A REVIEW ON REAL VEHICLE USAGE MODELLING OF DRIVERLESS MULTIPURPOSE VEHICLES IN VEHICLE ROUTING PROBLEMS

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ABSTRACT

Real vehicle usage rarely matches the predictions made during early phases of vehicle development and sales processes at commercial road vehicle manufacturers. The automotive industry needs multidisciplinary vehicle design methods to predict real-world vehicle operations by considering the vehicle level and the transport system level simultaneously, in a more holistic approach. The aim of this study was to analyse how realistic vehicle usage of driverless multipurpose vehicles can be modelled in Vehicle Routing Problems (VRPs) by conducting a systematic literature review. We found that real vehicle usage modelling of driverless multipurpose vehicles in VRPs mainly depended on the following elements: VRP variant, energy consumption model, energy consumption rate class, number of vehicle-specific design variables and transport system-level factors. Furthermore, we identified in the literature five classes of energy consumption rate edge behaviour in VRPs. These findings can support decision-making in the modelling process to select the most suitable combination of elements, and their level of detail for the overall modelling aim and purpose.

Keywords: Design engineering, Product modelling / models, Early design phases, Vehicle routing problem, Energy consumption

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1 INTRODUCTION

Predictions made during early phases of vehicle development and sales processes rarely match real vehicle usage. Real-world vehicle operations are complex to predict because they involve many factors at multiple scales, such as on the vehicle level and the transport system level that interact in dynamic ways. In the initial phases of vehicle development, there is large design freedom but limited product knowledge, whereas in the end-phases of development the opposite is true (O'Reilly et al., 2016). During the sales processes at commercial road vehicle manufacturers, the vehicle configuration selection is typically optimised once according to the customer's overall transport application (Romano et al., 2022) and a few frequent transport operations. Furthermore, the generic classification system used gives only a rough understanding of the customer's real operation and needs (Romano et al., 2022), and it is simultaneously difficult for the customers to foresee their operational costs (Ghandriz et al., 2021), and their changing needs. Thus, a large number of vehicles are not optimal for their real use.

One of the most important factors in achieving efficient vehicles and low emission levels (e.g. CO_2 and particles) is proper vehicle specification and the capability to reconfigure the specification multiple times throughout the life of the vehicle. In the near future, this may be possible. The technological trends of electrification, automation and connectivity in combination with sustainable development and the current urban traffic issues are driving the transformation of the mobility sector, by enabling disruptive technologies and demanding new transport and vehicle solutions.

Driverless multipurpose vehicles (DMVs) are an emerging vehicle type for city transport that is being explored worldwide (Ulrich et al., 2019). DMVs are disruptive in several ways. Firstly, they can change their transport application depending on the current demand in the city by transporting either people, goods, waste, or be used for other applications. Secondly, they can be built in such a way that every relevant subsystem can be quickly replaced to modify the vehicle specification for the customer's current transport operations due to their modular and electric system architecture. According to Hatzenbühler (2022), modular vehicles in urban environments can reduce fleet size, empty vehicle-kilometres driven and travel times resulting in a more efficient use of resources.

To cope with the transformation of the mobility sector, the automotive industry needs multidisciplinary vehicle design methods to predict real vehicle usage during early phases of vehicle development and sales processes. These design methods need to consider the vehicle level and the transport system level simultaneously, in a more holistic approach. One of the leading methods to enable this in a single problem formulation is Vehicle Routing Problems (VRPs).

VRPs are combinatorial optimisation problems that have been under intensive research over sixty years (Vidal et al., 2020). They have both theoretical interests for researchers and practical applications for industry. Freight transporters using commercial optimisation packages with vehicle routing algorithms gain advantages in operational planning, because they can determine the routes their vehicle fleets must drive to minimise costs (Vidal et al., 2020). VRPs are no longer used only for operational decisions, but also for strategic and tactical decisions, such as fleet sizing, location of charging stations and vehicle customisation (Vidal et al., 2020; Ghandriz et al., 2021).

