A Monte Carlo Simulation For The Evaluation Of Biofuels Costs And Emissions For Fermanagh Community Transport

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Abstract

Fermanagh Community Transport (FCT) uses 16 diesel minibuses to serve rural communities with little transport alternatives. Currently FCT faces a dilemma between financial and environmental pressures. This report models the cost and CO_{2e} emissions of FCT operating with biofuel blends using a Monte Carlo simulation. Three fuel use scenarios were modelled: diesel, FAME blends, and HVO blends. Results show diesel as the cheapest option (£25.06/day, mean) but the highest-emitting (98.64 $kgCO_2e$/day, mean). Lower blends offer reasonable trade-offs: 20% FAME/HVO blends provide 17-19% emission reductions at a 5-7% cost increase, and 30% blends offer 26-28% emission reductions for an 8-10% cost increase. HVO blends outperform equivalent FAME blends, offering lower emissions at lower costs. When operational issues are considered, these results suggest that low HVO blends represent a potentially viable short-term option for FCT.

1 Introduction

Fermanagh Community Transport (FCT) is a charity that provides pre-booked transport for elderly and disabled passengers across county Fermanagh. The FCT currently has a fleet of 16 diesel minibuses and volunteer social cars [1].

Between 1990 and 2023, greenhouse gas (GHG) emissions in Northern Ireland fell by 31.5%, less than the reductions in England(55.1%), Scotland(52.7%), and Wales(38.5%) [2]. With the Climate Change Act (Northern Ireland) 2022 proposing a 48% reduction by 2030 [3], this shows the need for viable low-emission options for diesel-based transport providers such as FCT.

For many individuals, the charity provides access to essential services and social activities. The financial sustainability of this organization is therefore essential, particularly with ongoing budget concerns [4]. This creates a dilemma between the need for FCT to be financially responsible and the greater need to reduce GHG emissions.

Prior to focusing on biofuels, alternative low-emission pathways were considered. We found multiple pathways explored as solutions to similar problems.

Route optimization is an effective approach, offering the ability to reduce both costs and emissions. For example, [5] shows an implementable framework for addressing the Vehicle Routing Problem (VRP). This work was in collaboration with FCT and shows how emission reductions can be achieved with minimal increased costs. Route optimization is not a disjoint pathway from the use of biofuels. Combining these pathways provides an effective approach for emission reductions.

Electric, hydrogen, and hybrid vehicles offer low emissions, but have practical and financial concerns. Electric vehicles are seen to have too low a range for rural transport, and hydrogen infrastructure costs an average of £432,000 per depot[6]. Hybrid-electric vehicles are shown to reduce WTW emissions by 75% in city bus scenarios [7], but face similar range and cost concerns making these options currently not feasible. However, hybrid-electric or hybrid-hydrogen vehicles running on biofuels might be possible as a long-term solution.

We then focused on biofuels, as FCT could use them in a short time-frame with little upfront cost. We considered many forms of biofuel, such as biogas and biomethanol, which offer environmental advantages, but lack major suppliers. In contrast, an HVO supplier operates pumps in 47 locations in Northern Ireland [8], and FAME suppliers are seen throughout the UK [9, 10].

The Department for Infrastructure's Transport Strategy 2035 [11] suggested that biofuels could be used as an interim solution. This drove us to model the daily fuel costs and emissions of FCT's vehicles upon switching from diesel to FAME or HVO blends.

This was done by exploring the costs and emissions of three scenarios for FCT:

1. Operations resume use of conventional diesel fuel.
2. Operations switch to a FAME/RME (Fatty Acid Methyl Esters) biodiesel-diesel blend (B5/B7/B10/B20/B30/B50/B100).
3. Operations switch to a HVO (hydrotreated vegetable oil)-diesel blend (HVO5/HVO7/HVO10/HVO20/HVO30/HVO50/HVO100).

