In Section 4, we present our proposed MOEA approach. Section 5, presents the experiental results. Final, our conclusions are drawn in Section 6.

2 RELATED WORKS

As mentioned in the introduction, the diversity in the demand and supply creates an unique multi-objective optimization problem where a number of objectives such as travel distance, trip duration and services provided needs to be concurrently matched and optimized for different stakeholders. In contrast to single objective optimization, a solution to a multi-objective optimization problem exists in the form of alternate tradeoffs known as the Pareto optimal set. In a Pareto optimal set, each objective component of any non-dominated solution can only be improved by degrading at least one of its other objective component. Therefore, the multi-objective optimization consists in discovery of a possible set of Pareto optimal solutions for which decision maker can select an optimal solution based on the current situation.

The evolutionary algorithm inspired by Darwin's theory of evolution has been used often in search of Pareto optimal set (Fonseca, 1995). It has been successfully applied to a wide variety of problems and shown to be capable of producing optimal or near-optimal solution for multi-dimensional problems (Ross, 1994). An evolutionary algorithm function with a population of solutions is represented in the form of chromosomes. Each chromosome is encoded with a number of genes, each gene representing a unit of information. The algorithm searches for new solutions through the process of combining (crossover) and altering (mutation) of existing chromosomes in the population. Upon creation of new chromosomes, they are evaluated. Better quality solutions remain while inferior solutions are eliminated from the population. Through multiple generations, it artificially simulates 'natural selection' in survival of the fittest.

There are many research studies on matching and optimizing transport related routing problem, under some restrictive assumptions. (Huang, 2015) designed an intelligent carpool system which matches new passenger(s) to an existing trip. (Baker, 2003) describes the use of genetic algorithm in vehicle routing problem (VRP) for goods delivery. (Tan, 2007) has extended the use of mutli-objective evolutionary computation to time constrained VRP with stochastic demand. The actual demand is revealed only when the vehicles arrive at the customers premises.

In this paper, a Multi-Objective Evolutionary Algorithm (MOEA) is applied to the pairing of requests to the transportation resources. The proposed approaches balance the benefits and trade-off between stakeholders.

3 PROBLEM FORMULATION

The resource planning considered in this paper is defined around the situation in which a number of potential passenger and customer requests have similar origin and destination. Such requests can then be paired with a vehicle taking a route similar to those requests. Passenger(s) or customer(s) submit their trip request to a central server via smart devices. Given this scenario, the problem at hand is to decide which requests should be matched and assigned to an available vehicle such that the benefits attained by the primary stakeholders is maximized. The four primary stakeholders that we consider in our work are the transport company, drivers, passengers and parcel's customers.

This section presents the challenges and constraints for the mutli-objective optimisation problem. Each of the functional groups has a different point of view to the optimization criteria. When a (pick-up and drop-off location) request information is sent to the transport company for pairing, the computed optimized result will be forwarded to the drivers for execution.

The definition of some of the frequently used notations for the SDMP, leading to the formulation of the mathematical model, is given as follows:

(1) *Passenger Requests:* The passenger request set $P = \{1, 2, 3, \ldots, i\}$ represents the i passenger request. Each passenger request contains pick-up and drop-off location, time of request, number of seats, carry-on luggage space and boolean service (such as WiFi or mobile device charging service) required. The pick-up and drop-off location will be use determine and calculate the trip distances. Time of request indicates the time in which the request is put forward to the transport company for pairing. Number of seats, carry-on luggage space and boolean service are the resources demand for the transportation to fulfil.

(2) *Customer Parcel Requests: Similar to the passenger request set,* $C = \{1, 2, 3, \ldots, n\}$ represents the n customer request for parcel delivery. Parcel space designates the number of storage units required while expiry time sets the requirement for just-in-time delivery of perishable product.

