A Load-Dependent Heterogeneous Vehicle Routing Approach for Hybrid Electric Cargo Bicycles Considering Rider Fatigue

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1 INTRODUCTION

In recent years, cycling has gained recognition as a sustainable option for last-mile delivery in logistics. As concerns about the environmental effects of car traffic, health, and urban livability grow, numerous cities are demonstrating a growing interest in encouraging the use of electric cargo bicycles (known as e-bike or e-cargo bike) for last-mile deliveries (Fontaine *et al.*, 2021, Fraselle *et al.*, 2021). These bicycles come with a small electric motor that assists the cyclist. This pedal-assist electric bicycle operates with two power sources. The first is electric propulsion, consisting of a battery and an electric motor, while the second is human power. The battery supplies power to the electric motor, enabling motion for the e-bike. The second power source originates from the rider's physical effort (Clancy, 2020).

Managing power sources is a critical aspect in the design of hybrid vehicles, particularly in the context of route planning for these vehicles, known as the vehicle routing problem (VRP) (Lee *et al.*, 2019). Some models are developed based on fixed energy consumption (Papaioannou *et al.*, 2023), while others consider load-dependent travel time with constant power of both the cyclist and the bike battery (Fontaine, 2022). Apart from the unique features of these bikes, such as available routes, load capacity, and battery capacity (Zheng *et al.*, 2023), cyclist physical fatigue should also be considered (Ebnealipour *et al.*, 2023), a factor often overlooked in previous studies.

In this study, we introduce a novel load-dependent energy consumption model that, for the first time in the literature, simultaneously considers both the motor and the cyclist's contributions to energy usage. This approach provides a more holistic understanding of the energy dynamics involved in hybrid cargo bicycle systems. Additionally, we address the heterogeneous vehicle routing problem, which involves determining the optimal assignment of various types of cargo bikes and riders to specific routes. This consideration is crucial for efficient route planning and resource allocation, ensuring that the most suitable bike and rider combination is selected for each delivery route based on factors such as load capacity, battery life, and rider stamina. By integrating these elements into our model, we aim to enhance the sustainability and effectiveness of last-mile delivery operations.

2 METHODOLOGY

The energy consumption model consists of both the human and battery (motor) energy consumption expressed as:

$$P_{\text{pot}} + P_{\text{air}} + P_{\text{bear}} + P_{\text{roll}} = \eta_{DT} \left(P_h + P_m\right) \tag{1}$$

P_{pot} represents the change in energy that occurs due to variations in elevation while riding, P_{air} represents the aerodynamic drag losses, P_{air} represents the losses due to friction in the wheel bearings, P_{roll} represents the losses due to the rolling resistance of the wheels, and P_h and P_m represent the human and motor power contributions respectively. η_{DT} represents the efficiency losses that occur while transmitting power from the motor/pedals to the rear wheel of the e-bike, referred to as the drive train efficiency, and represents an additional loss mechanism.

Human energy is calculated as:

$$P_h = \frac{\text{METs} \times 3.5 \times w \times 1.162}{200} \tag{2}$$

where w is the body mass of the rider. METs is metabolic equivalents of task (1 MET=3.5 ml/min/kg). To convert energy calculated in Kcal to watt-hour we use a conversion rate of 1.162. The study also assumes a METs value of 4.9. (Martnes & Bere, 2023).

The energy consumption for the motor is calculated as:

$$E_m = \frac{t}{\eta_m} \left(\frac{P_{\text{pot}} + P_{\text{air}} + P_{\text{bear}} + P_{\text{roll}}}{\eta_{DT}} - \frac{\text{METs} \times 3.5 \times w \times 1.162 \times 60}{200} \right) \tag{3}$$

where t is the total activity time (in hour), η_m is the electrical system efficiency assumed to be equal to 0.73. The total activity time is in hours, so a conversion from Kcal/min to Kcal/hour is needed.

Energy consumption for human can be computed as:

$$E_h = \frac{t}{\eta_h} \left(\frac{\text{METs} \times 3.5 \times w \times 1.162 \times 60}{200} \right) \tag{4}$$

where η_h is the human energy conversion efficiency assumed to be equal to 0.2.