In this study, we conduct a systematic literature review to answer the main research question: *how can real vehicle usage of driverless multipurpose vehicles be modelled in VRPs?* To model real vehicle usage with VRPs, it is essential to describe real energy consumption. This is challenging because VRPs are based on a graph representation with discrete sets of connected nodes and edges. As a result, the approach to compute the energy consumption rate (ECR) along individual edges and between edges becomes important. To the best of our knowledge, no review study in the VRP literature has comprehensively surveyed how ECR is estimated along and between edges. In this review, we extend the ECR edge behaviour classification by Xiao et al. (2021). Moreover, the literature lacks reviews that analyses how to model DMVs in VRPs. Thus, the main contributions of this review paper are twofold: (i) to analyse the ECR edge behaviour in VRPs, (ii) to evaluate how to model real vehicle usage of DMVs in VRPs.

2 METHODOLOGY

We conducted a systematic literature review in line with the approach outlined by Jesson et al. (2011). Systematic literature reviews provide a standardised, transparent and structured approach for selecting, synthesising and evaluating literature. This method is particularly useful for reviews that aim to answer specific research questions with a narrow focus and that seek to minimise bias and error (Jesson et al., 2011). Our systematic literature review process was divided into eight steps as illustrated in Figure 1. We started the process by mapping the field through a scoping review, which includes preparing a review plan, formulating research questions, developing search strings based on common keywords in the literature, and selecting potentially relevant work to be included in the review. In the first identification step, we searched the databases of Scopus, Web of Science and Transport Research International Documentation (TRID) to identify relevant studies. These databases were selected because they are well-established and cover important work published in our area of study. The inclusion and exclusion criteria evaluated relevant studies based on their titles, abstracts and keywords. We included studies that addressed VRPs for road transport with more detailed vehicle-level properties, such as energy/fuel consumption models, emission models, vehicle loading and vehicle customisation processes. We excluded studies that did not focus on vehicle-level properties in VRPs and studies analysing other types of vehicles and topics, such as drones, inventory management and wireless technology. Only studies in English published in year 2000 and later were considered. Studies published in peer-reviewed scientific journals and conferences were prioritised to ensure quality control. However, the literature search also included a small portion of grey literature, such as doctoral dissertations, books and conference papers to broaden the search. The search string was structured to find studies that focus on energy/fuel consumption and emission models in VRPs, because such studies typically included vehicle-specific properties that were relevant for real vehicle usage modelling of DMVs. We used the following search string in Scopus and Web of Science: *(TITLE-ABS-KEY("vehicle routing" OR "green logistics") AND TITLE-ABS-KEY("energy consumption" OR "fuel consumption" OR "emission model*") AND NOT TITLE-ABS-KEY("drone*" OR "aerial" OR "ship*" OR "inventory" OR "waste" OR "airport" OR "sensor*" OR "wireless"))*. In TRID, the following search string was used: *"vehicle routing" AND ("energy" OR "fuel" OR "emission*")*.

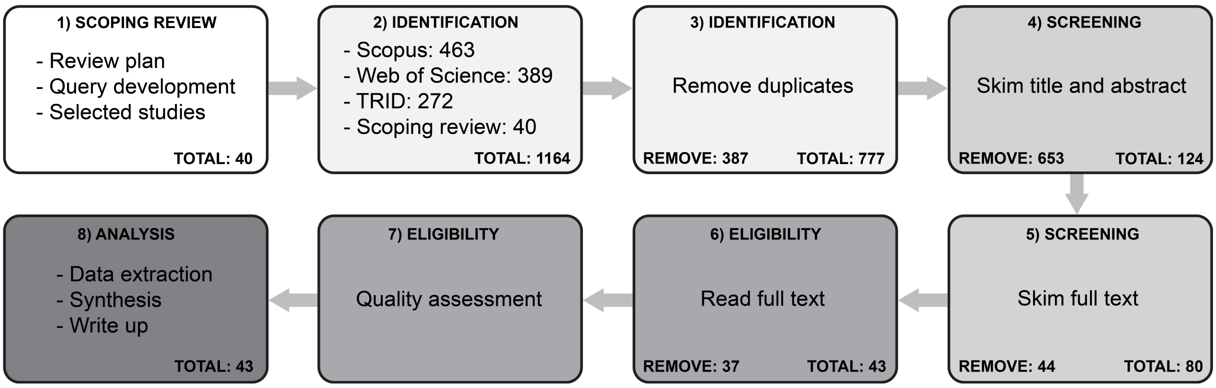

Figure 1. Flow diagram of the systematic literature review process, where REMOVE is the number of excluded studies in each step, and TOTAL is the remaining studies after removal

