A Fuel-Efficient Route Plan Method Based on Game Theory

Chi-Lun Lo[1,2], Chi-Hua Chen[3], Jin-Li Hu[4], Kuen-Rong Lo[1], Hsun-Jung Cho[2]

[1] Telecommunication Laboratories, Chunghwa Telecom Co., Ltd., Taiwan
[2] Department of Transportation and Logistics Management, National Chiao Tung University, Taiwan
[3] College of Mathematics and Computer Science, Fuzhou University, China
[4] Institute of Business and Management, National Chiao Tung University, Taiwan
cllo@cht.com.tw, chihua0826@gmail.com, jinlihu@mail.nctu.edu.tw, lo@cht.com.tw, hjcho001@gmail.com

Abstract

This study adopts a fuel consumption estimation method to measure the consumed fuel quantity of each vehicle speed interval (i.e., a cost function) in accordance with individual behaviors. Furthermore, a mobile app is designed to consider the best responses of other route plan apps (e.g., the shortest route plan app and the fast route plan app) and plan the most fuel-efficient route according to the consumed fuel quantity. The numerical analysis results show that the proposed fuel-efficient route plan app can effectively support fuel-saving for logistics industries.

Keywords: Fuel efficiency, Route plan, Game theory

1 Introduction

In recent years, the prices of diesel fuel and unleaded fuel have been increased to lead to higher cost of transportation for logistics industries [1]. For instance, the fuel cost of logistics industries was increased up to 35.8 billion dollars in Taiwan in 2015 [2]. Therefore, saving fuel consumption of fleet vehicles is an important challenge for logistics.

For fleet management, commercial vehicle operation systems (CVOSs) have been designed and implemented to collect the movement records of vehicles. These movement records can be periodically reported and used to track the location and speed of vehicle. Furthermore, the fuel invoices including the fuel quantity information after refueling can be uploaded into CVOS by driver. A fuel consumption estimation method (FCEM) based on a generic algorithm is hence proposed to analyze the movement records and the fuel quantity information for measuring the relationship the driver's behaviors and fuel consumption [3].

Although the fuel consumption can be estimated to detect fuel-wasting based on driver's behavior, some fuel-saving strategies (e.g., fuel-efficient route plans) should be developed and performed for reducing fuel cost. Therefore, this study adopts the proposed FCEM to measure the consumed fuel quantity of each vehicle speed interval (i.e., a cost function) in accordance with each individual's optimal behavior. Moreover, a mobile app is designed to consider the best responses of other route plan apps (e.g., the shortest route plan app and the fast route plan app) and plan the most fuel-efficient route based on the game theory.

The remainder of the paper is organized as follows. Section 2 discusses the related work of route plan methods. Section 3 remarks the detail processes of a FCEM. Section 4 presents the design of proposed fuel-efficient route plan app and the game model of route plan apps. Section 5 gives a numerical analysis to evaluate the performance of the propose route plan app. Finally, Section 6 concludes this paper and discusses suggestions for future work.

2 Literature Reviews

Several studies proposed and designed the route plans based on (1) the shortest distance or (2) the shortest travel time [4-17].

For route plans based on the shortest distance, Jia et al. used Particle Swarm Optimization (PSO) to minimize the total travel distance of all vehicles and solve the dynamic capacitated vehicle route problem [4]. This study assumed that the solution of shorter travel time and lower travel cost could be found in accordance with the shortest distance route plan. However, the traffic condition is dynamically changed. Therefore, the shortest distance route may be driven with longer travel time while the vehicle density of the shortest distance route is higher.

For route plans based on the shortest travel time, previous studies estimated the average travel time of each road segment and minimized the total travel time of each route [5-9]. Furthermore, some studies considered more factors (e.g., charge time of electric vehicle [9]) for a variety of applications. Although the traffic conditions were considered and analyzed in

*Corresponding Author: Chi-Hua Chen; E-mail: chihua0826@gmail.com
DOI: 10.3966/160792642019052003024

these studies [5-9], the fuel consumption estimation was not investigated. Therefore, the route plan method based on fuel consumption estimation is proposed and compared with the shortest distance route and the shortest travel time route.

3 Fuel Consumption Estimation Method

A FCEM based on a generic algorithm was proposed and evaluated to analyze the consumed fuel quantity of each vehicle speed interval [3] for individual driver. The method can generate a fuel consumption estimation function $g(u_i)$ in according with the vehicle speed u_i in Route i to estimate the fuel quantity in each 30 seconds. The details of process are illustrated as follows (shown in Figure 1).

