Proceedings of the 5th European International Conference on Industrial Engineering and Operations Management
Rome, Italy, July 26-28, 2022

Smart Sensing and Dispatching for Optimal Fleet Route Planning with Fuel Economy

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Abstract

In this paper, a fleet dispatching system is proposed. The system is able to aquiring data like truck weight, traffic condition, and driver's habit, and then use to Modified Fuel Considered Consumption Rate Considered Vehicle Routing Problem (MFCVRP) for route planning of the fleet. Doesn't like the traditional Capacitated Vehicle Routing Proble(CVRP), the MFCVRP considered more factors so it will provides a more efficient route planning in practice. A simulation is done to compare the MFCVRP and the CVRP to verify the advantage of the new model.

Keywords
Smart Sensing, Optimization, Route Planning

1. Introduction

Freight transport by trucks is one of the most common methods of transporting goods around the world. In addition, Covid-19 made people more willing to shop online, and services like one-day delivery are much more popular than before. However, unlike trains, ships, or aircraft. The transporting conditions for trucks are much more complex than the rest methods. The trucks are sharing the same road with millions of passenger cars as well as other commercial vehicles. Hence, more factors need to be considered to deliver goods on time than the rest of the methods. To solve such a problem, a better fleet management strategy is necessary.

One of the most critical aspects of fleet management is route planning for each truck. The goal of this planning problem is to find the most efficient way of dispatching tasks to each individual of the fleet. Usually, there are multiple destinations to visit each day. All with different distances, road conditions, and traffic conditions. They are dynamically changed all the time.

There are several constraints to this problem. For instance, the time that truck drivers spend on the road each day is limited to ensure safety. And the longest distance that a truck can go (range) without refilling is also limited. The second constraint is especially important as the current trend of vehicle's drivetrain is moving from internal combustion engine to fully electric. And an electric vehicle usually takes hours to do fully recharged.

Besides the physical capacity of the truck, the range is also affected by the road condition (does the truck need to climb to a high altitude location), traffic condition (highway cursing vs. city driving with frequently stop-and-go), driver's driving habit (does the drive know stepping light on paddles and maximumly utilized the kinetic energy), and also the cargo weight of the truck. The combined city/highway fuel consumption could decrease by about 0.4 L/ 100 km for cars and about 0.5 L / 100 km for light trucks for every 100 kg of weight reduction(Bandivadekar et al., 2008). This simply implies that weight plays a very important role in the trucks' range.

More useful information and data are always helpful for building a better fleet management strategy. This paper will be focused on designing a system that includes an onboard data acquisition/processing system, which is used to acquire the data for range analysis such as road conditions, traffic conditions, driver's driving habits, and most importantly, the cargo weight. As well as a cloud-based dispatching system that can assign the optimized tasks to the fleet based on the information provided, which will be implemented with the dispatching strategy based on Modified Fuel Consumption Rate Considered Vehicle Routing Problem (MFCVRP), a new model designed for solving such routing problem.

There are three technical challenges to this system. Firstly, the sensor kit must be universal, easy to install, and uncorrelated to any safety factors of the truck. Secondly, the raw data collected from the sensor must be accurate. And thirdly, all the data musts be helpful to make correct decisions that improve the transporting efficiency and reduce costs. The first part of the paper will discuss the overall design of the system, while the second part of the paper will discuss the advantage of the MFCVRP compared to the traditional Capacitated Vehicle Routing Problem (CVRP) based on a simulation result.

2. Literature Review

Weight detection is one of the required information for planning the route with the proposed method. Besides measuring the weight of the truck periodically, smart sensor integration like measuring the pressure inside the vehicle's suspension airbag (Right Weigh 2018), measuring the stress within the leaf spring (Chen 2011), and measuring the length of the shock absorbers (Ronen 1988) can return the real-time weight of the truck. These methods can be costly since they require specific structures on the truck.

There are many existing models for the fleet dispatching system. The Truck Dispatching Problem or Vehicle Routing Problem (VRP) was defined as an optimization problem about finding the optimal set of routes for the fleet to deliver goods to a set of consumers by Dantzig and Ramser back in 1959 (Dantzig & Ramser, 1959). This classic VRP aims for the minimum total distance covered by the fleet. The objective function is $D = \min \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij}\, X_{ij}$, where D is the total distance, n is the number of stops, d_{ij} is the distance between 2 stops, and X_{ij} is a conditional variable to show whether the two stops are connected. The optimal solution is achieved by aggregations, rapid corrections, and relative cost factors. This very first VRP model assumes only one product demand and all trucks of the fleet have the same capacity. It is very constrained, but it is a good starting point to understand the problem.