(3) *Vehicles and Capacity constraints:* Vehicles capacity is normal random variable. Seating capacity varies between 4 to 7 seats. Trunk space used to hold parcels and carry-on luggage up to 4 storage units. Boolean service is provided on 50% the vehicle fleet.

(4) *Node:* A node is denoted by c_n^{org}, c_n^{dest}, $p_i^{org}$and p_i^{dest}, which represent the pick-up and drop-off location of ith customers and passengers respectively.

(5) *Travel Distance and Routing plan:* The travel distance between two points org and $dest$ denoted by $TD_{org,dest}$ is estimated using city block calculation. The routing plan R consists a set of routes $\{q_1, q_2, \ldots, q_k\}$. The number of routes k is equal the number of paired resource and requests.

(6) *Other Assumptions:* It is assumed that each passenger or customer request can only be served by one driver with its available resource. If the demand exceeds available resources, the request will be dropped and conclude as fail to pair.

In addition, there are two types of constraints in the SDMP problem. Hard constraints are those which must be satisfied for the pairing to be considered legal, while soft constraints are essentially preferences. An example of hard constraint is the need to pair one vehicle with sufficient resource to meet the seating capacity requirement, on the other hand, soft constraint can come as a form of additional service such as boolean service (WiFi connectivity) for the passengers.

4 EVOLUTIONARY MULTI-OBJECTIVE OPTIMIZATION

From the discussion in previous sections, it is clear the SDMP is inherently a multi-objective problem. This section presents our proposed approach using MOEA specifically designed to solve the SDMP problem by concurrently optimizing the four objective functions. The proposed method comprises of two phases: 1) producing sets of candidate blocks; and 2) choosing of candidate for reproduction.

In the first phase, producing sets of candidate blocks using chromosome representation and greedy population initialisation to effectively generate potential solutions. The resource and request pairs are expressed in a chromosome representation which also contains information on the vehicle, passenger and customer requirements. The candidate solutions generated by this module are determined to be a feasible pairing before handing over to the Evolution module.

Upon completing the generation of candidate solutions, effectiveness of each candidate will be evaluated through the use of fitness functions. Candidate chromosome with better fitness score are selected for genetic operations, crossover and mutation. The mutation rate can be varied in different MOEA generations to better optimize existing candidate solutions.

4.1 Producing Sets of Candidate Blocks

Each route request by a passenger can be represented by (P_{ID}, P_{Org}, P_{Dest}, P_{Seat}, $P_{Time,}$, $P_{Boolean}$, $P_{Luggage}$), such that P_{ID} is the identity number, P_{Org} is the pick-up, P_{Dest} is the drop-off location, P_{Seat} is the required number of seats and P_{Time} is the time in which the request is raised. A similar chromosome structure is used for the customer requests (C_{ID}, C_{Org}, C_{Dest}, $C_{Storage}$, C_{Time}, C_{Expiry}). The available vehicle resources are represented by (V_{ID}, $V_{SeatCap}$, $V_{TruckCap}$, $V_{Boolean}$), where V_{ID} is the vehicle registration number, $V_{SeatCap}$ is the seat capacity, $V_{TruckCap}$ is the storage capacity and $V_{Boolean}$ is the availablity of Boolean service.

To efficiently construct an adaptive chromosome such that the representation is flexible to be updated and perform the genetic operations, the proposed chromosome representation consists of an Assignment Layer and Routing Layer. The Assignment Layer is a combination of different resource demand set, each set containing groups of request that are assigned to the vehicles. The column indices represent a vehicle while the index of the requests are stored in different rows.

An example is illustrated in Fig 1, $Passenger_1$, $Customer_1$ and $Customer_2$ are assigned to $Vehicle_1$, $Passenger_{16}$ and $Passenger_{17}$ are assigned to $Vehicle_2$. Available storage space are shown as dotted boxes. $Vehicle_1$ has a capacity of 4 storage units and 3 are occupied, $Vehicle_2$ has 2 assigned storage and 3 more available. The numbers of segments can be dynamically modified to suit the quantity of available resources.

