Rideshare Operations Management for Heterogeneous Vehicles to Minimize Total CO_2 Emissions *

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IThis paper suggests/introduces an ecological operation management process/method for shared mobility system, which reduces total CO_2 emissions with a new trend where several users going to a common destination share a ride in the same vehicle. Simulation models that include each of the powertrain characteristics of eCosMos conventional vehicles and battery electric vehicles are used to accurately calculate the CO_2 emissions from each vehicle for each driving route. an optimization is formulated by designing a cost function correlated to the total amount of CO_2 emissions calculated with the simulator. An operations management technology was developed to optimize the routes and user allocation by incorporating them into a constraint satisfaction problem (CSP) that minimizes the total amount of CO_2 emissions from multiple vehicles. The effect on eCosMos has been validated with simulation. It shows more than 40% CO_2 emission reductions compared to conventional rideshare technologies for cases in which total driving distance is minimized.

Key words :
dispatch control, rideshare, energy management, CO_2 emissions reduction

1. Introduction

In recent years, it has become increasingly necessary to reduce CO_2 emissions as a countermeasure to global warming. Paris Agreement sets out a global framework to limit global warming to well below 2°C, which needs an extremely huge reduction of CO_2 emissions. Therefore, it is critical to deal with the use of automobiles that has a big impact on this problem. On the other hand, since it is difficult to dramatically improve individual vehicle efficiency anymore, novel approaches are required to achieve the goal. Because of this background, we, DENSO, are proceeding with development to reduce CO_2 emissions not only by performance improvement of individual vehicles but also by operations management or cooperative control of multiple vehicles. Fig. 1 shows our perspective of energy management technology ranging from level 1 to 4. Level 1 is "in-car energy management". Level 2 is "predictive energy management". Level 3 is "energy management for passenger and freight transport", where transportation companies reduce their CO_2 emissions. Finally, level 4 is "energy management in a smart city". In this paper, a rideshare operations management technology reducing the total CO_2 emissions belonging to energy management level 3 is introduced, where several users going to the same destination share a ride in the same vehicle.

In general, it is well known that whole CO_2 emissions from multiple vehicles can be reduced if the use of vehicles is reduced with ridesharing. However, the optimal solutions derived from conventional ridesharing systems necessarily do not mean optimal also in the sense of CO_2 emissions, because they just minimize the sum of route cost. Based on this idea, some previous researches focus on fuel consumption reduction to reduce CO_2 emissions. Meanwhile, it is not easy to model the CO_2 emissions in the real world, because it is influenced by various kinds of elements such as vehicle efficiency, vehicle speed profile, route profile, and auxiliary machine power consumption, which are not considered in existing researches.

In this research, ecological operations management for shared mobility system (eCosMos) is proposed to reduce the total amount of CO_2 emissions further by considering each powertrain characteristic to calculate the CO_2 emissions from each vehicle for each driving route accurately. To realize this goal, an operations management technology has been developed to find the optimal routes and user allocation for minimizing the total amount of CO_2 emissions from multiple vehicles.

This paper is organized as follows. Section 2 describes previous researches and their technical issue analysis. Section 3 presents the overview of eCosMos and its problem formulation. The methodologies to calculate CO_2 emissions from conventional vehicles and battery electric vehicles used for eCosMos are described in section 4. Afterward, the numerical experiment results based on a simulation provided in section 5 show the CO_2 emissions reduction performance of eCosMos. Lastly, the conclusion and future work are given in section 6.

2. Previous Research Review and Technical Issue Analysis

Rideshare operations management is often regarded as a vehicle routing problem (VRP), which considers the optimal set of routes for fleet vehicles to deliver goods to a given set of customers. While the sum of route costs is minimized in common VRP, green vehicle routing problems (G-VRP) minimize the total CO_2 emissions from multiple vehicles directly by