A more specific application in this area is applied to frozen food delivery (Zhang & Chen 2014). Compared to the classic VRP, this application is still calculating the transportation cost $\varpi_{\mu v k}$ of vehicle k between consumer u and v by distance, but introduces 4 additional costs, (1) multi-product demand, (2) the cost of refrigeration Λ, which is related to the transportation time and number of stops, and (3) the cargo damage cost Θ, which is related to the time and the demand of consumers, and (4) the penalty cost Π_{pv}, which is also time-related and happens when the food is delivered out of the consumer's required time window. The objective function is $Z = \min \Theta + \sum_{k=1}^{K} \sum_{\mu=1}^{H} \sum_{v=1}^{H} \varpi_{\mu v k} + \Lambda + \Pi_{pv}$. The solution is solved by the genetic algorithm.

Minimizing the total distance covered by the fleet does not necessarily mean the cost to the fleet is minimal. One of the most significant expenses for a fleet for its daily operations is fueling. According to the Canadian government website (Canada 2021), the fuel consumption rate of a vehicle is highly positively correlated to the cargo weight of the vehicle. And cargo weight plays a critical role for a truck compared to a family car. Instead of minimizing the distance covered by the fleet, The Fuel Consumption Rate Considered Vehicle Routing Problem (FCVRP) is aiming at minimizing the total fuel cost (Xiao et al. 2011). The objective function can be written as $Z_{FCVRP} = \min \sum_{j=1}^{n} F x_{0j} + \sum_{i=0}^{n} \sum_{j=0}^{n} c_0 d_{ij} (f_0 x_{ij} + a l_{ij})$. Here, F is fixed cost, l_{ij} is the cargo weight between stops i and j, and the remaining variables are part of the fuel consumption model $f = a(m + l) + b$, which is a linear fuel consumption regression model. The problem is solved by a string-model-based simulated annealing algorithm.

3. Design Overview

The overall system is divided into two parts which are the onboard data acquisition/processing system and the cloud-based dispatching system. The overall system structure is shown in figure 1.

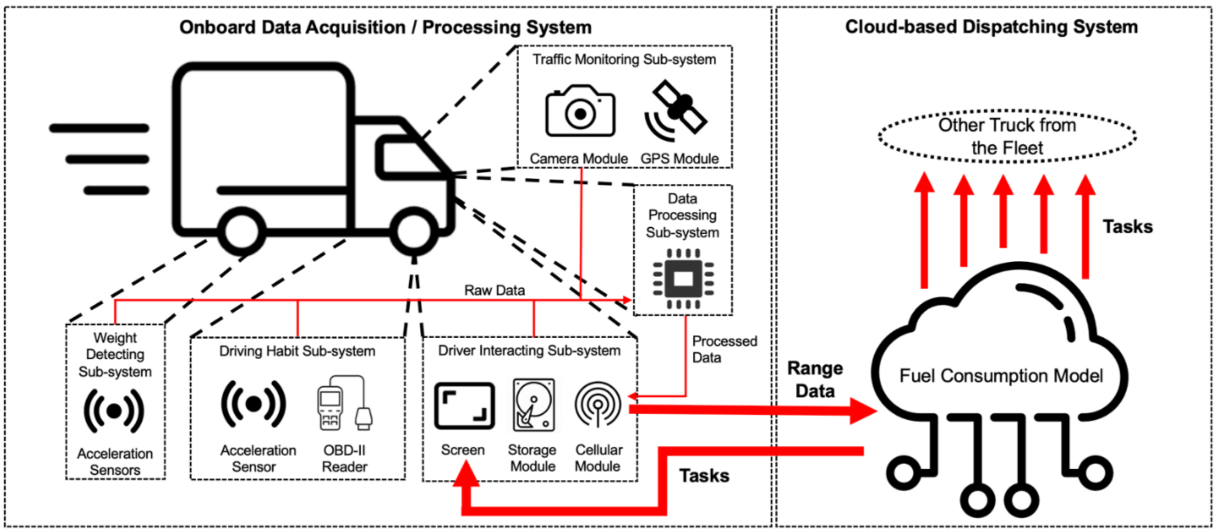

Figure 1. Overall System Structure

There are four subsystems on the truck, which are the weight detecting subsystem, driving habit monitoring subsystem, traffic monitoring subsystem, driver interaction subsystem, and data processing subsystem. Table 1 summarizes the key information of the onboard system.