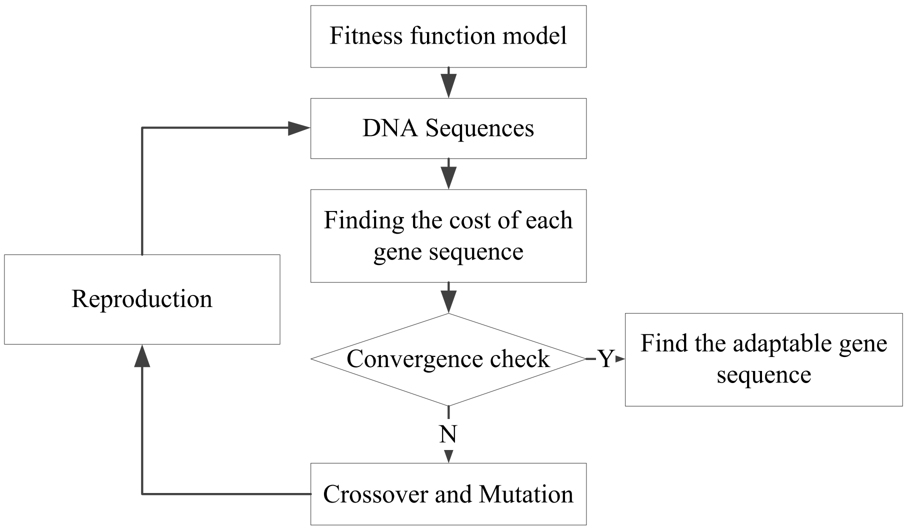


Figure 1. The process of fuel consumption estimation method based on a generic algorithm [3]

(1) The movement records (e.g., vehicle speed) and the fuel invoices (e.g., fuel quantity) are retrieved and analyzed.

(2) A fitness function model and the score of each DNA (deoxyribonucleic acid) sequence are defined as Equations (1) and (2) to estimate the values of consumed fuel quantities $\{q_1, q_2, .., q_{14}\}$. For instance, Driver 1 drove a car which was equipped with OBU 1 during 2016; c_1 records idle speed (i.e., the value of u_i is zero) reported by OBU 1 during 2016, and average fuel consumption is q_1 liters in each 30 seconds while the average speed is idle speed; c_2 records the speed between 0 km/h and 10 km/h reported by OBU 1 during 2016, and average fuel consumption is q_2 liters in each 30 seconds while the average speed is between 0 km/h and 10 km/h; consequently, c_{14} records the speed higher than 120 km/h reported by OBU 1 during 2016, and average fuel consumption is q_{14} liters in each 30 seconds while the average speed is higher than 120 km/h. Furthermore, the summation of fuel quantities of OBU 1 during January 2016 is F liters.

$$\sum_{k=1}^{14} c_k \times q_k \approx F \quad \textbf{(1)}$$

$$E = \left| \sum_{k=1}^{14} c_k \times q_k - F \right| \quad \textbf{(2)}$$

(3) The sets of initial DNA sequences (i.e., the sets of consumed fuel quantities) can be randomly generated, and the score of each DNA sequence can be measured by using Equation (2). The value of E is the fuel consumption estimation errors. Therefore, this study used a generic algorithm to generate the adatable DNA sequences for minimizing the absolute value of sum of estimation errors.

(4) The process of the convergence check can be performed according to the maximum number of iterations, and an adaptable DNA sequence is outputted as the estimated results of the fuel consumption.

(5) The processes of gene crossover and gene mutation can be performed to generate child's DNA sequences.

(6) The processes of gene reproduction can be performed to support that the generated child's DNA sequences are substituted for original maternal DNA sequences for evolution. The score of each DNA sequence is calculated, and the generic algorithm is performed again.

A fuel consumption estimation function $g(u_i)$ can be obtained by the FCEM. The vehicle speed u_i can be adopted into the function $g(u_i)$ to query the consumed fuel quantity c_i for individual driver. A case study of fuel consumption estimation function $g(u_i)$ is showed in Table 1.

Table 1. A case study of fuel consumption estimation function [3]

Vehicle speed interval (unit: km/hr)	Consumed fuel quantity in each 30 seconds (unit: liter)	Consumed fuel quantity in each hour (unit: liter)
$u_i = 0$	0.007	0.840
$0 < u_i <= 10$	0.020	2.400
$10 < u_i <= 20$	0.033	3.960
$20 < u_i <= 30$	0.055	6.600
$30 < u_i <= 40$	0.013	1.560
$40 < u_i <= 50$	0.038	4.560
$50 < u_i <= 60$	0.069	8.280
$60 < u_i <= 70$	0.150	18.000
$70 < u_i <= 80$	0.142	17.040
$80 < u_i <= 90$	0.080	9.600
$90 < u_i <= 100$	0.048	5.760
$100 < u_i <= 110$	0.077	9.240
$110 < u_i <= 120$	0.284	34.080
$120 < u_i$	0.492	59.040

4 Fuel-Efficient Route Plan App

For the design of fuel-efficient route plan app, the real-time traffic condition and the consumed fuel quantity of individual driving behavior are considered. However, the traffic condition may be influenced by other route plan apps (e.g., the shortest route plan app and the fast route plan app). Therefore, this study expresses the route plan as a game model to analyze the best responses of competitors to determine the fuel-efficient route plan. In this section, players in this game model are presented in Subsection 4.1, and the scenarios and candidate strategies of route plan are defined in Subsection 4.2. Finally, Subsection 4.3 shows the best response of each player.