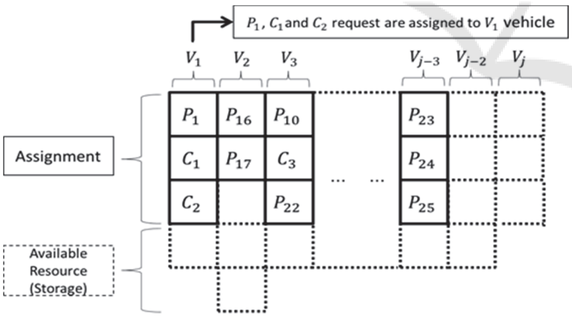

Figure 1: Chromosome representation of Assignment Layer.

The order in which the driver should pick-up and drop-off which passenger or parcel is represented in the Routing Layer. An example is illustrated in Fig. 2.

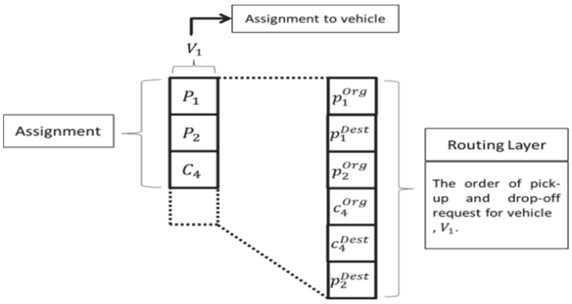

Figure 2: Expanded view of a chromosome, each vehicle with the newly assigned request will have the waypoints matrix update based on nearest distance order.

When a new generation is started, the Population Initialisation module uses a 4 steps process to generate the population. The population can be described as $Population^g = \{ chromo_1, \cdots, chromo_{ps} \}$, where g is the number of generations, ps is the population size and $chromo$ is the a candidate solution. First, the current assignments are copied over from the previous result. They form a basis for all candidate solutions to be built upon. Request that have been assigned will not be re-assigned to another vehicle. Hence, the transferring of current result ensures continuity between evaluations.

Second, a micro-function updates newly available vehicles that have joined the evaluation, these resource elements are inserted at the end of each chromosome with no request assigned. All vehicles which are logging off will also be removed from the chromosome, assessment for fare charges and next projected location will continue to update but no new request will be assigned. Third, new requests are extracted from the data set based on the evaluation time interval. These new requests will be randomly assigned into the base chromosome; each generated chromosome will be checked for feasibility so as to meet the hard and soft constraints. Fig 3 shows new requests will be assigned to at least one vehicle with vacant resource and no unique request repeated within a candidate chromosome. Finally, Fig 4 shows the individual assignment will have their route waypoints re-organize based on nearest distance order.

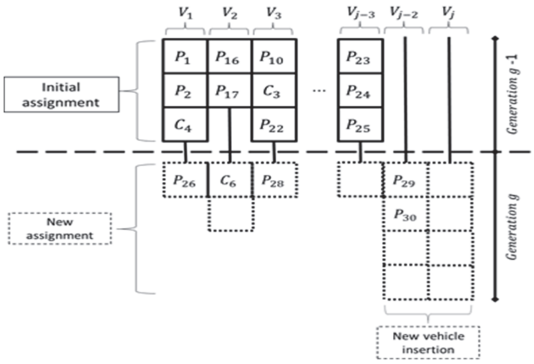

Figure 3: Assigning new of request to available vehicle.

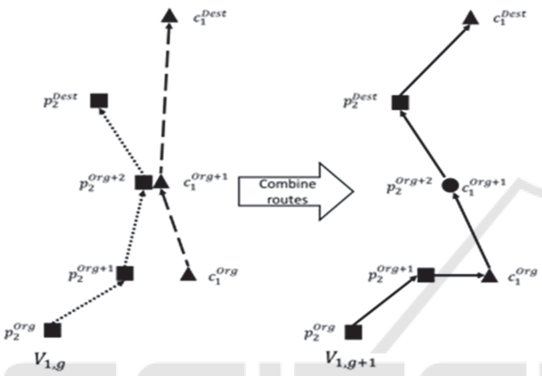

Figure 4: Reorganisation of the route priority upon assignment of new request.