Table 1. Data Processing Sub-System Functions

Sub-System	Input Data	Method	Output Data	Other Used Data
Weight Detecting	Suspension Acceleration	Fourier Transform	Weight	Vehicle Transfer Function from Calibration
		Regression		
Driving Habit Monitoring	Longitudinal Acceleration	Regression	Fuel-Consumption Index (FCI)	History FCI of the Driver
	Throttle Position			Truck's General Fuel Consumption Rate
	Air-Fuel Ratio			
Traffic Monitoring	Image	Machine Vision Techniques	Instantaneous Traffic Condition	Pre-Selected Parameters
		Neural Networks		Trained Neural Network Model
	Location	Obtained from Other Source	Overall Traffic Condition	--
Driver Interaction	History FCI of the Driver	--		
	Truck's General Range			
	Truck's General Fuel Consumption Rate			
	Truck's Cargo Capacity			

The weight detecting system can provide real-time truck cargo weight using the principle of frequency analysis. As shown in figure 4, there are two acceleration sensors, one mounted on the frame and another one mounted on the axle of the truck (represented as yellow dots in the figure). The truck is modeled as one degree-of-freedom mass-spring-damper system. The transfer function for this system is

$$|\mathbf{H}(\omega)| = \left| \frac{1 + \frac{2i\xi\omega}{\omega_n}}{1 - \left(\frac{\omega}{\omega_n}\right)^2 + \frac{2i\xi\omega}{\omega_n}} \right| \tag{1}$$

where ω is the system frequency, ω_n is the suspension natural frequency and $\omega_n = \sqrt{\frac{k}{m}}$, ζ is the damping ratio and $\zeta = \frac{c}{2\sqrt{mk}}$, m is the truck mass, k is the spring stiffness constant, and c is a constant. With the acceleration data provided by the sensors, the natural frequency of the truck can be found through a flourier transform. With few calibrations runs with a known weight. The mass m of the real-time truck weight can be found via regression.

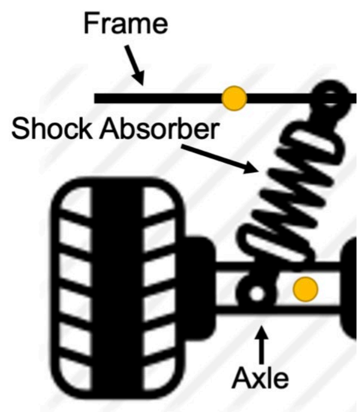

Figure 2. Installation of Weight Detection Sub-system

The driving habit subsystem is used for collecting data for real-time computing fuel consumption rate. The first main component of this subsystem is the acceleration sensor. It will collect the longitudinal acceleration of the truck. If a truck has a very high longitudinal acceleration frequently, it must be accelerating or braking hardly. With this driving style, more fuel is consumed at a unit time and hence turns out to be a shorter range overall. This information will be confirmed by the onboard diagnostics (OBD-II) reader, which will read the data such as throttle position and air-fuel ratio from the engine control unit (ECU) of the truck. Those are all directly related to the fuel consumption rate of the truck.

The traffic monitoring subsystem includes a camera module and a GPS module. The camera should be installed behind the windshield and is used to record the real-time traffic condition via images. This helps determine the instantaneous traffic condition. The GPS module can provide the location of the truck, which can be used to determine the overall traffic condition by acquiring traffic conditions for the nearby roads from other sources. Combining both information, an accurate traffic condition should be obtained.

The driver interaction subsystem has three main parts. A screen in which the driver can log in and look for the assigned task, and all the information obtained by the previous subsystems. A data storage module that will store all the data for future system calibrations, as well as a calibrated model for the current truck, including general range, fuel consumption rate, and cargo capacity. And a cellular module that is used to communicate with the cloud-based dispatching system in real-time.

The data processing subsystem is used to process all the raw data from the previous subsystems. The processes include fast Fourier transformation, machine vision techniques, and neural networks, as summarized in table 1. After the weight, FCI, traffic condition, and drive/truck's general performance are achieved. An accurate real-time range can be estimated and ready to send to the dispatching system.

3.1. IDEF0 Diagram of the System

The top level IDEF0 diagram of the system is shown in figure 3. As the system is design to run as autonomously as possible. Therefore, the only control element is the fleet optimal operation efficiency, which acts like a feedback control loop. The mechanisms are the two main part of the system ---- Onboard Data Acquisition / Processing System and Cloud-based Dispatching System. The input is modeled as the raw data that all the sensors inside the system obtained such as road image from camera module and acceleration data from acceleration sensors. As well as some human input parameters like the current driver and truck information. The outputs of this system are optimized task assignment for individual truck and higher overall fleet operation efficiency. As the second output is constructed by the first output.