4.1 Players

Three players who design and provide a route plan app join this game. The preferred strategy of each player is described as follows.

(1) Player 1 selects the shortest route plan based on the lowest geo-distance. Player 1 plays as a traditional navigation system which does not consider the traffic condition to determine a route plan.

(2) Player 2 selects the fastest route plan based on the lowest travel time. Player 2 plays as an Internet-based navigation system which does consider the traffic condition to determine a route plan.

(3) Player 3 selects the fuel-efficient route plan app based on the traffic condition and fuel consumption estimation. Player 3 is proposed to plan the fuel-saving route in accordance with the traffic condition and individual behaviors.

4.2 Scenarios and Candidate Strategies

In this game, two routes (i.e., Route 1 and Route 2) from Node 1 to Node 2 are selected as candidate strategies for players (as Figure 2 shows). There are Q vehicles distributed in these two routes, and k_i vehicles are driven in Route i. The length of Route i is defined as d_i km, and the average speed of Route i is defined as u_i km/hr. The travel time t_i can be measured in accordance with d_i/u_i hr. Each player can develop the route plan according to their own preferred strategies. Table 2 summarizes notations in this game-theoretic model.

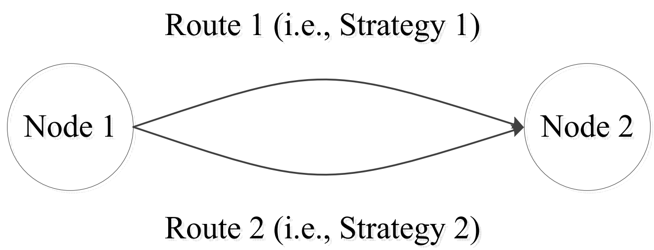


Figure 2. Candidate strategies in the game model

Table 2. Notations

Parameter	Description
Q	The number of total vehicle from Node 1 to Node 2 (unit: car)
d_i	The length of Route i (unit: km)
u_i	The average speed of Route i (unit: km/hr)
k_i	The number of vehicles in Route i (unit: car)
s_i	The safe distance between each two vehicles in Route i (unit: m)
t_i	The travel time of Route i (unit: hr)
l	The length of vehicle (unit: m)
p_j	The market share of Player j (unit: %)
$g(u_i)$	The consumed fuel quantity of vehicle speed u_i in each hour (unit: liter)
f_i	The consumed fuel quantity of Route i (unit: liter)

4.2.1 Assumptions

The assumptions and limitations are given as follows for measuring the best response of each player.

- Player 1's strategy is not influenced by traffic condition.
- Player 2's strategy can be influenced by traffic condition, so Player 2's strategy is developed based on the best response of Player 1.
- Player 3's strategy is developed based on the best response of Players 1 and 2. The game tree is showed in Figure 3.

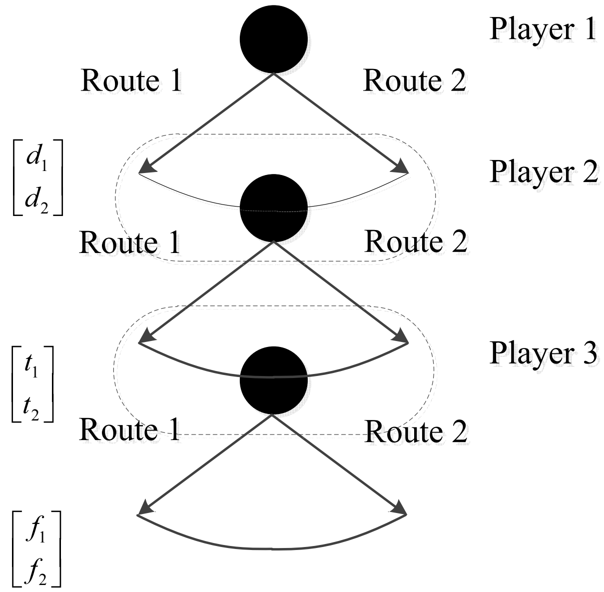


Figure 3. Game tree for route plans

- The market share of Player 3 (i.e., p_3) is about zero.
- The values of Q, p_1, p_2, d_1, and d_2 are predefined, and d_1 is longer than d_2.
- Each vehicle can be driven with the aspirational vehicle speed with the adaptable safe distance in the recommended route.
- The adaptable safe distance between each two vehicles in Route i is assumed as $u_i/2$ m [18-19]. For instance, the adaptable safe distance is 50 m when the speed is 100 km/hr.