Where B5, B7, ..., B100 and HVO5, HVO7,...,HVO100 represent the typical blends offered by suppliers with 5%,7%,...,100% biofuel percentage in the fuel blend(with the other part being diesel) for FAME and HVO respectively. The literature shows that it is common practice to mix these biofuels with diesel and has investigated the most effective way to mix these fuels [12]. This property allows for a compromise between diesel and biofuel properties.

This report finds possibilities for FCT to reduce emissions through biofuels. We use a Monte Carlo simulation with 10,000 iterations to model uncertainty in distance, fuel consumption, and prices to estimate daily costs and emissions to support decision-making.

2 Methods

This section presents the Monte Carlo simulation used to estimate daily fuel costs and emissions under different fuel options. Variables were assigned probability distributions, and repeated sampling was used to estimate expected values and uncertainty. This approach was chosen because FCT's daily operations are highly uncertain in route distances, fuel consumption, emissions, and fuel prices, making a Monte Carlo simulation an appropriate method for handling the range in possible outcomes in such a system with numerous random variables.

2.1 Stochastic Inputs and Model Parameters

Table 1 summarizes all the Monte Carlo simulation's core inputs. Daily distance travelled by an FCT vehicle is highly variable, so a unique distribution was generated using simulated routes. Routes were constructed across 32 pick-up towns and 6 drop-off towns (populations $> 1{,}000$), with populations found using NISRA Census data [13]. Town-to-town distances were obtained through the Google Distance Matrix API [14]. Origins and destinations were sampled with probabilities weighted by town populations, each simulated route assumed 16 passengers, and the stop order was determined using a nearest-neighbour heuristic following [15].

A correspondence with FCT suggested the Mercedes-Benz Sprinter 515 Progressive was a commonly used vehicle. Diesel consumption was modeled using a uniform distribution between the manufacturer's urban and rural values [16]. This was done in order to simplify a typical route environment. FAME and HVO consumption were computed via diesel consumption using Equation 2.

Fuel prices were represented using triangular distributions, providing a simple way to model volatile prices using the minimum, median, and maximum. More complex pricing models could be used, but they would require additional data and would not change the overall comparison between the fuels. For diesel, 2025 weekly ULSD pump-price data [17] was used, with the minimum, median, and maximum forming the triangular parameters.

For HVO, UK pricing data is limited, but supplier information indicates a typical 10–15% premium relative to diesel [18]. Accordingly, we applied a 10% increase to the diesel minimum, a 12.5% increase to the median, and a 15% increase to the maximum. For FAME biodiesel, a supplier quoted a price of £1.44/L [9] which is approximately 7.46% above the diesel median, so we applied a 7.46% increase to all distribution parameters.

This report uses well-to-wheel (WTW) emissions, combining tank-to-wheel (TTW) exhaust emissions with well-to-tank (WTT) upstream emissions [19]. Although biofuels release CO_{2e} during combustion, these emissions are assumed as biogenic and treated as net-zero under UK Government conventions[20]. We therefore choose our biofuels to have zero TTW emissions.

Diesel TTW emissions were modeled using a triangular distribution, with the high-, medium-, and low-speed values taken from the manufacturer's guide [16]. This was done in order to simplify a typical route environment. WTT emissions factors were taken from the UK Government GHG Conversion Factors [21], and energy densities from [22].

Variable / Parameter	Symbol	Value / Distribution/ Equation
Stochastic inputs		
Daily distance (km)	K	Sampled from route distance simulation
Diesel/FAME/HVO consumption (L/km)	$R_{\mathrm{DSL}}/R_{\mathrm{FAME}}/R_{\mathrm{HVO}}$	$\mathcal{U}(0.103, 0.107)/Eq.\ 2/Eq.\ 2$
Diesel/FAME/HVO price (£/L)	$P_{\mathrm{DSL}}/P_{\mathrm{FAME}}/P_{\mathrm{HVO}}$	$Tri(1.38, 1.43, 1.47)/Tri(1.48, 1.54, 1.61)/Tri(1.52, 1.6, 1.7)$
Diesel/FAME/HVO TTW emissions (kgCO$_2$/km)	$EF^{\mathrm{TTW}}_{\mathrm{DSL}}/EF^{\mathrm{TTW}}_{\mathrm{FAME}}/EF^{\mathrm{TTW}}_{\mathrm{HVO}}$	$Tri(0.271, 0.282, 0.332)/0/0$
Fixed parameters		
Diesel/FAME/HVO WTT emissions (kgCO$_2$/L)	$EF^{\mathrm{WTT}}_{\mathrm{DSL}}/EF^{\mathrm{WTT}}_{\mathrm{FAME}}/EF^{\mathrm{WTT}}_{\mathrm{HVO}}$	2.51 / 0.168 / 0.0356
Diesel/FAME/HVO Energy density (MJ/L)	$EN_{DSL}/EN_{FAME}/EN_{HVO}$	41 / 32.7 / 34.4