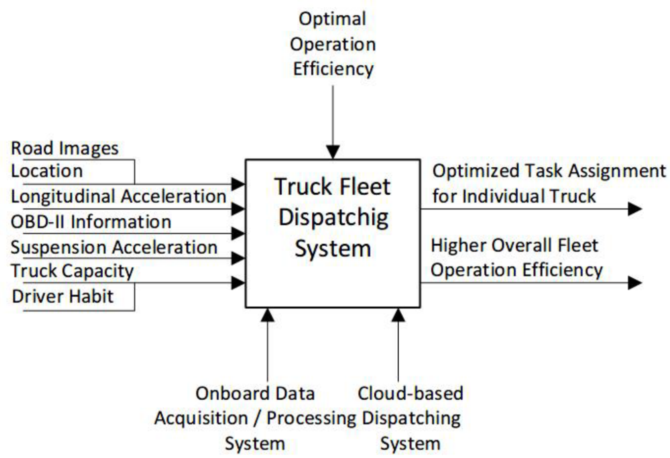

Figure 3. Top-Level System IDEF0 Diagram

For A0, the acceleration sensors mounted on the truck suspension would record the relative lateral acceleration data. The OBD-II reader in A1 would read truck's ECU information and output air-fuel ration and throttle position. And the additional acceleration sensor mounted inside the truck would provide the longitudinal acceleration data. Light would go into the in-cabin camera module of A3, and transfer into road images. As well as the location information obtained by the GPS module. All those output data would be sent to A4.
A3 is special compared to others. It has a screen so that the driver can control this function. Driver and truck information will be put in so that the best model and history data can be retrieved from the storage module. Those would also be sent to A4.

The input of A4 from the output of previous function boxes. With Fourier transform, regression, machine vision techniques, neural networks, and information from other sources. The range of the truck can be estimated. More detail about this function box is described in the next section. This will be sent back to A3 and will be sent to B via the cellular module in A3.

After receiving the range information of all the trucks among the fleet. By FCVRP and the goal of optimal operation efficiency, optimized task assignments can be sent back to A3 again for each individual truck. More details about this are described in equation (2). Once the individual finishes the task, a higher overall fleet operation efficiency is achieved. Those are two outputs of this system.