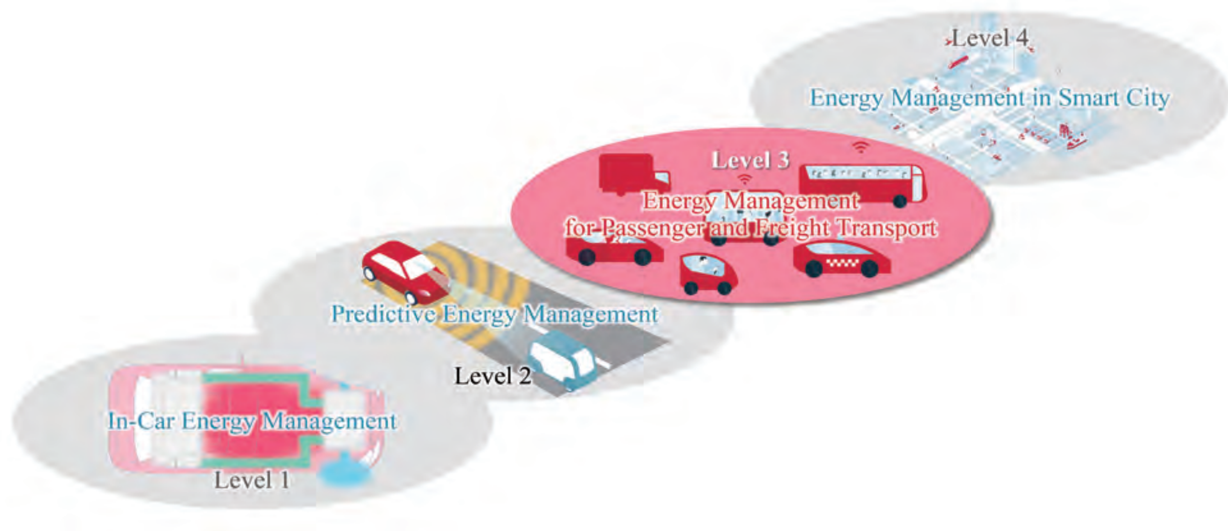

Fig. 1 Future energy management technology perspective

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designing cost functions with fuel consumption. In existing researches of G-VRPs, simple cost functions are used such as a regression function whose variable is average vehicle speed [1] or a function corrected with vehicle weight [2]. Since the CO_2 emissions are influenced by various factors, these simplified functions for regression are supposed to have huge errors from the actual numbers. In general, the major factors to change the CO_2 emissions can be divided into two groups: the influence of vehicle specification and driving environment including surrounding traffic flow. As examples of the former one, CO_2 emissions are influenced by vehicle size, type, and powertrain specification. Since the vehicles used for rideshare are often heterogeneous with various kinds of powertrain systems, it is desirable to take these characteristics into the CO_2 emissions model to improve accuracy. On the other hand, even when the same vehicle travels on the same route, the CO_2 emissions vary depending on the energy consumption of auxiliary machines such as an air conditioner, traffic flow, and the number of passengers. CO_2 emissions change with respect to these factors related to the driving environment are non-linear, which is one of the reasons why simplified regression function cannot express the CO_2 emissions accurately. For real-world use, these major factors to influence the CO_2 emissions should be considered to calculate the more realistic CO_2 emissions to improve operations management system performance.

Therefore, in this research, an operations management technology, namely eCosMos, has been proposed to find the optimal routes and user allocation for minimizing the total amount of CO_2 emissions from multiple vehicles. For the calculation of the CO_2 emissions, a simulation model including each powertrain characteristic for rideshare operations management is introduced to calculate the CO_2 emissions from each vehicle for each driving route more accurately. Then, an optimization problem is formulated by designing a cost function described with the total amount of CO_2 emissions calculated with the simulator. In this research, CO_2 emissions can be described with a function whose input variables are vehicle type, route, and the number of users. Therefore, by considering the ease of expressing the constraints, this problem is formulated with a constraint satisfaction problem (CSP) [3] to derive the optimal solution. CSPs are mathematical problems defined as a set of objects whose state must satisfy several constraints.

3. Rideshare Operations Management

3.1 Problem Setting

In this research, the rideshare is considered, where users move from the same starting station to other stations, which are destinations for users, as shown in Fig. 2. Vehicles can go through several stations until reaching the terminal stations. For this ridesharing, there are multiple types of vehicles whose maximum number of passengers and CO_2 emissions characteristics are different. The purpose is to minimize the total CO_2 emissions by considering each vehicle's characteristics.

3.2. Problem Formulation

As mentioned in section 2, the rideshare operations management problem is formulated with CSP. The notations for set and constant numbers for the optimization problem are described in Table 1 and Table 2, respectively. Here, the set of driving phases starts from 0 to ρ. Variables for the optimization problem are s_j^p, d_j^p, and n_j^p as shown in Table 3.