Table 1: Summary of all the Monte Carlo simulations core inputs, any input not in this table is derived from values/distributions in this table. The table lists each variable's name, units, symbol, and assigned value/distribution or equation it is derived from with Subsections 2.1, 2.2 providing justification.

2.2 Core Cost and Emissions Equations

We model the daily fuel cost C and well-to-wheel (WTW) emissions E_{WTW} for a route distance K (km) with fuel consumption R (L/km), fuel price P (£/L), tank-to-wheel (TTW) emissions E_{TTW} (kgCO$_2$e/km), and well-to-tank (WTT) emissions E_{WTT} (kgCO$_2$e/L) by:

$$C = KRP, \qquad E_{\mathrm{WTW}} = K(E_{\mathrm{TTW}} + RE_{\mathrm{WTT}}). \tag{1}$$

Fuel consumption was assumed inversely proportional to the energy density of the fuel. This simplification implies that if energy density is multiplied by X fuel consumption is multiplied by $\frac{1}{X}$, as we expect:

$$R = \frac{R_{\mathrm{DSL}}\, EN_{\mathrm{DSL}}}{EN}, \tag{2}$$

We simplified blend properties as follows. For biofuel blends with volumetric fraction $X \in [0, 1]$ we model price,energy density, fuel consumption,WTT emissions, and TTW emissions by:

$$\begin{aligned} P_X &= (1 - X)\, P_{\mathrm{DSL}} + X\, P_{\mathrm{BIO}}, \\ EN_X &= (1 - X)\, EN_{\mathrm{DSL}} + X\, EN_{\mathrm{BIO}}, \\ R_X &= \frac{R_{\mathrm{DSL}}\, EN_{\mathrm{DSL}}}{(1 - X)\, EN_{\mathrm{DSL}} + X\, EN_{\mathrm{BIO}}}, \\ E_{\mathrm{WTT},X} &= (1 - X)\, E_{\mathrm{WTT,DSL}} + X\, E_{\mathrm{WTT,BIO}}, \\ E_{\mathrm{TTW},X} &= (1 - X)\, E_{\mathrm{TTW,DSL}}. \end{aligned} \tag{3}$$

Substituting the equations (3) into (1) yields the complete cost and emissions model for any blend:

$$\begin{aligned} C_X &= K R_X P_X, \\ E_{\mathrm{WTW},X} &= K(E_{\mathrm{TTW},X} + R_X E_{\mathrm{WTT},X}). \end{aligned} \tag{4}$$

2.3 Monte Carlo Simulation Framework

FCT operations are highly uncertain; to handle this uncertainty, we use a Monte Carlo simulation to demonstrate the full range of likely cost and emissions outcomes.

We repeatedly sample from the probability distributions defined in Subsection 2.1. In each iteration, we draw random values for daily distance traveled (K), fuel consumption rate (R), TTW emissions factor (E_{TTW}), and fuel price (P), representing one day of FCT operations. These values are then used to find that day's fuel cost C and WTW emissions E_{WTW} computed from the equations in Subsection 2.2.