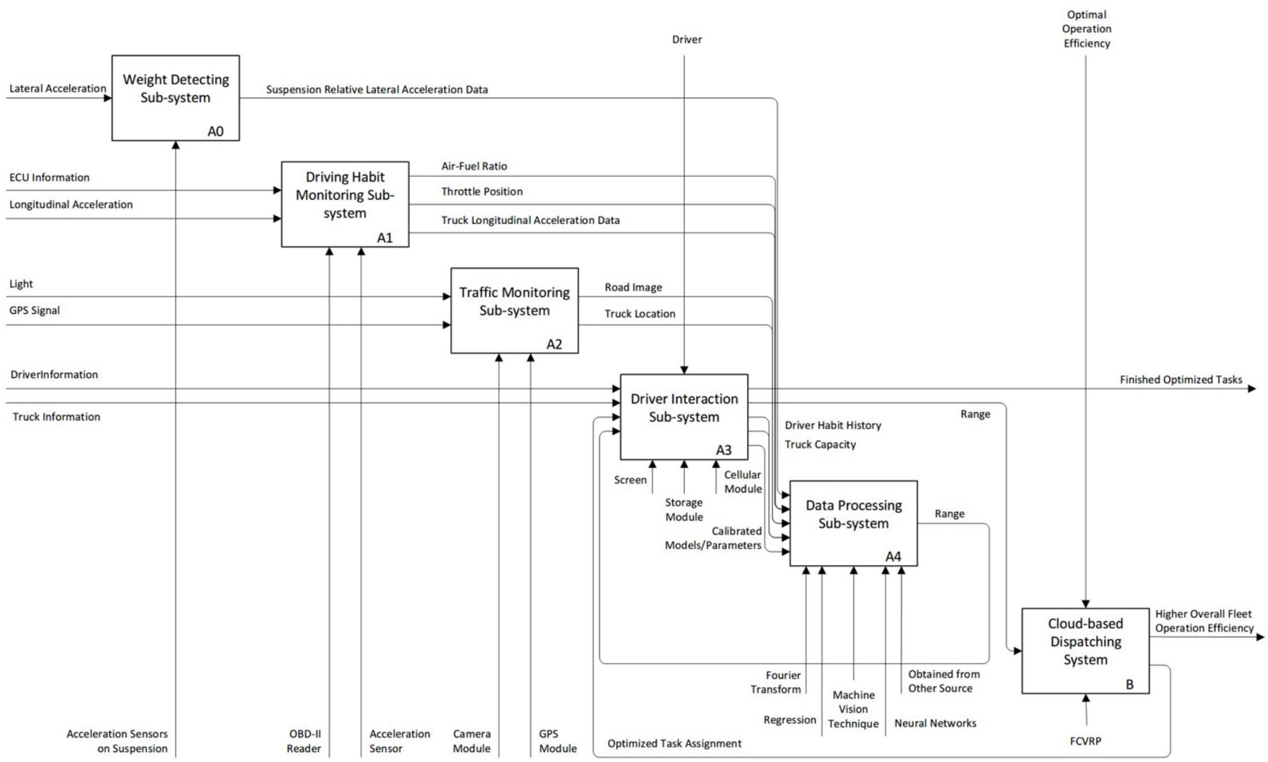

Figure 4. Detailed Overall System IDEF0 Diagram

3.2 Detailed Data Processing Sub-system (A4) IDEF0 Diagram

The detailed data processing subsystem IDEF0 diagram is shown in figure 7. This diagram shows the details inside the function box A4 in figure 6. There are six function boxes in this diagram, which are Weight Data Process (A4a), Instantaneous Traffic Data Process (A4b-I), Overall Traffic Data Process (A4b-II), Drive / Truck Data Process (A4c), Driving Habit Data Process (A4d), and Overall Data Process (A4e).

For A4a, the Fourier Transform would convert the suspension acceleration data and frame acceleration data into the natural frequency of the truck. With the calibrated model retrieved from the storage module in A3. The weight of the truck can be found by regression. More details of this are described in equation (1).
The road image captured by the camera module will first go through machine vision techniques in A4b-I. And be converted into image data that are easily distinguished by machine. This type of data would then be used to identify how many cars are on the road via neural networks. The number of cars can be used as the instantaneous traffic condition. By searching for traffic conditions around the truck's location, the overall traffic condition can also be obtained from A4b-II.

With the manually input information of drive and truck, A4c would search for the matching history data. Alone with the output from A2, those data would be input to A4d, and the fuel consumption index (FCI) can be found via regression. With the output from A4a, A4b-I, A4b-II, and A4d, the estimated range can be calculated by the neural network from A4e.