The optimization problem described with CSP is as follows:

$$\min \sum_{j\in J}\sum_{p\in P} f_j^p \tag{1}$$

$$\text{s.t.} \quad (s_j^p = s)\wedge(d_j^p = d)\wedge(n_j^p = n) \to f_j^p = \tilde{f}_j(s,d,n) \quad j\in J,\ p\in P,\ s,d\in D,\ n\in N, \tag{2}$$

$$v_{j,s,d}^p = \begin{cases} n_j^p & \left((s = s_j^p)\wedge(d = d_j^p)\wedge(a_{s_j^p,d_j^p} = 1)\right) \\ 0 & \text{(otherwise)} \end{cases} \quad j\in J,\ p\in P,\ s,d\in D, \tag{3}$$

$$\left\{\sum_{p\in P\setminus\{\rho\}}\left(\sum_{s\in D} v_{j,s,d}^p - \sum_{\delta\in D} v_{j,d,\delta}^{p+1}\right) + \sum_{s\in D} v_{j,s,d}^{\rho}\right\} = m_d \quad d\in D, \tag{4}$$

$$s_j^p = d_j^{p-1} \quad p\in P\setminus\{0\}, \tag{5}$$

$$\sum_{d\in D} v_{j,s,d}^0 = 0 \quad j\in J,\quad s\in D\setminus\{\sigma\}, \tag{6}$$

$$\sum_{s\in D\setminus\{\sigma\}} v_{j,s,\sigma}^p = 0 \quad j\in J, \tag{7}$$

$$\sum_{s} v_{j,s,d}^p - \sum_{\delta} v_{j,d,\delta}^{p+1} \ge 0 \quad i\in J,\quad p\in P\setminus\{\rho\},\quad d\in D. \tag{8}$$

Equation 1 is a cost function to be minimized. Equation 2 is a condition in which $\tilde{f}$ has a value. Equation 3 defines a new parameter to express other constraints. In Eq. 4, it is guaranteed that all the users can reach their destinations. Equation 5 expresses that vehicles start from the points to which they reached at the last phase. Equation 6 expresses a constraint of start points. Equation 7 means that vehicles go to other points than the start point. Equation 8 means that nobody rides on vehicles except for at the starting point. Vehicles go to several stations until reaching the terminal stations. To express it, driving phase $p \in P$ is introduced. For each p, a start point $s_j^p \in D$, an end point $d_j^p \in D$, and the number of users $n_j^p \in N$ can be determined. Besides, if Eq. 5 is satisfied, vehicles can go through several stations before reaching the

Table 1 Notation for sets

Notation	Description
J	Set of drivers
P	Set of driving phases
D	Set of stations (the starting station and other stations)
N	Set of the number of users

Table 2 Notation for constant numbers

Notation	Description
σ	Index of the starting station
ρ	The maximum number of the phase P
$a_{s,d}$	Binary variable expressing whether the route from $s \in D$ to $d \in D$ is available
$\tilde{f}_j(s,d,n)$	CO_2 emissions table with respect to start point $s \in D$, end point $d \in D$, and the number of passengers $n \in N$
m_d	The number of users going to $d \in D$

Table 3 Notation for variables

Notation	Description
s_j^p	The start point of driver $j \in J$ at phase $p \in P$
d_j^p	The end point of driver $j \in J$ at phase $p \in P$
n_j^p	The number of users riding on the vehicle of driver $j \in J$ at phase $p \in P$
f_j^p	CO_2 emissions from the vehicle of driver $j \in J$ at phase $p \in P$

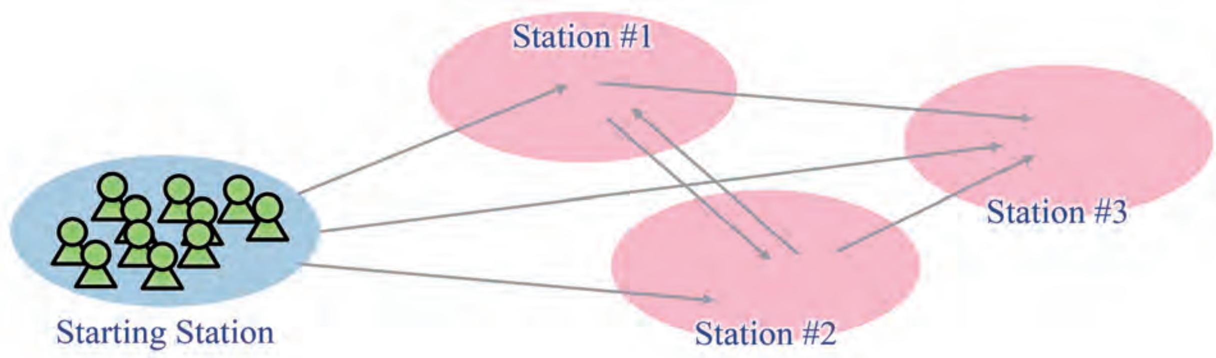


Fig. 2 Vehicle routing problem considered in this research

terminal stations. Here, when finding the optimal solution, it is allowed that the start point is identical to the end station, namely $s_j^p = d_j^p$. On the other hand, actual routes for each vehicle are determined by omitting these parts. $\hat{f}$ is calculated offline to be stored in a table before the optimization. The methodology to calculate the CO_2 emissions for each route is described in section 4.