The initial search in the three databases combined with the selected work from the scoping review resulted in a total of 1164 studies. After removing 387 duplicates, 777 studies entered the screening process. In this process, we skimmed the studies in two steps while implementing the inclusion and exclusion criteria; as a result, 80 studies advanced to the first eligibility step. These studies were read in full text and data from each paper were mapped into a matrix with relevant categories, such as VRP variant, energy consumption model and ECR class. From the papers read in full text, we removed 37 studies because they did either mainly focus on solution algorithms or lacked vehicle-specific properties in the problem formulation. In the last eligibility step, non-peer reviewed studies were controlled by forward and backward citation analysis to ensure quality control. Lastly, the final 43 studies were included in the analysis step with data extraction, synthesis and writing process, from which seven studies originated from the initial scoping review process.

3 RESULTS

In the following section, we aim to shed light on essential elements to consider in the modelling process of real vehicle usage of DMVs in VRPs.

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3.1 Vehicle routing problem variants for modelling driverless multipurpose vehicles

We found that there existed several variants of VRPs that included detailed vehicle-specific properties and were relevant for modelling real usage of DMVs. The most relevant VRP variant was the Electric Vehicle Routing Problem (EVRP) since DMVs are envisioned to primarily be built on a battery electric vehicle architecture platform. The EVRP is similar to the classical VRP formulation but includes properties related to electric vehicles and their performance, such as range, battery capacity, recharging strategy and charging locations (Xiao et al., 2021).

Other relevant variants were the Green Vehicle Routing Problem (GVRP) (Macrina et al., 2019b), the Pollution Routing Problem (PRP) (Bektaş and Laporte, 2011) and variants that included hybrid vehicles, such as plugin-hybrid and fuel-cell electric vehicles (Bahrami et al., 2020). Although many of these variants were not directly simulating battery electric vehicles, they tended to include energy/fuel consumption models and environmental aspects in the problem formulation that might be useful in an EVRP. Hatzenbühler (2022) suggests that the variants: Truck and Trailer Routing Problem (TTRP), Swap Body Vehicle Routing Problem (SB-VRP) and Dial-a-Ride Problem (DARP) may be useful in the modelling of modular vehicles that allow for sequential or simultaneous transport of goods and passengers.

The last variants that might be beneficial in the modelling of DMVs were the vehicle customisation-routing problem (Ghandriz et al., 2021), the packing-routing problem (Krebs and Ehmke, 2021) and location-routing problem (Dukkanci et al., 2019; Hulagu and Celikoglu, 2022). In these problems, instead of making two decisions independently which can lead to suboptimal solutions, the vehicle customisation, the loading and stability of the vehicle or the location of charging stations are integrated into the routing formulation.

3.2 Factors affecting real vehicle usage and energy consumption

Real vehicle usage may be defined as the real-world behaviour of a vehicle during its use. Many different factors from various scales and categories affect vehicle operations. A vehicle's energy consumption is closely related to its usage since most of the factors affecting energy consumption also affect real vehicle usage. As a result, we used these terms almost interchangeably. The main difference is that energy supply infrastructure, such as charging stations, does not directly affect energy consumption of individual vehicles. However, it is often necessary to include energy supply infrastructure to model real vehicle usage of electric vehicles.