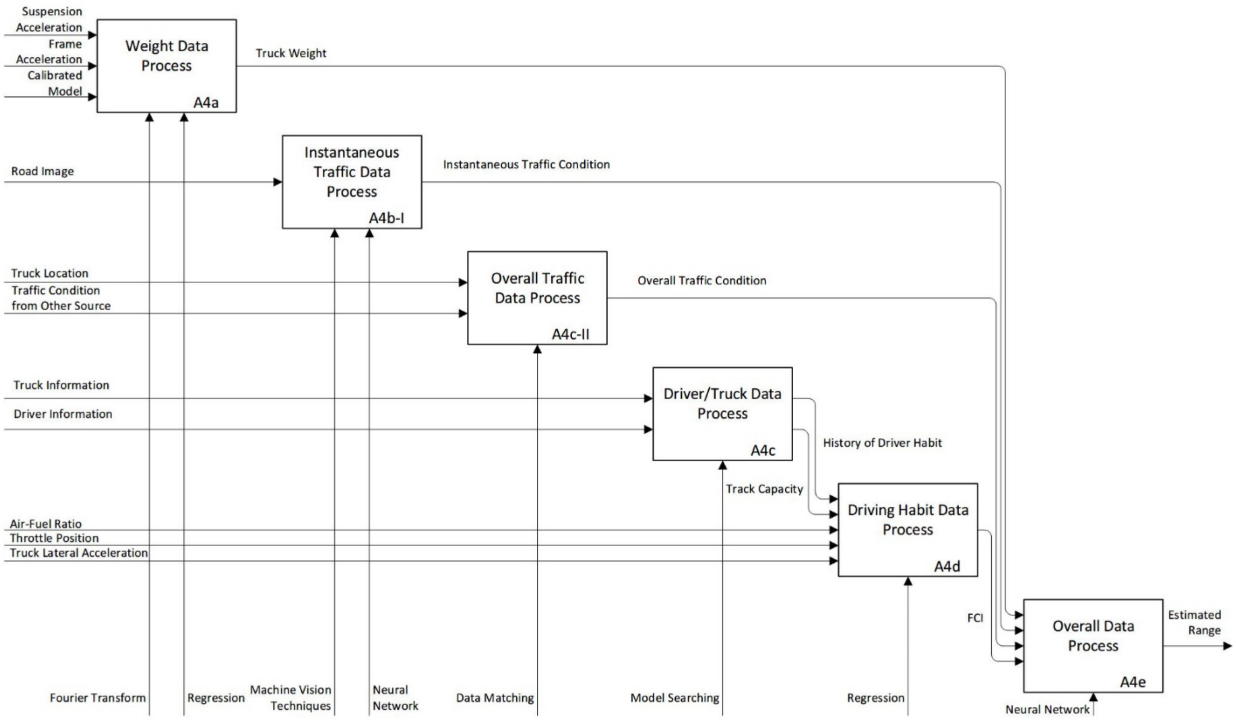

Figure 5. Detailed Data Processing Sub-System IDEF0 Diagram

3.3. Use Case Analysis of the System

As the IDEF0 clearly defined the “mostly autonomously” system, the use case analysis can be used to find the potential of interacting with any people or group outside the system. Four actors are selected the truck driver and consumer are the primary actor, and the fleet technician and fleet manager are the secondary actors.

Since the system can accurately estimate the truck’s range with the acquired data and has a screen for the truck driver to interact with. Firstly, the drive can access all the data. Secondary, the numerical data can be converted into driving habit suggestions. And thirdly, if the drive found any abnormal task assignment. The driver can also report the model error and apply it for a task change. Finally, the truck driver can report the delivery to the consumer. The fleet manager can manually adjust the task assignment if they found the model is wrong or drivers applied so. The model adjusting job would be assigned to the fleet technicians. If there is a new truck join the fleet. Both the manager and technician can register it to the system, and the latter can do the initial calibration for the truck through the system. In addition, the consumer can submit delivery suggestions, and those can be accessed by the fleet manager.
The relationships between the use cases are shown in the use case diagram (figure 6).

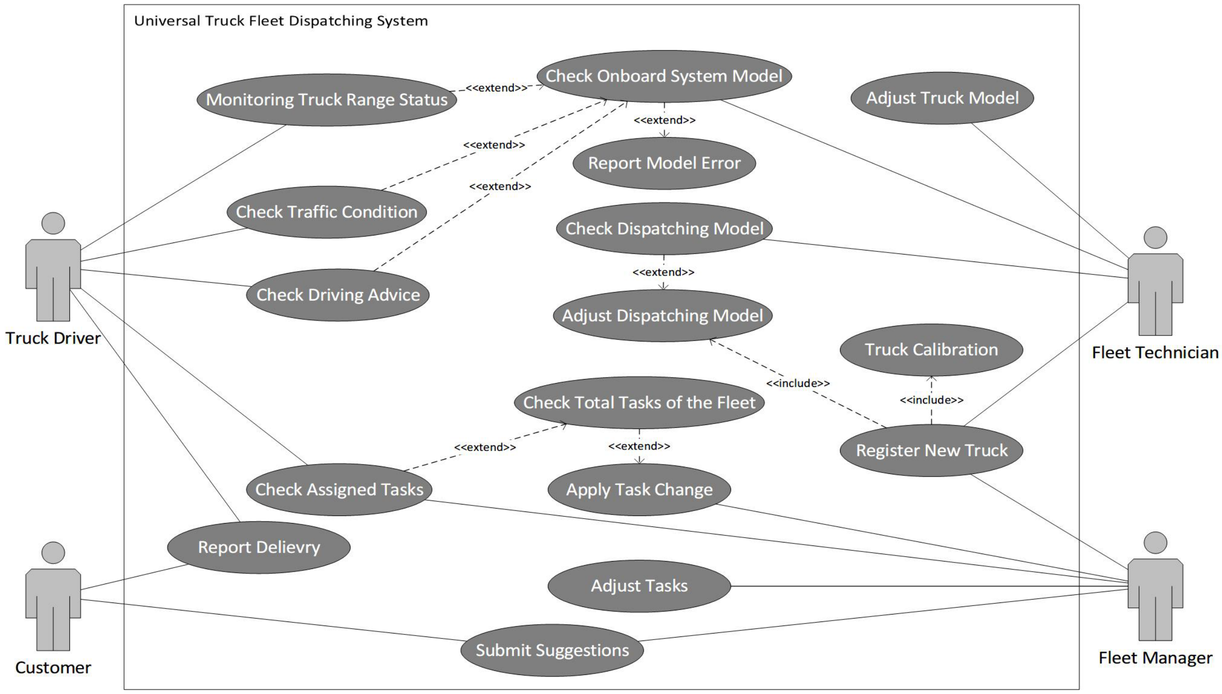

Figure 6. Use Case Diagram of the System

4. Conceptual Model for Cloud-Based Dispatching System

The Modified Fuel Consumption Rate Considered Vehicle Routing Problem, or MFCVRP, is the model designed for the proposed dispatching system. The objective is to minimize the total fuel consumed by the fleet. The fuel consumption rate is assumed to be linearly increasing as the weight of the cargo increases. Two base FCR, when the truck is empty and is fully loaded, should be calibrated and input into the system so that the slope of this linear relationship can be found. The traffic condition and the driving style can also be simplified as indices. If the traffic from two nodes is heavy, the index should be high so that it will be performed as a penalty when calculating the final cost of the objective function. The objective function and the constraints can be found below:

$$Z_{MFCVRP} = \min \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} t_{ij} (f_0 X_{ij} + a l_{ij}) \quad (2)$$

s.t.
$$X_{ij} \in \{0, 1\} \quad (3)$$
$$\sum_{j=0}^{n} X_{ij},\ i = 1, \ldots, n \quad (4)$$
$$\sum_{j=0}^{n} X_{ij} - \sum_{j=0}^{n} X_{ji} = 0,\ i = 1, \ldots, n \quad (5)$$
$$if\ X_{ij} = 1 \implies u_i + q_j = u_j \quad (6)$$
$$q_i \leq u_i \leq C \quad (7)$$
$$\sum_{j=0, j\neq 1}^{n} l_{ji} - \sum_{j=0, j\neq 1}^{n} l_{ij} = q_i \quad (8)$$

Here, l_{ij} is the cargo weight from node i and j and a is the linear coefficient of the relationship between the cargo weight and the fuel consumption rate.

5. Simulation Model – Consumer and Fleet Generation

5.1 Consumer Location and Distance Matrix (D)

The number of the consumer can be changed, and the x and y location of the consumer are generated by a random integer within the range of -50 to 50. And the depot is set to (0,0). The distance between any two locations is simplified as the Euclidean Distance Formula d=√ ((x_i-x_j)^2+(y_i-y_j)^2). The distances are stored in a (n+1) by (n+1) symmetric matrix where n is the number of consumers, the element of row i and column j represents the distance between and location.

5.2 Consumer Demand Vector Generation (q)

A maximum consumer demand q_{max} is needed for user to input. The demand for every consumer is defined as an 1 by n vector with random integers within the range of 0 to q_{max}.

5.3 Traffic Condition Matrix Generation (Ti)

The traffic condition will be simplified as an index, the higher means heavy traffic and thus more costly and vice versa. A number $\boldsymbol{ti_{max}}$ is needed for user to input, and the consumer demand will be a random number within the range of $\mathbf{1}$ and $\mathbf{1} + \boldsymbol{ti_{max}}$. To simplify the problem, the traffic condition on the same road will be the same for both directions ($\boldsymbol{ti_{ij}} = \boldsymbol{ti_{ji}}$). The traffic condition matrix is also a symmetric matrix like the distance matrix.

5.4 Consumer Location and Distance Matrix (D)

The user is required to input the number of trucks n_{truck}, the maximum capacity of the truck c_{max}, the empty weight of the truck w_{empty}, and an index for random fuel efficiency generation mpg_{index}. The truck capacity vector ($\mathbf{c}$) is represented as a 1 by n_{truck} integer vector within the range of 20000 and $20000 + c_{max}$. The truck empty weight vector ($\mathbf{w}_{empty}$) is represented as a 1 by n_{truck} integer vector within the range of 5000 and $5000 + w\_empty$. The fuel efficiency is a function of the $\mathbf{c}$, $\mathbf{w}_{empty}$, and the mpg_{index}. First, the randomized fuel efficiency vector $\mathbf{fe}_{index}$ (1 by n_{truck}) is generated within the range of 0 and mpg_{index}. Then, two 1 by n_{truck} vectors are generated, which represents the fuel efficiency of the empty truck $\mathbf{fe}_{empty} = 5 + 5000 * \frac{\mathbf{mpg}_{index}}{\mathbf{w}_{empty}}$, and the fuel efficiency of the truck loading the maximum load $\mathbf{fe}_{max} = 5 + 5000 * \frac{\mathbf{mpg}_{index}}{\mathbf{c}}$.

6. Simulation Result

The input parameters are shown in table 2, the generated truck capacity, empty truck fuel efficiency, and fully loaded truck fuel efficiency is shown in table 3, and the generated consumer location and demand is shown in figure 7. The routing plan from both models is shown in table 4 and 5, and the costs are shown in table 6.