4. Energy Consumption Calculation

4.1 Driving Power Calculation

The external force applied to the vehicle can be expressed by the sum of air rolling resistance, gradient resistance, increased resistance when driving on a curve, and acceleration resistance. Therefore, by using the vehicle speed $v(t)$, the equation of motion is expressed as follows:

$$F_{\mathrm{drv}}(t) = m\frac{\mathrm{d}v(t)}{\mathrm{d}t} + F_{\mathrm{r}}(v(t)) + mg\sin\theta(t) + F_{\mathrm{c}}(t), \tag{9}$$

where $F_{\mathrm{drv}}(t)$ is the vehicle driving force, m is the vehicle mass, $F_{\mathrm{r}}(v(t))$ is the road load, g is gravitational acceleration, θ is the slope, and $F_{\mathrm{c}}(t)$ is the increased resistance when driving on a curve. Here, by assuming that the cornering force is equivalent to the centrifugal force, $F_{\mathrm{c}}(t)$ can be expressed as follows:

$$F_{\mathrm{c}}(t) = m\frac{v^2}{r}\tan\beta, \tag{10}$$

where r is a radius of gyration and β is a slip angle determined from the cornering force as explained in [4]. Vehicle output power $P_{\mathrm{drv}}(t)$ used for CO_2 emissions calculation is calculated as follows:

$$P_{\mathrm{drv}}(t) = F_{\mathrm{drv}}(t)v(t) + P_{\mathrm{aux}}, \tag{11}$$

where P_{aux} is the auxiliary machine power consumption such as air conditioner consuming power. In this research, for the sake of simplicity, P_{aux} is assumed to be 0kW. Although conventional vehicles without electrification and battery electric vehicles are considered in 4.2 and 4.3 respectively, the framework proposed in this research can be applied even to other vehicle types such as hybrid electric vehicles or fuel cell electric vehicles.

4.2 CO_2 Emissions Calculation for Conventional Vehicles

As an engine efficiency map, the BSFC characteristic of the diesel engine shown in [5] is used. It is assumed that the characteristics of any diesel engines can be expressed by scaling this engine characteristic based on the maximum engine output power. The fuel consumption power P_{fuel} can be expressed as follows:

$$P_{\mathrm{fuel}} = \frac{P_{\mathrm{drv}}}{\eta_{\mathrm{eng}}(N_{\mathrm{eng}}, T_{\mathrm{eng}})\eta_{\mathrm{mec}}}, \tag{12}$$

where P_{drv} is the vehicle driving power, $\eta_{\mathrm{eng}}(N_{\mathrm{eng}}, T_{\mathrm{eng}})$ is the engine efficiency, and η_{mec} is the mechanical transfer efficiency. Here, the engine speed N_{eng} and the engine torque T_{eng} can be expressed as follows:

$$N_{\mathrm{eng}} = k_1 v(t), \tag{13}$$

$$T_{\mathrm{eng}} = k_2\frac{P_{\mathrm{drv}}}{\eta_{\mathrm{mec}}N_{\mathrm{eng}}}, \tag{14}$$

where k_1 and k_2 are coefficients. Continuously variable transmissions (CVT) can choose the most efficient driving point against the requested engine output power. By assuming that the engine driving point can be set as the most efficient condition by CVT without delay, the engine efficiency can be expressed as a function whose variable is the engine output power as follows:

$$P_{\mathrm{fuel}} = \frac{P_{\mathrm{drv}}}{\eta_{\mathrm{eng}}(P_{\mathrm{eng}})\eta_{\mathrm{mec}}}. \tag{15}$$

Fig. 3 shows the engine efficiency map used for the numerical experiment described in section 5 when the maximum engine power is 140kW. Here, the transmission transfer efficiency is assumed as constant (75%). By using P_{fuel}, the CO_2 emissions from conventional vehicles can be calculated as follows:

$$C_{\mathrm{cnv}} = \frac{k_{\mathrm{f}}}{1000k_{\mathrm{fuel}}k_{\mathrm{dns}}}\int_0^T P_{\mathrm{fuel}}\mathrm{d}t, \tag{16}$$

where k_{f}, k_{fuel}, and k_{dns} are the CO_2 emissions rate with respect to fuel consumption (2.619 kg/L), the lower calorific value (43.2 MJ/kg), and the density of light oil (0.82 g/cm^3), respectively.