Several studies categorised factors that affect fuel and energy consumption into various combinations of the following aspects: driver, vehicle, road, traffic, environment, weather and operations (Demir et al., 2014; Romano et al., 2022). We organised the factors that affect real vehicle usage of electric vehicles into three main categories: driver related, vehicle related and transport system-level related as shown in Figure 2. The transport system level was divided into five subcategories: mission, road, traffic, weather and supply. The supply category referred mainly to aspects related to energy and service supply, such as charging stations and service depots for DMVs. The vehicle category was divided into the subcategories of properties and performance. We did not focus on the driver-related aspects because DMVs

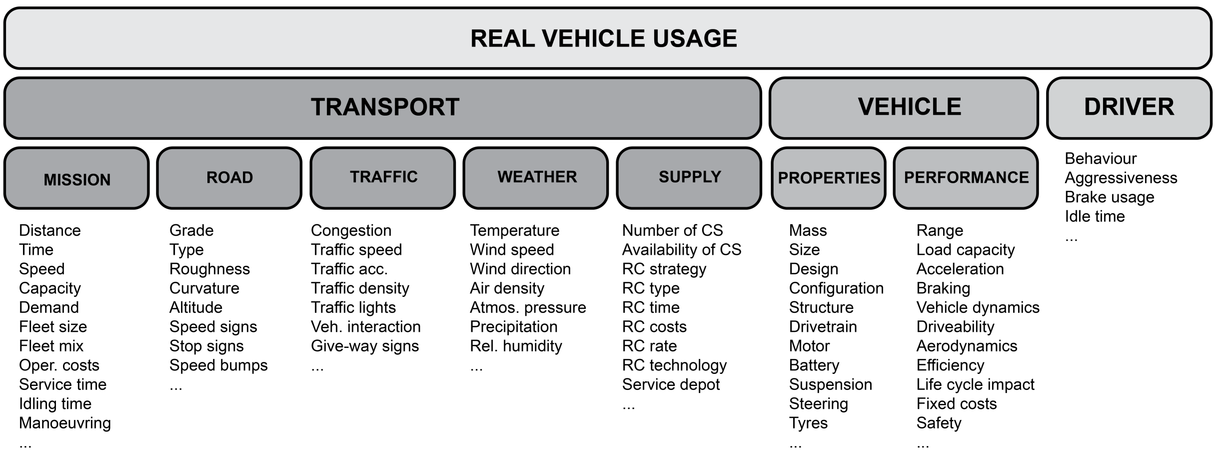

Figure 2. Factors affecting real vehicle usage, where charging stations (CS), recharging (RC)

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are envisioned to be self-driven at level-5 autonomy or similar. It is well established in the VRP literature that energy consumption of electric vehicles mainly depends on the factors: total vehicle mass (vehicle mass, payload mass), speed, acceleration/braking, aerodynamics (drag coefficient, vehicle frontal area, air density), efficiencies (e.g. driveline, motor), road properties (rolling coefficient, road grade) (Demir et al., 2014; Goeke and Schneider, 2015; Basso et al., 2019). Additional influential factors are: rotational inertia (Abousleiman et al., 2017), ambient temperature (Rastani et al., 2019), vehicle auxiliary power (e.g. air conditioning, heating system) (Basso et al., 2019), congestion (Figliozzi, 2010; Franceschetti et al., 2013), regenerative braking (Abousleiman et al., 2017), battery characteristics (e.g. battery depreciation) (Zang et al., 2022).

3.3 Energy consumption models

A large portion of the VRP literature included emission, fuel and energy consumption models. Even though fuel consumption and emission models were mostly related to internal combustion engine powered vehicles, parts of their formulations could often be used in energy consumption estimates. In the literature, the models were frequently organised into the categories of factor, macroscopic, mesoscopic and microscopic models (Demir et al., 2014; Behnke and Kirschstein, 2017; Basso et al., 2019).
Factor models are the simplest models that only use conversion factors (e.g. kWh/km), which are multiplied with the amount of activity (Basso et al., 2019). These models are closely related to macroscopic approaches. Macroscopic models focus on the scale of networks or fleets and use aggregate network parameters, such as average speed to estimate emissions and other parameters (Demir et al., 2014). Microscopic models also called instantaneous or modal models in the literature are more complex. They estimate the instantaneous (i.e. second-by-second) energy/fuel consumption and emission rates at a more detailed level (Demir et al., 2014). A common microscopic model used in VRPs is called Comprehensive Modal Emission Model (CMEM) (Demir et al., 2011). In contrast to macroscopic and microscopic models, we found that mesoscopic models were less clearly defined in the literature, but they are expected to lie between the two other model approaches.