4.2.2 Aspirational Vehicle Speed and Travel Time

For the calculation of aspirational vehicle speed and travel time, this study assumes that the value of safe distance (unit: m) is the half value of speed (unit: km) [18-19]. Therefore, the required safe distance of each vehicle is estimated in accordance with the vehicle length and the adaptable safe distance (shown in Equation (3)). Therefore, the number of vehicle in Route i can be determined by Equation (4) according to the required safe distance of each vehicle. After the transposition of Equation (4), the aspirational vehicle speed can be calculated as $\frac{2000d_i}{k_i} - 2l$ by Equation (5). Furthermore, the length of Route i can be considered to estimate the aspirational travel time by Equation (6).

$$s_i + l = \frac{u_i}{2} + l \tag{3}$$

$$k_i = \frac{1000 \times d_i}{s_i + l} = \frac{1000 \times d_i}{\frac{u_i}{2} + l} \tag{4}$$

$$u_i = \frac{2000 \times d_i - 2 \times l \times k_i}{k_i} = \frac{2000 d_i}{k_i} - 2l \tag{5}$$

$$t_i = \frac{d_i}{u_i} = \frac{d_i}{\frac{2000 d_i}{k_i} - 2l} \tag{6}$$

4.2.3 The Cost Function of Each Player

The cost functions of strategies for players in this game are remarked as follows.

- The cost of Player 1's Strategy 1 is d_1 in accordance with the length of Route 1.
- The cost of Player 1's Strategy 2 is d_2 in accordance with the length of Route 2.
- The cost of Player 2's Strategy 1 is t_1 in accordance with the travel time of Route 1.
- The cost of Player 2's Strategy 2 is t_2 in accordance with the travel time of Route 2.
- The cost of Player 3's Strategy 1 is f_1 which is defined as Equation (7). The fuel consumption of Route 1 is estimated as f_1.

$$f_1 = t_1 \times g(u_1) \tag{7}$$

- The cost of Player 3's Strategy 2 is f_2 which is defined as Equation (8). The fuel consumption of Route 2 is estimated as f_2.

$$f_2 = t_2 \times g(u_2) \tag{8}$$

4.3 The Best Response of Each Player

The best responses of players are discussed in the follow subsections.

4.3.1 The Best Response of Player 1

The preferred strategy of Player 1 is the shortest route plan. Therefore, Strategy 2 will be selected when d_1 is longer than d_2. The navigation system built by Player 1 will recommend users to drive their vehicle through Route 2, so $p_1 \times Q$ vehicles will be driven in Route 2.

4.3.2 The Best Response of Player 2

The preferred strategy of Player 2 is the fast route plan. Player 2 develops a mix strategy in accordance with the ratio of r for Strategy 1 and the ratio of $(1 - r)$ for Strategy 2. In the recommendation of Player 2's app, $p_2 \times Q \times r$ vehicles will be driven in Route 1, and $p_2 \times Q \times (1-r)$ vehicles will be driven in Route 2. Therefore, the objective function of Player 2 can be expressed as Equation (9) in accordance with game theory [20], and the total cost of Player 2 is defined as

π in Equation (9). The adaptable value of r can be estimated by Equation (10) for the best response of Player 2. The proofs of Equation (10) are presented in Appendix A.

4.3.3 The Best Response of Player 3

The preferred strategy of Player 3 is the most fuel-efficient route plan. The aspirational vehicle speed and travel time can be estimated in accordance with the adaptable value of r in Equation (10) based on the best responses of Player 1 and Player 2. Player 3 can adopt the estimated vehicle speeds (i.e., u_1 and u_2) and travel time (i.e., t_1 and t_2) into Equations (7) and (8) to calculate the costs of Strategy 1 and Strategy 2 for the development of the route plan.