4.3 CO_2 Emissions Calculation for Battery Electric Vehicles

On the other hand, the electric power consumption of battery electric vehicles P_{elc} can be expressed as follows:

$$P_{\mathrm{elc}} = \begin{cases} \dfrac{P_{\mathrm{drv}}}{\eta_{\mathrm{mot}}(N_{\mathrm{mot}}, T_{\mathrm{mot}})\eta_{\mathrm{mec}}} + P_{\mathrm{btl}} & (P_{\mathrm{drv}} \geq 0) \\ \eta_{\mathrm{mot}}(N_{\mathrm{mot}}, T_{\mathrm{mot}})\eta_{\mathrm{mec}}P_{\mathrm{drv}} + P_{\mathrm{btl}} & (\text{otherwise}) \end{cases}, \tag{17}$$

where $\eta_{\mathrm{mot}}(N_{\mathrm{mot}}, T_{\mathrm{mot}})$ is the motor efficiency and P_{btl} is the power loss at the battery. Here, by assuming that the battery internal resistance R_{bat} is constant (0.1Ω), P_{btl} can be expressed as follows:

$$P_{\mathrm{btl}} = R_{\mathrm{bat}}\left(\frac{P_{\mathrm{bat}}}{V_{\mathrm{bat}}}\right)^2, \tag{18}$$

where P_{bat} is the battery output power expressed as

$$P_{\mathrm{bat}}(P_{\mathrm{drv}}) = \begin{cases} \dfrac{P_{\mathrm{drv}}}{\eta_{\mathrm{mot}}\eta_{\mathrm{mec}}} & (P_{\mathrm{drv}} \geq 0) \\ \eta_{\mathrm{mot}}\eta_{\mathrm{mec}}P_{\mathrm{drv}} & (\text{otherwise}) \end{cases}, \tag{19}$$

and V_{bat} is the battery voltage. Since $\eta_{\mathrm{mot}}(N_{\mathrm{mot}}, T_{\mathrm{mot}})$ does not vary compared to engines used for conventional vehicles, η_{mot} can be treated as a constant

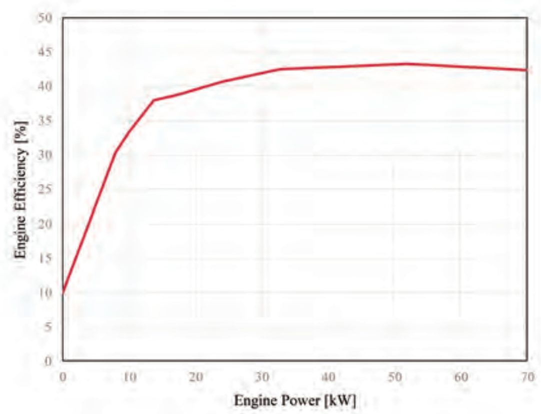


Fig. 3 Engine efficiency with respect to the engine output power

number (93%). Therefore, P_{elc} can be expressed as follows:

$$P_{\mathrm{elc}} = P_{\mathrm{bat}}(P_{\mathrm{drv}}) + P_{\mathrm{btl}}(P_{\mathrm{bat}}(P_{\mathrm{drv}})). \tag{20}$$

By using P_{elc}, the CO_2 emissions from battery electric vehicles can be calculated as follows:

$$C_{\mathrm{elc}} = \frac{k_{\mathrm{c}}}{1000 \times 3600}\int_0^T P_{\mathrm{elc}}\mathrm{d}t, \tag{21}$$

where k_{c} is the CO_2 emissions rate with respect to the generated electric energy at power plants (440 g/kWh).