More formally let

$$\mathbf{X} = (K, R, E_{\text{TTW}}, P)$$

denote the vector of uncertain variables. For each realization $\mathbf{X}_i$, we compute:

$$C_i = f(\mathbf{X}_i), \quad E_{\text{WTW},i} = g(\mathbf{X}_i),$$

Where functions f and g use the cost and emissions equations.

Repeating this process for $N = 10{,}000$ iterations generates samples $\{C_i\}$ and $\{E_{\text{WTW},i}\}$ that allow us to approximate the probability distributions of daily costs and emissions. We then estimate expected values via:

$$\mathbb{E}[C] = \frac{1}{N}\sum_{i=1}^{N} C_i, \quad \mathbb{E}[E_{\text{WTW}}] = \frac{1}{N}\sum_{i=1}^{N} E_{\text{WTW},i},$$

with variability determined using percentiles.

The use of $10,000$ iterations allows us to make use of the law of large numbers and to ensure stable convergence of our estimates of the means. The model makes use of the following assumptions:

1. All uncertain inputs are sampled independently, blend properties move with volumetric percentage as detailed by Equations (3). These assumptions are reasonable for the blends and sufficient for our comparison needs.
2. Biofuel TTW emissions are treated as net-zero [20], and WTT emissions are as the UK Government standard factors [21] state. Further that measured energy density is representative of the real fuels [22]. This ensures consistency with conventions.
3. The route distance simulation, 16 passengers, and Mercedes Sprinter 515 specifications [16] and their assigned distributions represent typical operations. In reality, we have variation such as to seasonal effects, driver behavior, vehicle condition, and passenger demand. This assumption allows for us to simplify our model greatly.
4. Prices reflect current data [17, 9, 18]. We ignore market change, bulk discounts, and operational cost differences between fuels. We use a simplification of pricing which is suitable for our comparison needs.

These assumptions allow us to simplify a typical FCT day in order to make predictions for the purpose of the organization. Further work could involve more realistic assumptions for FCT's operations, and offer more complex models to deal with real-world randomness such as the consideration of seasonal effects, or passenger demand.

3 Results and Discussion

This section shows results from the Monte Carlo simulation implemented with 10,000 iterations for each fuel scenario within Python. Table 2 summarizes the general findings. The results were produced in Python by generating samples representing a single day of operations using the distributions and parameter values described in Subsection 2.1. The equations detailed in Subsection 2.2 were then applied to compute daily fuel costs and emissions for each iteration. Repeating this process produced arrays of length 10,000, which were subsequently used for plotting and characterizations.

3.1 Cost Analysis

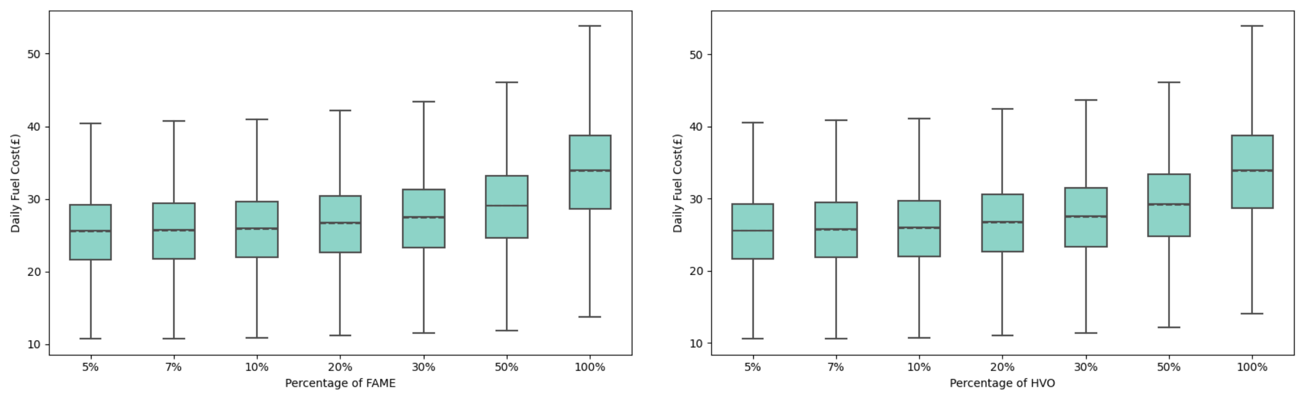
Figure 1 shows that both higher FAME and HVO content lead to an increase in daily fuel costs (£). This is driven by the larger parameters of the triangular distributions used to price these fuels, as described in Subsection 2.1. However, the increase in cost is also due to the lower energy densities of FAME and HVO relative to diesel. As described in Subsection 2.2, fuel consumption is inversely proportional to energy density; hence, these fuels both cost more per liter and require a greater number of liters per kilometer. We also see that the interquartile range increases for both fuels as the biofuel percentage increases. This is likely due to the greater spread between the minimum and maximum parameters in the triangular distributions used for FAME and HVO. This increased price variability should be considered, as it may lead to greater financial risk for FCT.