3.4 Classification of energy consumption rate edge behaviour

VRPs are described mathematically by graphs consisting of connected nodes and edges. Consequently, the way properties are specified along and between edges becomes crucial. The ECR edge behaviour is a key property to consider in order to model real-world vehicle operations of DMVs in VRPs. In the review by Xiao et al. (2021), they divide the ECR edge behaviour into three classes. In this paper we extended their classification by analysing a larger body of literature and divided the ECR edge behaviour into five classes as presented in Figure 3. Our ECR classification divided studies into classes based on the approach they used to determine the ECR edge values. Note that for all classes the final ECR value is constant along an individual edge during the vehicle routing solution process.

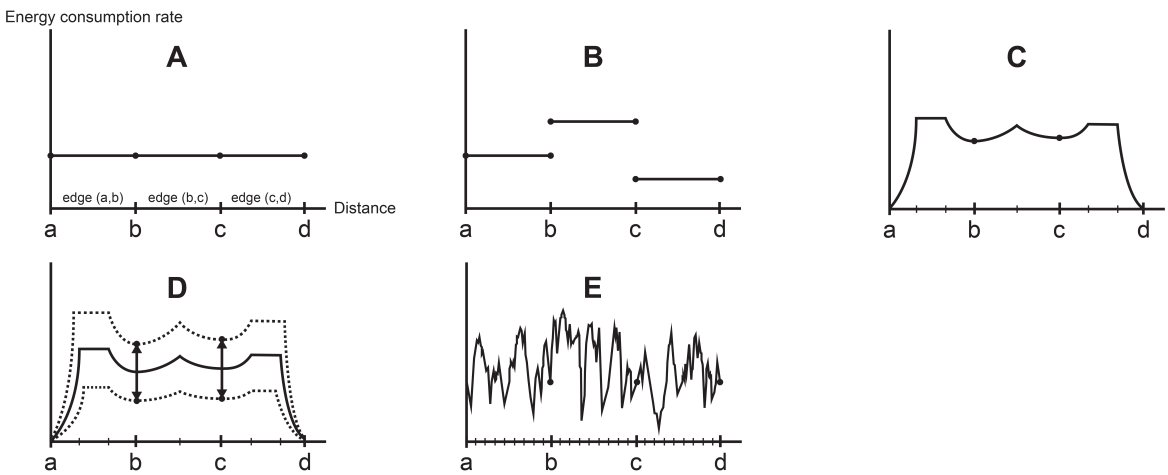

Figure 3. Classification of energy consumption rate edge behaviour

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In class A, the ECR is assumed to be a fixed value for all edges in the graph. This is identical to say that the energy consumption is proportional only to the distance travelled.
In class B, the ECR is computed for each edge depending on the changing design variables during the vehicle routing solution process, resulting in different ECR values for all edges in the graph. Additionally, in this class, problems that involve more complexity such as time-dependent problems (Franceschetti et al., 2013) and speed optimisation (Demir et al., 2012) may be included, as long as they do not compute several ECR values along an edge.
In class C, the ECR is estimated based on an approach that divides each individual edge into a few segments, often two to five segments with a corresponding simple driving cycle. This approach allows the ECR to vary along each edge in a linear/non-linear manner. It is common that this approach occurs as a pre-processing step before the actual vehicle routing solution process. Additionally, the ECR edge values are also influenced by the changing design variables during the solution process as in class B.
In class D, the ECR is determined similarly to either class B or C but is extended to be stochastic. Several of the factors influencing energy consumption are uncertain. This class therefore includes probabilistic energy consumption estimations and may involve machine learning techniques.
In class E, the ECR is computed similarly to class C; however, in this case each edge is divided into small segments. As a pre-processing step, the ECR is determined for every second for each edge based on the corresponding real-world driving cycle. This approach shares similarities with longitudinal vehicle dynamics models that use driving cycles to estimate energy consumption and vehicle performance.
Tables 1 and 2 present together the summary of the ECR classes, VRP variants, energy consumption models, vehicle-specific design variables and transport system-level factors used in the reviewed literature. The distribution of ECR classes ranged as follows: B-52%, A-21%, C-14%, D-10%, E-3.0%. The ECR class B was frequently implemented in combination with a microscopic energy consumption model. Almost 70% of the EVRP studies used a microscopic model. Approximately half of the studies considered the design variables payload mass (L) and speed (S) in their problem formulations. In addition, nearly all EVRP variants included road and supply transport system-level factors, while only one EVRP study took weather effects into account.