5. Numerical Experiment

5.1 Route Profile

In this research, we consider the problem where all the vehicles depart from the common starting station to three stations situated in Aichi, Japan shown in Fig. 4. Available routes and their distance are listed in Table 4. "-" in the list means that the route is not available. Fig. 5 shows the average vehicle speed for each route. Since vehicles use a highway to get to the third station, their average vehicle speed is higher than others. Other than the highway, vehicles drive on urban roads with traffic lights, which decrease the average vehicle speed. The average CO_2 emissions and their distribution of conventional vehicles for each route are shown in Fig. 6. On the other hand, the average CO_2 emissions and their distribution of

Table 4 Distance from a start point to an end point (#0: starting station, #1 - #3: each station)

		End Point			
		#0	#1	#2	#3
Start Point	#0	-	23 km	30 km	83 km
	#1	-	-	7 km	66 km
	#2	-	-	-	58 km
	#3	-	-	-	-

battery electric vehicles for each route are shown in Fig. 7.

Vehicle speed profiles are calculated from the average vehicle speed for the given road segments. In addition to the average vehicle speed information, the information of slope and curvature is also derived from Google Maps Platform [6].

The specifications of the three vehicles considered in this research are as shown in Table 5. It is assumed that two vehicles of each vehicle type are available.

For CSP optimization, OR-Tools [7] by Google is used.

5.2 Simulation Result

As trials, we have conducted two case studies. The number of customers going to each station is shown in Table 6. In each case, the following four conditions are considered:

- Conventional operations management (direct): the average CO_2 emissions of feasible solution results (available vehicles: two small vehicles and one medium vehicle)
- eCosMos (direct): the optimal solution in the case of non-stop to the terminal station
- eCosMos (indirect): the optimal solution when allowing vehicles to go to the terminal station via other stations
- Conventional operations management (indirect): the case when minimizing the sum of every vehicle driving route

Table 5 Vehicle specifications of the vehicles considered in this study

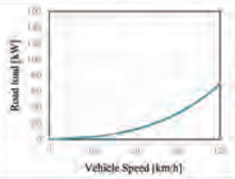
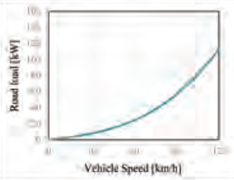
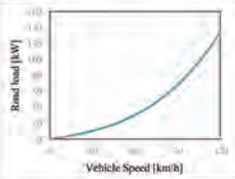
	Small	Medium	Large
Max. number of passengers [persons]	21	35	48
Vehicle weight [kg]	3,670	11,212	15,520
Max. engine/motor output power [kW]	110	162	265
Road load [kW]			
The number of available vehicles	2	2	2

Fig. 4 Map illustrating the starting station and other stations

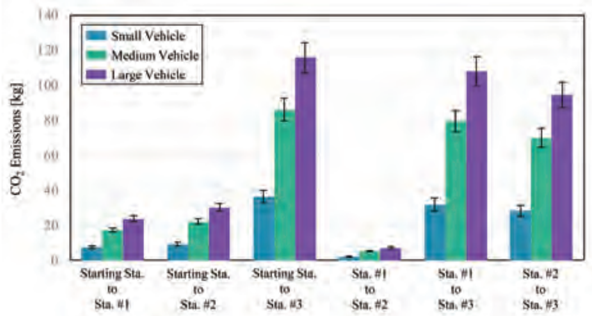


Fig. 6 CO_2 emissions from conventional vehicles for each route

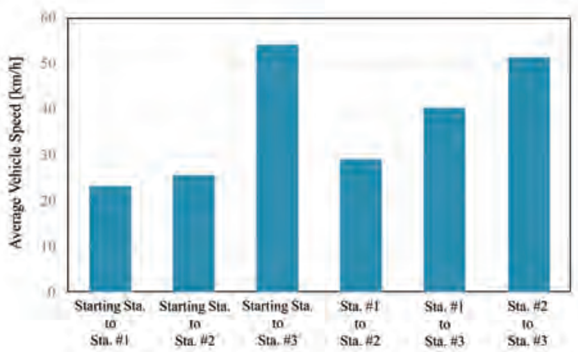


Fig. 5 Average vehicle speed for each route (Sta.: Station)

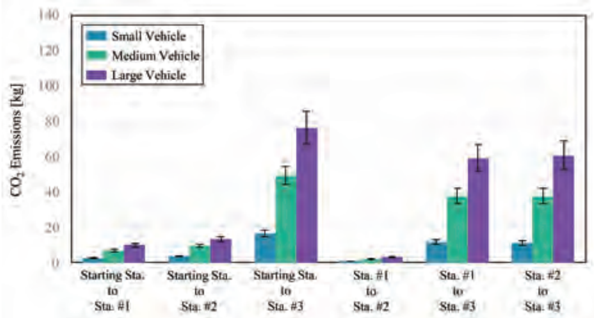


Fig. 7 CO_2 emissions from battery electric vehicles for each route

Conventional operations management systems find the optimal routes and user allocation without considering powertrain characteristics. However, intuitively, it is wasteful to carry users in an unnecessarily large vehicle. Therefore, “conventional operations management (direct)” is defined as the average CO_2 emissions of feasible solution results with as small vehicles as possible, namely two small vehicles and one medium vehicle.