The total energy consumption is then expressed as:

$$E_{Total} = E_m + E_h \tag{5}$$

The proposed routing model ensures that each rider returns to the depot for recovery before meeting the physical fatigue level. The experimental studies in the literature indicate that within a specific range of age and weight, the calories burned are approximately 180 kcal because the rider reaches the threshold of fatigue. The basis for determining someone's tiredness is total calorie burnt, and the calorie burning rate is disregarded. For the fatigue level estimation based on the age and mass of the rider, refer to (Ebnealipour *et al.*, 2023). Considering Equation 5 as the objective function and constraints related to the traditional Vehicle Routing Problem with Time Window (VRPTW) proposed in (Pureza *et al.*, 2012), while considering both motor battery capacity and human fatigue level constraints. The detailed calculation of each power can be found in (Clancy, 2020).

To solve the formulated problem, we apply the Grey Wolf Optimizer (GWO) (Mirjalili *et al.*, 2014), a metaheuristic algorithm inspired by the social hierarchy and hunting behavior of grey wolves in nature. This optimization technique is known for its effectiveness in exploring and exploiting the search space to find optimal solutions. By mimicking the leadership and teamwork of wolves, the GWO algorithm navigates through the solution space, gradually converging toward the best solution. In our implementation, we have carefully adapted the GWO algorithm to the specific characteristics and constraints of the formulated problem, ensuring that it efficiently searches for the most optimal routing and energy management strategies.

3 RESULTS

In Table 1, we compare the outcomes of the proposed model (referred to as Model 1), which primarily focuses on minimizing energy consumption, against a traditional model aimed at minimizing travel time (referred to as Model 2). To ensure a fair comparison, we consider both workload balance and rider fatigue level in both models. This enables us to evaluate the effectiveness of our approach not only in reducing energy consumption but also in maintaining manageable workloads for riders and addressing their fatigue levels. These factors are critical for the sustainability and efficiency of last-mile delivery operations.

Model 1 consistently demonstrates lower energy consumption compared to Model 2 across all scenarios while the difference in the travel times between the two models are not significant. Model 1 consistently maintains a higher average percentage of human energy left after the route compared to Model 2. For instance, in the instance with 20 nodes, Model 1 retains 26 percent of human energy on average, while Model 2 retains only 13 percent. Overall, the comparison highlights the effectiveness of the proposed model in creating more sustainable and efficient routes for last-mile delivery operations with cargo e-bikes.

Table 1 – *Comparison of the models performance across three instances*

Number of Locations	Energy Consumption (watt-hour)		Travel Time (Hour)		Average Percentage of Human Energy Left (%)		Workload Balance	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
20	**4974.59**	6054.96	**1.91**	2.23	**26.04**	12.95	**0**	**0**
60	**20768.49**	23410.75	13.39	**12.85**	**5.75**	2.61	**1**	2
100	**34359.78**	36479.59	**29.73**	30.65	**9.27**	8.43	**3**	**3**

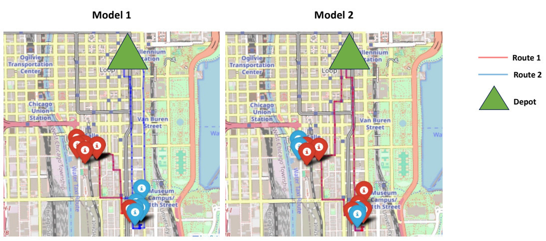

Figure 1 – *Example visual comparison of the optimized routes for the instance with 20 nodes.*

4 DISCUSSION

This study introduced a novel approach that considers both the motor and rider's contributions to energy usage, aiming to enhance the sustainability and effectiveness of last-mile delivery operations with cargo e-bikes. Both developed and examined models show promising results; however, Model 1's approach to energy optimization stands out as a significant advancement in sustainable logistics. By prioritizing energy efficiency and rider well-being, this model aligns with the broader goals of reducing carbon emissions and promoting healthier working conditions. The incorporation of human energy retention as a key metric highlights the importance of considering the physical limits and well-being of riders in the design of delivery routes. This approach not only benefits the environment and the riders but also has the potential to enhance the overall efficiency and reliability of last-mile delivery services. As urban areas continue to seek sustainable transportation solutions, the findings from this study offer valuable insights into the design and implementation of eco-friendly delivery systems.

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