Scenario	Mean Cost (£/day)	95% CI Cost (£/day)	Mean Emissions ($kgCO_2e$/day)	95% CI Emissions ($kgCO_2e$/day)
Diesel	25.06	[15.09, 35.74]	98.64	[59.37, 139.52]
FAME B100	33.81	[20.18, 48.31]	3.92	[2.35, 5.60]
HVO100	33.65	[20.03, 47.82]	0.79	[0.48, 1.12]
FAME B20	26.63	[16.23, 37.85]	81.60	[48.93, 116.31]
HVO20	26.48	[15.93, 37.61]	80.59	[48.20, 115.08]
FAME B30	27.40	[16.72, 38.91]	72.56	[43.51, 103.42]
HVO30	27.26	[16.41, 38.70]	71.2	[42.57, 101.60]
Percentage change vs Diesel baseline				
FAME B100	+34.9%	—	−96.0%	—
HVO100	+33.3%	—	−99.2%	—
FAME B20	+6.3%	—	−17.3%	—
HVO20	+5.7%	—	−18.3%	—
FAME B30	+9.32%	—	−26.4%	—
HVO30	+8.8%	—	−27.8%	—

Table 2: Summary statistics from the Monte Carlo simulation (N = 10,000). All values are reported to two decimal places (or one decimal place for percentages) and were computed in Python using `np.mean` and `np.percentile` applied to the simulated output arrays. All results reflect one simulated day of FCT operations.

In Table 2, we notice that HVO100, HVO30, and HVO20 show lower estimated mean daily costs than B100, B30, and B20, respectively, despite the fact that in Subsection 2.1 we cited the parameters for the price of FAME to be lower than HVO. This is a consequence of the higher energy density of HVO in Subsection 2.2, we set energy density inversely proportional to fuel consumption, and thus HVO has a lower fuel consumption. This implies that although HVO blends costs more per liter, they will use fewer liters per journey leading to a lower overall cost.

These figures were produced by taking our produced arrays of length 10,000 and using the `ax.boxplot()` function implemented within Python.



(a) FAME (b) HVO

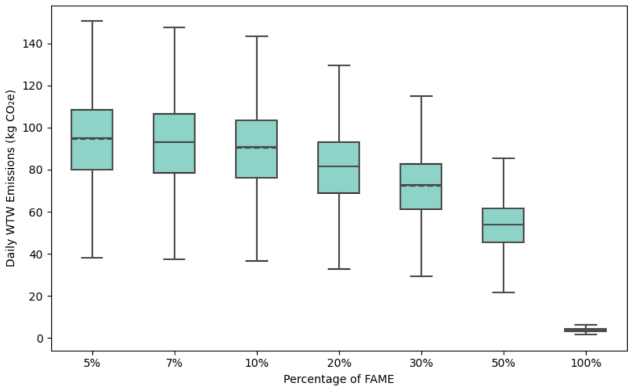
Figure 1: Daily estimated fuels costs distributions for (a) FAME and (b) HVO biofuel blends based on 10,000 simulation iterations. Box plots show median (dashed line), mean (solid line), interquartile range (box), and range (whiskers). Cost increases with blend percentage for both fuels, driven by higher per-liter prices and energy density effects.