5.2.1 Case 1

At first, let us assume that all the vehicles are conventional vehicles driven by diesel engines whose specifications are shown in 4.2. Fig. 8 shows the result of CO_2 emissions. By comparing “conventional operations management (direct)” and “eCosMos (direct)”, it can be seen that, even in the case that vehicles go to the terminal station directly, CO_2 emissions can be reduced with eCosMos. Besides, in the case of going through several stations, namely eCosMos (indirect), additional CO_2 emissions reduction can be realized. On the other hand, by comparing “eCosMos (indirect)” and “conventional operations management (indirect)”, it can be seen that the conventional rideshare operations management rather increases CO_2 emissions. In this case, “eCosMos (indirect)” can reduce fuel consumption by 11.5 L compared to “conventional operations management (direct)”. The user allocation results of “eCosMos (direct)” and “eCosMos (indirect)” are shown in Table 7 and Table 8, respectively. S*, M*, and L* are small vehicles, medium vehicles, and large vehicles, respectively. In the case of “conventional operations management (indirect)”, all users are delivered by one medium vehicle.

Next, let us assume that medium vehicles and large vehicles are replaced by battery electric vehicles while small vehicles remain to be conventional vehicles. Fig. 9 shows the result of CO_2 emissions. As in the case that all the vehicles are conventional vehicles shown in Fig. 8 CO_2 emissions are reduced with eCosMos. On the other hand, “conventional

Table 6 The number of customers going to each station

	Case 1	Case 2
Station #1	10	20
Station #2	6	10
Station #3	10	18

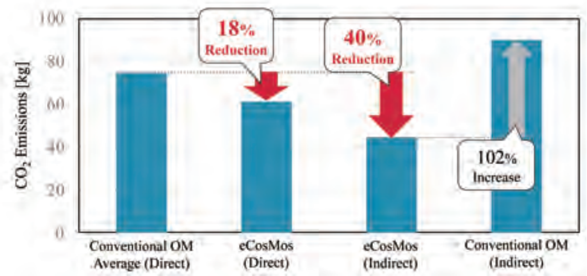


Fig. 8 CO_2 emissions at case 1 when all the vehicles are conventional vehicles (OM: operations management)

Table 7 User allocation result of “eCosMos (direct)” at case 1 (all the vehicles are conventional vehicles)

	S1	S2	M1	M2	L1	L2
Station #1			10			
Station #2	6					
Station #3		10				

Table 8 User allocation result of “eCosMos (indirect)” at case 1 (all the vehicles are conventional vehicles)

	S1	S2	M1	M2	L1	L2
Station #1	10					
Station #2		6				
Station #3		10				

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operations management (indirect)" increases CO_2 emissions again. The user allocation results of "eCosMos (direct)" and "eCosMos (indirect)" are shown in Table 9 and Table 10, respectively. In this case, since the medium battery electric vehicle can go to station #1 with lower CO_2 emissions than small conventional vehicles, the medium vehicle is used to go to station #1.

Table 9 User allocation result of "eCosMos (direct)" at case 1 (medium and large vehicles are battery electric vehicles)

	S1	S2	M1	M2	L1	L2
Station #1			10			
Station #2	6					
Station #3		10				

Table 10 User allocation result of "eCosMos (indirect)" at case 1 (medium and large vehicles are battery electric vehicles)

	S1	S2	M1	M2	L1	L2
Station #1			10			
Station #2		6				
Station #3		10				

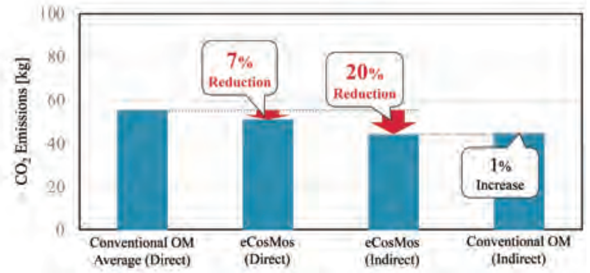

Fig. 9 CO_2 emissions at case 1 when medium and large vehicles are battery electric vehicles (OM: operations management)