$$\begin{aligned}&\min \pi \\ &= \min\left(k_1 \times t_1 + k_2 \times t_2\right) \\ &= \min\left(p_2 \times Q \times r \times t_1 + \left(p_2 \times Q \times (1-r) + (1-p_2) \times Q\right) \times t_2\right)\end{aligned} \quad (9)$$

$$\begin{aligned}&\frac{\partial \pi}{\partial r} = p_2 \times Q \times (t_1 - t_2) = 0 \\ &\Rightarrow t_1 = t_2 \\ &\Rightarrow \frac{d_1}{\frac{2000 d_1}{p_2 \times Q \times r} - 2l} = \frac{d_2}{\frac{2000 d_2}{p_2 \times Q \times (1-r) + (1-p_2) \times Q} - 2l} \\ &\Rightarrow r = \begin{cases} \dfrac{p_2 \times \left[\sqrt{(2000 \times d_1 \times d_2)^2 + Q^2 \times l^2 \times (d_1 - d_2)^2} - (2000 \times d_1 \times d_2) + Q \times l \times (d_1 - d_2)\right]}{2 \times p_2^2 \times Q \times l \times (d_1 - d_2)} \\ \dfrac{p_2 \times \left[-\sqrt{(2000 \times d_1 \times d_2)^2 + Q^2 \times l^2 \times (d_1 - d_2)^2} - (2000 \times d_1 \times d_2) + Q \times l \times (d_1 - d_2)\right]}{2 \times p_2^2 \times Q \times l \times (d_1 - d_2)} \rightarrow negative \end{cases}\end{aligned} \quad (10)$$

5 Numerical Analyses

This section gives two case studies to illustrate the fuel consumption of the proposed route plan method which is compared with the shortest distance route and the shortest travel time route.

5.1 Case 1: Effects of d_1 on the c_1 and c_2

For the purpose of demonstration, this study adopted some parameters as follows to present the game in Subsection 5.1: Q = 2,300 cars, d_2 = 10 km, l = 5 m, p_1 = 0.4, and p_2 = 0.6. Because the strategy of Player 1 was the shortest distance route plan, the best response of Player 1 was to recommend 920 users to drive their vehicles though Route 2. Furthermore, the value of r was determined by Equation (10) for the best response of Player 2 (shown in Table 3). For instance, the value of r was estimated as 0.89 while the route length of d_1 was 13 km. For the users of Player 2's app, 1,226 vehicles were recommended to drive through Route 1, and 154 vehicles were recommended to drive through Route 2. Therefore, the vehicle speeds of Routes 1 and 2 were, respectively, 11.21 km/hr and 8.62 km/hr; the travel times of Routes 1 and 2 were, respectively, 1.16 and 1.16 hr. For the best response of Player 3, Table 1 was adopted as the parameter values for fuel consumption function g(ui), while the consumed fuel quantities of Strategies 1 and 2 were, respectively, 4.59 and 2.78 liters which were calculated by Equations (11) and (12). Therefore, Route 2 was recommended to the users of Players 1's and 3's apps, and the consumed fuel quantity was estimated as 2.78 liters. Moreover, the average consumed fuel quantity of the route which was recommended by Player 2's app was measureed as 4.39 liters by Equation (13). Figure 4 shows the fuel consumption comparison of each player.

Table 3. Case 1: Experimental results

d_1	r	k_1	k_2	u_1	u_2	t_1	t_2	f_1	f_2
11	0.86	1180	1120	8.64	7.86	1.27	1.27	3.05	3.05
12	0.87	1205	1095	9.92	8.26	1.21	1.21	2.90	2.90
13	0.89	1226	1074	11.21	8.62	1.16	1.16	4.59	2.78
14	0.90	1244	1056	12.51	8.94	1.12	1.12	4.43	2.69
15	0.91	1259	1041	13.82	9.22	1.09	1.09	4.30	2.60
16	0.92	1273	1027	15.15	9.47	1.06	1.06	4.18	2.54
17	0.93	1284	1016	16.47	9.69	1.03	1.03	4.09	2.48
18	0.94	1295	1005	17.81	9.89	1.01	1.01	4.00	2.43
19	0.94	1304	996	19.15	10.08	0.99	0.99	3.93	3.93
20	0.95	1312	988	20.49	10.24	0.98	0.98	6.44	3.87

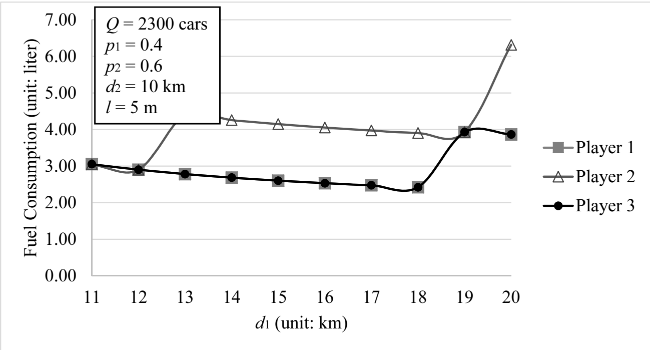


Figure 4. Case 1: Fuel Consumption

$$f_1 = t_1 \times g(u_1) = 1.16 \times 3.960 \approx 4.59 \quad \textbf{(11)}$$

$$f_2 = t_2 \times g(u_2) = 1.16 \times 2.400 \approx 2.78 \quad \textbf{(12)}$$

$$\begin{aligned} & r \times f_1 + (1-r) \times f_2 \\ & = 0.89 \times 4.59 + 0.11 \times 2.78 \approx 4.39 \end{aligned} \quad \textbf{(13)}$$