Table 1. Review of the literature with focus on the variants: GVRP, PRP, ELRP and GLRP

Reference	Class	Variant	Model	Variable
Yu et al. 2021	B	GVRP	Micro	L, G
Macrina et al. 2019b	C	GVRP	Micro	L, S, A, E, VT
Macrina et al. 2019a	A	GVRP	Factor	-
Kancharla and Ramadurai 2018b	E	GVRP	Micro	L
Erdoğan and Miller-Hooks 2012	A	GVRP	Factor	-
Figliozzi 2010	B	GVRP	Macro	S
Kara et al. 2007	B	GVRP	Factor	L
Koç et al. 2014	B	PRP	Micro	L, S, VT
Franceschetti et al. 2013	B	PRP	Micro	L, S*
Demir et al. 2012	B	PRP	Micro	L, S, G
Bektaş and Laporte 2011	B	PRP	Micro	L, S, G
Hulagu and Celikoglu 2022	C	ELRP	Micro	L, S, G
Dukkanci et al. 2019	B	GLRP	Micro	L, S

ECR class (Class), VRP variant (Variant), Energy consumption model (Model), Vehicle-specific design variables (Variable): Payload mass (L), Speed (S), Acceleration (A), Grade (G), Efficiency (E), Vehicle type (VT), Time-dependent speed (S*), Stochastic variable (SV).

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Table 2. Review of the literature with focus on EVRPs including transport system-level factors

Reference	RO	TR	WE	SU	Class	Variant	Model	Variable
Basso et al. 2022	•			•	D	EVRP	Micro	L, S, A, G, E
Zang et al. 2022				•	A	EVRP	Factor	-
Ding et al. 2022	•			•	C	EVRP	Micro	L
Basso et al. 2021	•	•		•	D	EVRP	Micro	L, S, A, G, E
Rastani and Çatay 2021	•			•	B	EVRP	Micro	L
Rastani et al. 2019			•	•	A	EVRP	Factor	-
Pelletier et al. 2019	•				D	EVRP	Micro	L,S,A,G,E,SV
Basso et al. 2019	•	•		•	C	EVRP	Micro	L, S, A, G, E
Kopfer and Vornhusen 2019				•	B	EVRP	Macro	L, VT
Zhang et al. 2018	•			•	B	EVRP	Micro	L, S
Kancharla and Ramadurai 2018a	•			•	B	EVRP	Micro	L
Montoya et al. 2017				•	A	EVRP	Factor	-
Murakami 2017	•	•			B	EVRP	Micro	L, S, A, G, E
Basso et al. 2016	•	•		•	B	EVRP	Micro	L, S*, G, E
Goeke and Schneider 2015	•			•	B	EVRP	Micro	L, S, G
Conrad and Figliozzi 2011				•	A	EVRP	Factor	-

Transport system-level factors: Road category (RO), Traffic category (TR), Weather category (WE), Supply category (SU). All EVRP studies included the Mission category.