4.2 Choosing of Candidate for Reproduction

In order to evaluate the quality of individual chromosomes, the fitness function is used to determine the fitness score of each chromosome. To facilitate the Evolutionary Algorithm, a fixed time interval evaluation window is used to execute requests as a batch.

4.2.1 Selection and Elitism

Upon evaluation of the population, the chromosomes are sorted into highest fitness scores in ascending order. The top chromosome will be directly transferred to the next generation while the remaining candidates will be filtered through a selection process. Tournament selection is used to select the candidate chromosomes for the genetic operations. First, some number of t chromosomes are randomly copied from the population and the two best individuals from this group are placed in the intermediate pool as parents of the genetic operations. With every generation, the bad chromosomes will be lost and replaced by copies of the better candidates. Some bad chromosomes may contain quality trait, hence, to reduce the selection pressure size of the tournament is set to $t \ll ps$.

4.2.2 Crossover

The first process used to produce new candidate chromosome is crossover operator. In the tournament selection, two parent chromosomes ($Chromo_{parent}$) are selected and will be recombined in hopes of producing better offspring. Fig 5 illustrates an example of the crossover process, $Chromo_{parent\ 1}$ and $Chromo_{parent\ 2}$ are selected for mating and the subsequent recombination produces $Chromo_{child}$. f_{sum} is the fitness value of each chromosome to be maximised. The crossover process does not change the initial chromosome, but copies and transfers higher quality segments to the offspring. Duplicate of the same passenger maybe be generated through this process, therefore a post process evaluation will verify if the chromosome is a feasible solution. Invalid chromosome will be handed over to the Chromosome Repair function.

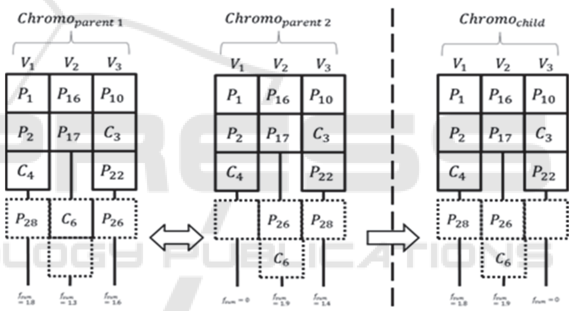

Figure 5: Crossover operation of two parent chromosomes to produce a single child chromosome.

4.2.3 Mutation

There are two mutation process customized to the Genetic Evolution Module. The first type interchanges new passenger requests between two vehicles. As shown in Fig. 6 (Left), a single $Chromo_{parent}$ is selected and the positions of the individual requests are identified. The identified individual will be swapped with the parent chromosome to produce an offspring. This swap mutation is not only restricted to passenger requests, it can also be in the mixture of passenger request and vacant seat, where probability m_g govern its activation.

The second mutation process shown in Fig 6 (Right) is based on operation of multiple swaps. First the tournament selection identifies a single $Chromo_{parent}$, this chromosome must contain negative fitness score in some of the vehicle segment. All passenger requests with negative fitness score are remove from the chromosome and stored in a temporary passenger request pool. The mutation operator will re-assign these requests to vacant seats of the chromosome. The process is intended to reduce the number of poor quality assignment within a chromosome while increasing the likelihood of higher occupancy rate of available vehicles.