5.2 Case 2: Effects of Q on the c_1 and c_2

For the purpose of demonstration, this study adopted some parameters as follows to present the game in Subsection 5.2: d_2 = 15 km, d_2 = 10 km, l = 5 m, p_1 = 0.4, and p_2 = 0.6. For instance, the value of r was estimated as 0.87 while the value of Q was 1400 cars. Because the strategy of Player 1 was the shortest distance route plan, the best response of Player 1 was to recommend 560 users to drive their vehicles though Route 2. Furthermore, the value of r was determined by Equation (10) for the best response of Player 2 (as Table 4 shows). For the users of Player 2's app, 741 vehicles were recommended to be driven through Route 1, and 99 vehicles were recommended to be driven through Route 2. Therefore, the vehicle speeds of Routes 1 and 2 were 30.50 km/hr and 20.33 km/hr, respectively; the travel times of Routes 1 and 2 were 0.49 hr and 0.49 hr, respectively. For the best response of Player 3, Table 1 was adopted for parmeter values of the fuel consumption function g(ui), and the consumed fuel quantities of Strategies 1 and 2 were 0.77 liters and 3.25 liters which were calculated by Equations (7) and (8). Therefore, Route 1 was recommended to the users of Player 3's app, and the consumed fuel quantity was estimated as 0.77 liters. However, Route 2 was recommended to the users of Player 1's app, and the consumed fuel quantity was estimated as 3.25 liters. Moreover, the average consumed fuel quantity of the route recommended by Player 2's app was measureed as 1.06 liters. Figure 5 shows the fuel consumption comparison of each player.

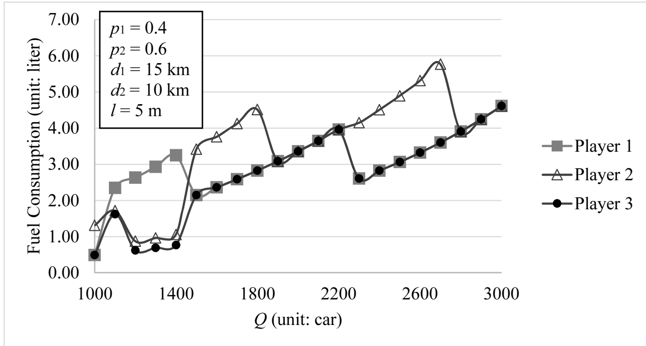


Figure 5. Case 2: fuel consumption

Table 4. Case 2: Experimental Results

Q	r	k_1	k_2	u_1	u_2	t_1	t_2	f_1	f_2
1000	0.87	521	479	47.60	31.74	0.32	0.32	1.44	0.49
1100	0.87	575	525	42.16	28.11	0.36	0.36	1.62	2.35
1200	0.87	630	570	37.62	25.08	0.40	0.40	0.62	2.63
1300	0.88	685	615	33.79	22.53	0.44	0.44	0.69	2.93
1400	0.88	741	659	30.50	20.33	0.49	0.49	0.77	3.25
1500	0.89	797	703	27.66	18.44	0.54	0.54	3.58	2.15
1600	0.89	853	747	25.17	16.78	0.60	0.60	3.93	2.36
1700	0.89	910	790	22.97	15.31	0.65	0.65	4.31	2.59
1800	0.90	967	833	21.02	14.01	0.71	0.71	4.71	2.83
1900	0.90	1025	875	19.28	12.85	0.78	0.78	3.08	3.08
2000	0.90	1083	917	17.71	11.80	0.85	0.85	3.35	3.35
2100	0.91	1141	959	16.29	10.86	0.92	0.92	3.65	3.65
2200	0.91	1200	1000	15.00	10.00	1.00	1.00	3.96	3.96
2300	0.91	1259	1041	13.82	9.22	1.09	1.09	4.30	2.60
2400	0.92	1319	1081	12.75	8.50	1.18	1.18	4.66	2.82
2500	0.92	1379	1121	11.76	7.84	1.28	1.28	5.05	3.06
2600	0.92	1439	1161	10.84	7.23	1.38	1.38	5.48	3.32
2700	0.93	1500	1200	10.00	6.67	1.50	1.50	5.94	3.60
2800	0.93	1561	1239	9.22	6.14	1.63	1.63	3.91	3.91
2900	0.93	1623	1277	8.49	5.66	1.77	1.77	4.24	4.24
3000	0.94	1685	1315	7.81	5.21	1.92	1.92	4.61	4.61

6 Conclusions and Future Work

This study adopts a FCEM to measure the consumed fuel quantity of each vehicle speed interval (i.e., a cost function) in accordance with each individual's optimal behavior. Furthermore, a mobile app is designed to consider the best responses of other route plan apps (e.g., the shortest route plan app and the fast route plan app) and plan a fuel-efficient route according to the consumed fuel quantity. The numerical analysis results showed that the proposed fuel-efficient route plan app can support fuel-saving for logistics industries.