4 DISCUSSION AND CONCLUSION

The purpose of this review paper was to analyse how real vehicle usage of DMVs can be modelled in VRPs. We identified in the literature five classes of ECR edge behaviour along and between individual edges, as shown in Figure 3. Additionally, we found that real vehicle usage modelling of DMVs in VRPs mainly depended on the following elements: VRP variant, energy consumption model, ECR class, number of vehicle-specific design variables and transport system-level factors.

The EVRP is the most suitable VRP variant to describe DMVs since it includes vehicle and transport level properties that characterise real usage of DMVs, such as vehicle battery capacity and charging infrastructure. However, using an EVRP will not automatically describe modular vehicles because they require additional details in the VRP. Moreover, there exist several modularity concepts of DMVs; thus, the EVRP must be customised to describe a specific modularity concept. For example, Hatzenbühler (2022) illustrates this customisation process by combining parts of the variants TTRP and SB-VRP to describe modular vehicles that consist of a platform module with an exchangeable top module.

In real life, the energy consumption for a moving vehicle changes on a second-by-second basis. As a result, microscopic models, so-called second-by-second models are the most appropriate energy consumption model to describe real usage of DMVs; additionally, they incorporate more vehicle-specific properties than factor and macroscopic models. However, as pointed out by Behnke and Kirschstein (2017), most of the microscopic models used in VRPs are actually simplified microscopic models (i.e. mesoscopic models) since integrating instantaneous information directly into combinatorial optimisation problems tends to be too complex.

In the literature, there are no defined number of vehicle-specific design variables that must be included in the problem to make realistic energy estimations. Nevertheless, some authors argue that including vehicle payload mass, speed, acceleration and road grade are essential for a realistic energy consumption model (Kancharla and Ramadurai, 2018b; Macrina et al., 2019b). Less than one fifth of the EVRP studies considered these design variables together in their formulations as shown in Table 2.

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Selecting the right class of ECR edge behaviour for a specific modelling purpose is essential because it affects model complexity and accuracy. In the studied literature, it is most common to use ECR classes A and B, as presented in Tables 1 and 2. In recent years, more elaborate classes have been developed (C, D, E). These classes provide in general more realistic energy estimations than the classes (A, B) since they use multiple values of ECR along individual edges to approximate the energy consumption. Hulagu and Celikoglu (2022) underline that the complexity to estimate realistic energy consumption stems from the fact that various factors, such as traffic, road and environment must be evaluated together. In other words, to model real vehicle usage it is important to integrate many of the relevant transport system-level factors into the model simultaneously. Nearly all EVRP studies in Table 2, include mission, road and supply transport system-level factors. At most, the studies by Basso et al. (2016, 2019, 2021) include four out of five factors in the problem. On the other hand, real-world vehicle usage modelling does not only depend on the number of transport system-level factors included but also on how they are implemented into the problem. In general, good models tend to balance simplicity, validity and robustness, which needs to be considered when selecting factors and other modelling aspects.

Finally, we give an example on how to think more holistically about the findings from this study. If the purpose is to make the most accurate energy consumption predictions of DMVs with VRPs, then we recommend to select ECR class (C, D, E) along with a microscopic model with multiple design variables (L, S, A, G, E) and to include several transport system-level categories, similar to the approaches in the studies Pelletier et al. (2019); Basso et al. (2021). If the purpose is to integrate the vehicle-specification process and routing, similar to the vehicle customisation-routing problem by Ghandriz et al. (2021), then we recommend to use a lower ECR class (A, B, C) that can give a sufficient energy consumption accuracy, coupled with a microscopic model that include two design variables (L, S) and two or three transport system-level factors. Integrated problems tend to be more complex than classical VRPs since they consider two domains in one formulation, hence a lower ECR class, fewer design variables and transport system-level factors may be feasible.

The findings from this study can support decision-making in the modelling process to select the most suitable combination of elements, and their level of detail for the overall modelling aim and purpose. The main limitation is that the systematic literature review was performed by one person, despite the recommended procedure to be more than one to reduce bias and error. A further study may develop a vehicle customisation-routing problem based on an EVRP variant tailored for DMVs characteristics, so that the next generation of vehicles may become more properly specified for their real use.

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