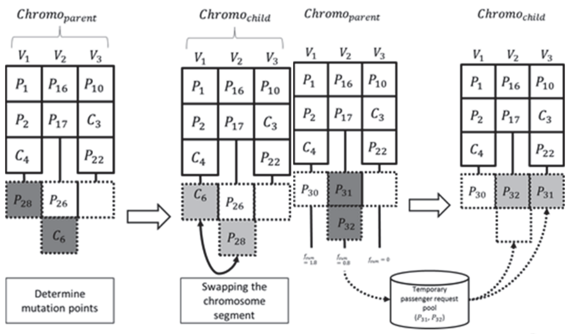

Figure 6: Mutation through swapping (Left) and Mutation through replacement of negative fitness score segments (Right).

5 PRELIMINARY RESULT AND ANALYSIS

In this section, the method we propose is compared with the method of random assignment. The performance of both methods is evaluated via benchmark simulation on SMRT Corporation Singapore (https://www.smrt.com.sg) Taxi Dataset (July 2014). In all our experiments, the parameters of the evolutionary algorithm are as follows: population size of 100, crossover probability of 0.8 and mutation probability of 0.05 to 1.0. The termination criterion is 300 generations. Each time window for computation is set at 5 minutes. The algorithms are implemented using Matlab and all scenarios were independently tested 5 times to acquire an average performance.

The first and foremost objective of the algorithms is to optimize the occupancy of the vehicles. Table 1 shows that the proposed algorithm is able to increase occupancy during peak hours when demand exceeds supply. At the beginning of the experiment (time index 36), there is a surplus in supply of vehicles as compared to the demand, hence a low rate of matches are possible. As the simulation proceeds into the morning rush hour (time index 102), there is a high rate of matching with the average exceeding 2.55 passengers per taxi. It is also observed that time index 180 shows higher pairing as compared to time index 141 due to the shift changeover.

Table 1: Result of successfully paired requests with vehicles.

		Run 1		Run 2		Run 3	
Timex Index	Request	Avg.	Var.	Avg.	Var.	Avg.	Var.
36 (3:00AM)	59	0.55	0.71	0.61	0.78	0.59	0.66
102 (8:30AM)	346	2.63	1.02	2.65	0.89	2.55	1.08
141 (11:45AM)	272	1.56	1.07	1.61	1.34	1.68	1.45
180 (3:00PM)	273	1.72	1.10	1.89	1.30	1.79	1.40
222 (6:00PM)	316	2.26	1.37	2.18	1.32	2.14	1.38

From the preliminary result shown in Fig 7, our proposed method demonstrated that it can successfully pair multiple requests into the given resources much better than the benchmark method. Experiment conducted using one day's worth of simulation dataset, shows on average 17.7% improvement over the benchmark.

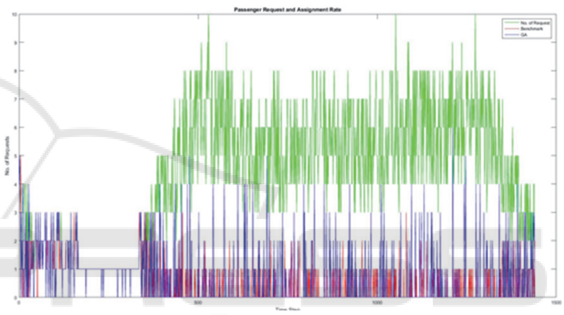

Figure 7: Successful pairing of resource with multiple requests (Period : 1 day).

6 CONCLUSION

In this paper, we proposed a potential method using Multi-Objective Evolutionary Algorithm which pairs transport requests to a fleet of transport vehicles. The proposed algorithm provides an improved solution over the benchmark. However, the analysis is not complete until all the fitness functions of various stakeholders are formulated based on real world scenarios. The SMRT Corporation Singapore Taxi Dataset is relsatively small as compared to the New York city open taxi dataset. Therefore, the data points used may not be sufficient to establish the true advantage of the evolutionary algorithm.

The proposed future work includes comparing our method with other state-of-the-art evolutionary algorithms such as NSGA-II, or SPEA2, etc.. Further, we plan to improve the fitness functions for the stakeholders that better represent real world scenarios.

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