In the future, the route plan app can be implemented in accordance with the proposed method for reducing fuel consumption. Furthermore, the complex road network including several routes (i.e., multiple strategies) can be considered and selected by players. Furthermore, the market share of Player 3 can be increased to influence Player 2's strategy.

Acknowledgments

The research was funded by Fuzhou University, grant number 510730/XRC-18075.

References

[1] Petroleum Price Information Management and Analysis System. Bureau of Energy, Ministry of Economic Affairs, https://www2.moeaboe.gov.tw/oil102/oil1022010/english.htm.

[2] S. Y. Chan, *The Basic Information of Truck Freight Transportation*, https://tie.tier.org.tw/db/content/index.asp?sid=0F365625735542181625&mainIndustryCategorySIds=0A007646527679642419.

[3] C. L. Lo, C. H. Chen, T. S. Kuan, K. R. Lo, H. J. Cho, Fuel Consumption Estimation System and Method with Lower Cost, *Symmetry*, Vol. 9, No. 7, Article ID 105, July 2017. doi: 10.3390/sym9070105.

[4] Y. H. Jia, W. N. Chen, T. Gu, H. Zhang, H. Yuan, Y. Lin, W. J. Yu, J. Zhang, A Dynamic Logistic Dispatching System With Set-Based Particle Swarm Optimization, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 48, No. 9, pp. 1607-1621, September, 2018. doi: 10.1109/TSMC.2017.2682264.

[5] Z. He, K. Chen, X. Chen, A Collaborative Method for Route Discovery Using Taxi Drivers' Experience and Preferences, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 19, No. 8, pp. 2505-2514, August, 2018. doi: 10.1109/TITS.2017.2753468.

[6] Z. Li, I. V. Kolmanovsky, E. M. Atkins, J. Lu, D. P. Filev, Y. Bai, Road Disturbance Estimation and Cloud-aided Comfort-based Route Planning, *IEEE Transactions on Cybernetics*, Vol. 47, No. 11, pp. 3879-3891, November, 2017. doi: 10.1109/TCYB.2016.2587673.

[7] K. Dorling, J. Heinrichs, G. G. Messier, S. Magierowski, Vehicle Routing Problems for Drone Delivery, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 47, No. 1, pp. 70-85, January, 2017. doi: 10.1109/TSMC.2016.2582745.

[8] J. Lin, W. Yu, N. Zhang, X. Yang, L. Ge, Data Integrity Attacks against Dynamic Route Guidance in Transportation-based Cyber-Physical Systems: Modeling, Analysis, and Defense, *IEEE Transactions on Vehicular Technology*, Vol. 67, No. 9, pp. 8738-8753, June, 2018. doi: 10.1109/TVT.2018.2845744.

[9] H. Yang, Y. Deng, J. Qiu, M. Li, M. Lai, Z. Y. Dong, Electric Vehicle Route Selection and Charging Navigation Strategy Based on Crowd Sensing, *IEEE Transactions on Industrial Informatics*, Vol. 13, No. 5, pp. 2214-2226, October, 2017. doi: 10.1109/TII.2017.2682960.

[10] J. R. Cheng, B. Y. Lin, K. Q. Cai, X. Y. Tang, B. Y. Zhang, ETC Intelligent Navigation Path Planning Method, *Journal of Internet Technology*, Vol. 19, No. 2, pp. 619-631, March, 2018. doi: 10.3966/160792642018031902030.

[11] M. A. Hossain, I. Elshafiey, A. Al-Sanie, High Precision Vehicle Positioning: Towards Cooperative Driving Based on VANET, *Journal of Internet Technology*, Vol. 19, No. 1, pp. 289-295, January, 2018. doi: 10.3966/160792642018011901028.

[12] B. J. Chang, Y. H. Liang, B. J. Huang, Distributed Wireless Sensing-based Routing and Adaptive Least-travel-time Navigation in VANET, *International Journal of Ad Hoc and Ubiquitous Computing*, Vol. 12, No. 2, pp. 75-87, February, 2013. doi: 10.1504/IJAHUC.2013.052346.

[13] G. H. Yu, Research on Mobile Internet Big Data Detecting Method for the Redundant Data, *International Journal of Internet Protocol Technology*, Vol. 11, No. 1, pp. 29-37, January, 2018. doi: 10.1504/IJIPT.2018.10012655.