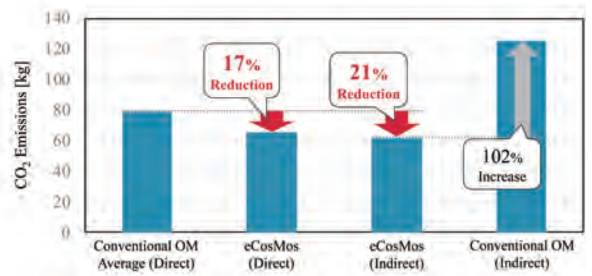

Fig. 10 CO_2 emissions at case 2 when all the vehicles are conventional vehicles (OM: operations management)

5.2.2 Case 2

As in the case of 5.2.1, at first, let us assume that all the vehicles are conventional vehicles driven by diesel engines. Fig. 10 shows the result of CO_2 emissions. As in the case of 5.2.1, eCosMos can reduce CO_2 emissions, while the conventional rideshare operations management rather increases it. In this case, "eCosMos (indirect)" can reduce fuel consumption by 6.4 L compared to "conventional operations management (direct)". The user allocation results of "eCosMos (direct)" and "eCosMos (indirect)" are shown in Table 11 and Table 12, respectively. In the case of "conventional operations management (indirect)", all users are delivered by one large vehicle.

Next, let us assume that medium vehicles and large vehicles are replaced by battery electric vehicles while small vehicles remain to be conventional vehicles. Fig. 11 shows the result of CO_2 emissions. As in the case that all the vehicles are conventional vehicles, CO_2 emissions are reduced with eCosMos. The user allocation results of "eCosMos (direct)" and "eCosMos (indirect)" are shown in Table 13 and Table 14, respectively. While Table 8 is different from Table 10, where a medium battery electric vehicle is used to reduce CO_2 emissions, Table 12 is the same as Table 14. From these results, it can be seen that considering powertrain characteristics is important to realize ecological operations management to reduce CO_2 emissions.

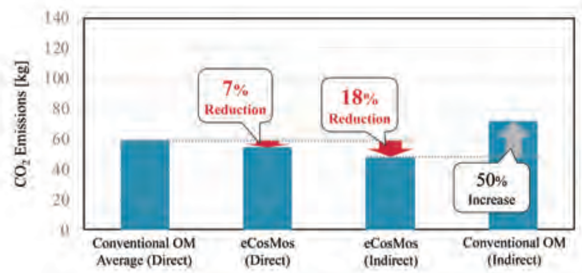

Fig. 11 CO_2 emissions at case 2 when medium and large vehicles are battery electric vehicles (OM: operations management)

Table 11 User allocation result of "eCosMos (direct)" at case 2 (all the vehicles are conventional vehicles)

	S1	S2	M1	M2	L1	L2
Station #1			20			
Station #2		10				
Station #3	18					

Table 12 User allocation result of "eCosMos (indirect)" at case 2 (all the vehicles are conventional vehicles)

	S1	S2	M1	M2	L1	L2
Station #1			20			
Station #2			10			
Station #3	18					

Table 13 User allocation result of "eCosMos (direct)" at case 2 (medium and large vehicles are battery electric vehicles)

	S1	S2	M1	M2	L1	L2
Station #1			20			
Station #2		10				
Station #3	18					

Table 14 User allocation result of "eCosMos (indirect)" at case 2 (medium and large vehicles are battery electric vehicles)

	S1	S2	M1	M2	L1	L2
Station #1			20			
Station #2			10			
Station #3	18					

6. Conclusion

In this work, a novel rideshare operations management technology was developed to reduce the total CO_2 emissions. To realize it, an optimization problem was formulated to find the optimal routes and user allocation by incorporating the problem into a CSP for minimizing the total amount of CO_2 emissions from multiple vehicles. Besides, simulation models including each powertrain characteristic of conventional vehicles and battery electric vehicles for our rideshare operations management were introduced to calculate the CO_2 emissions from each vehicle for each driving route accurately. The effect of this technology was validated with simulation, showing more than 40% CO_2 emissions reductions in some cases compared to conventional rideshare operations management. The validation indicated that CO_2 emissions can be reduced further by considering powertrain characteristics.

Future issues are as follows:

- Developing necessary functions for real-world use such as adaptation for large-scale operation or round trip.
- Improving the accuracy of CO_2 emissions calculation by estimating powertrain system parameters and predicting vehicle speed profiles.
- Evaluating CO_2 emissions reduction in the actual operation of passenger and freight transport.

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特集