Table 2. Input Parameters

Parameter	Symbol	Setting
Number of Consumer	$n_{customer}$	10
Maximum Traffic Condition Index	Ti_{max}	3
Maximum Consumer Demand	q_{max}	30000
Number of Truck	n_{truck}	3
Maximum Truck Capacity Index	c_{max}	50000
Maximum Truck Empty Weight Index	w_{max}	5000
Fuel Efficiency Index	fe_{index}	30

Table 3. Generated Fleet Performance Factors

Factor	Symbol	Truck 1	Truck 2	Truck 3
Capacity	c	60578	66605	69597
Empty Weight	w_{empty}	5903	5228	8641
Empty Fuel Efficiency	fe_{empty}	5.364	6.390	5.436
Fully Loaded Fuel Efficiency	fe_{max}	8.234	22.709	8.515

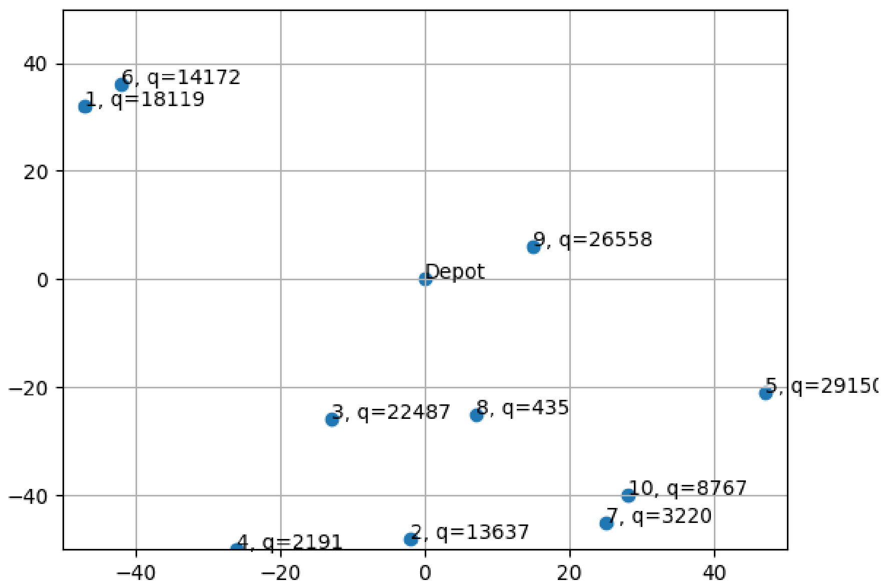

Figure 7. Consumer Location and Demand

Table 4. Routing Plan from CVRP Solver

Truck	Route
1	Depot => 8 => 7 => 10 => 5 => 9 => Depot
2	Depot => 6 => 1 => Depot
3	Depot => 2 => 4 => 3 => Depot

Table 5. Routing Plan from MFCVRP Solver

Truck	Route
1	Depot => 1 => 6 => Depot
2	Depot => 8 => 10 => 2 => 3 => 4 => Depot
3	Depot => 9 => 5 => 7 => Depot

Table 6. Cost from Both Models

Model	CVRP Cost (Total Distance)	MFCVRP Cost
CVRP	390.6624	18014.3377
MFCVRP	451.7042	16453.7223

From table 6, the routing plan from the MFCVRP model has a total traveling distance of about 61 more than that from the CVRP model. However, after considering the traffic condition and fuel consumption, it has a MFCVRP cost that is about 1560 lower than that of the CVRP model. Although the CVRP cost and the MFCVRP cost are in different orders and MFCVRP cost is just a cost factor and does not have an actual meaning. This result is enough to show that the minimal traveling distance does not necessarily mean the minimum cost if considering traffic and fuel costs, which are something that cannot be ignored in the real world.

6. Conclusion

The universal truck fleet dispatching system is proposed and be preliminary designed. It contains two parts, the onboard data acquisition / processing system obtains the truck weight, traffic condition, driver's driving habit, and other data to estimate the range of the truck. This information is sent to the cloud-based dispatching system to assign the optimized tasks to each individual truck in the fleet. And then naturally, the operation efficiency of the whole fleet will be increased.

This simulation proofs that the minimal traveling distance covered by the fleet does not always mean the minimal cost in the real world because there are a lot more factors that affect the cost other than distance. Considering and bringing in more factors usually can lead to a more accurate result. In this simulation specifically, traffic condition and fuel consumption were considered in addition to the distance. However, there are still a few things that can be improved in the future. 1) There are still some data left unused from the data acquisition subsystem like the driver's driving style, dynamically changed traffic condition, and time window constraints. 2) Consumer location can be modeled based on the real-world map. 3) Parameters need to be fine-tuned to better represent the real word situation. 4) Better and more suitable solver or solving methods should be further researched.

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Biography

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