[14] C. C. Lo, Y. H. Kuo, Traffic-aware Routing Protocol with Cooperative Coverage-oriented Information Collection Method for VANET, *IET Communications*, Vol. 11, No. 3, pp. 444-450, February, 2017. doi: 10.1049/iet-com.2015.1016.

[15] D. K. N. Venkatramana, S. B. Srikantaiah, J. Moodabidri, CISRP: Connectivity-aware Intersection-based Shortest Path Routing Protocol for VANETs in Urban Environments, *IET Networks*, Vol. 7, No. 3, pp. 152-161, May, 2018. doi: 10.1049/iet-net.2017.0012.

[16] C. H. Chen, An Arrival Time Prediction Method for Bus System, *IEEE Internet of Things Journal*, Vol.5, No. 5, pp. 4231-4232, August, 2018. doi: 10.1109/JIOT.2018.2863555.

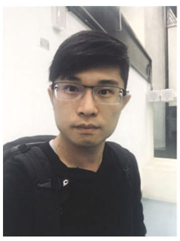
[17] C. H. Chen, C. A. Lee, C. C. Lo, Vehicle Localization and Velocity Estimation Based on Mobile Phone Sensing, *IEEE Access*, Vol. 4, pp. 803-817, March, 2016. doi: 10.1109/ACCESS.2016.2530806.

[18] E. Bertolazzi, F. Biral, M. D. Lio, A. Saroldi, F. Tango, Supporting Drivers in Keeping Safe Speed and Safe Distance: The SASPENCE Subproject within the European Framework Programme 6 Integrating Project PReVENT, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 11, No. 3, pp. 525-538, September, 2010. doi: 10.1109/TITS.2009.2035925.

[19] Traffic Safety Information, https://www.freeway.gov.tw/Publish.aspx?cnid=516&p=2230.

[20] C. Leboucher, H. S. Shin, R. Chelouah, S. Le Ménec, P. Siarry, M. Formoso, A. Tsourdos, A. Kotenkoff, An Enhanced Particle Swarm Optimization Method Integrated with Evolutionary Game Theory, *IEEE Transactions on Games*, Vol. 10, No. 2, pp. 221-230, June, 2018. doi: 10.1109/TG.2017. 2787343.

Biographies



Chi-Lun Lo is working toward a Ph.D. degree in the Department of Transportation and Logistics Management of National Chiao Tung University (NCTU), Taiwan. He also serves as a researcher for the Business Solutions Laboratory in the Telecommunication Laboratories, Chunghwa Telecom Co. Ltd., Taiwan, R.O.C.

Chi-Hua Chen is a distinguished professor (a Minjiang Scholar and a Qishan Scholar) at the College of Mathematics and Computer Science of Fuzhou University in China. He received a Ph.D. degree from the Department of Information Management and Finance of NCTU in 2013. His recent research interests include Internet of things and deep learning.

Jin-Li Hu is currently a professor at Institute of Business and Management, NCTU, Taiwan. He received PhD in Economics, SUNY at Stony Brook, USA. His research interest includes applied game theory, efficiency and productivity, and energy policy.

Kuen-Rong Lo received a Ph.D. degree in electronic engineering from the NCTU, Taiwan, in 2000. He currently is an IoT (Internet of Things) Laboratory Managing Director in the Telecommunication Laboratories, Chunghwa Telecom Co. Ltd., responsible for the ITS (Intelligent Transport Systems) technologies and related service systems.

Hsun-Jung Cho received a Ph.D. degree in urban and regional planning (major in Transportation Networks) from the University of Pennsylvania, Philadelphia, in 1989. Following 1989, he joined the Department of Transportation Engineering and Management (TEM), NCTU, Hsinchu, Taiwan. His research interests include sensitivity analysis of network equilibrium, network design, traffic simulation, intelligent transportation systems, and urban planning.

Appendix A. Partial Differential Equation Proof

The partial differential equation proof of Equation (10) is expressed as Equation A(1).

$$
\begin{aligned}
\frac{\partial \pi}{\partial r} &= \frac{\partial\left(p_2 \times Q \times r \times t_1 + \left(p_2 \times Q \times (1-r) + (1-p_2) \times Q\right) \times t_2\right)}{\partial r} \\
&= \frac{\partial\left(p_2 \times Q \times r \times t_1\right)}{\partial r} + \frac{\partial\left(p_2 \times Q \times (1-r) \times t_2 + (1-p_2) \times Q \times t_2\right)}{\partial r} \\
&= p_2 \times Q \times t_1 + \frac{\partial\left(p_2 \times Q \times (1-r) \times t_2\right)}{\partial r} \\
&= p_2 \times Q \times (t_1 - t_2)
\end{aligned} \qquad \mathbf{A(1)}
$$