3.2 Emissions Analysis

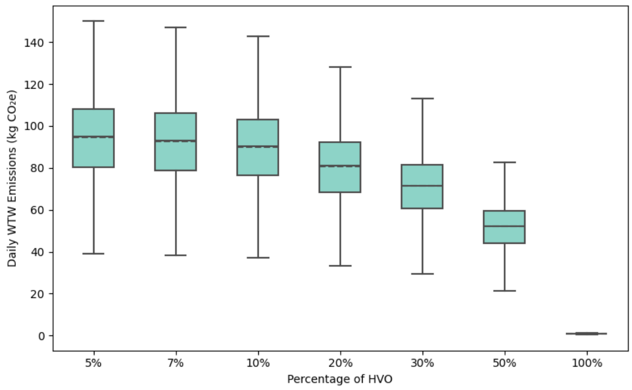
The box plots shown in Figure 2 indicate that, daily WTW emissions decrease as the percentage of biofuel in the blend increases. This is driven by the WTT emissions found in Subsection 2.1, where the WTT emissions associated with diesel are larger than those of our biofuels. In addition, TTW emissions were set to zero for biofuels, which also contributes to these reductions. The interquartile range decreases for both fuels with increasing biofuel content, caused by the assumption of zero TTW emissions for FAME and HVO compared with the uniform distribution used for diesel. This reduced variability yields more predictable emission reductions for FCT.

We see in Table 2 that HVO100, HVO30, and HVO20 exhibit slightly lower estimated mean daily WTW emissions than B100, B30, and B20, respectively. This difference occurs because the WTT emissions of HVO are smaller than FAME.

These figures were produced by taking our produced arrays of length 10,000 and using the `ax.boxplot()` function implemented within Python.



(a) FAME



(b) HVO

Figure 2: Daily WTW emissions distributions for (a) FAME and (b) HVO biofuel blends based on 10,000 Monte Carlo iterations. Box plots show median (dashed line), mean (solid line), interquartile range (box), and range (whiskers). Emissions decrease with blend percentage for both fuels, driven by primary lower WTT emissions.

3.3 Cost-Emissions Trade-offs

The scatter plot in Figure 3 shows the relationship between mean daily cost and mean daily WTW emissions for all fuel scenarios. Points for Diesel, HVO20, B20,HVO30, B30, HVO100, and B100 are shown with error bars representing 95% confidence intervals with points to the left being those of higher biofuel content. Together with Table 2, the results show an approximately linear cost-emissions relationship for both FAME and HVO blends.

The size of the gradient of the HVO line is smaller than that of FAME, indicating that HVO delivers emission reductions with a smaller associated increase in daily cost. This is in combination with Table 2 and the results in Subsections 3.1, 3.2 suggests that low HVO blends are the most viable pathway. For example HVO20 requires a 5.7% increase in mean daily costs for a 18% mean reduction in WTW emissions. Scenarios such as this suggest that although FCT is suffering from budget issues [4],low HVO blends allow FCT to achieve notable emissions reductions for only a modest increase in daily fuel cost.

There is large uncertainty in both the cost and emissions estimates for each scenario, as shown in Table 2 by the wide confidence intervals, and in Figure 3 by the large error bars. This uncertainty is driven by the highly variable route distances of FCT vehicles. This variability in cost is important for FCT to consider, especially during a period of financial concerns [4], hence any fuel strategy should account for this variability. Based on FCT's current financial situation, we suggest that low HVO blends could be adopted as an interim solution, a position that is suggested by the Department for Infrastructure's Transport Strategy 2035 [11]. An exact recommendation of fuel blend is not possible for us, but Figure 3 provides guidance for the cost of each blend allowing for FCT to chose the most suitable blend depending on its exact financial context.

This figure was produced by plotting key fuel blends against their mean daily costs and emissions, including the corresponding 95% confidence intervals, and then adding linear trend lines for each fuel type within Python.

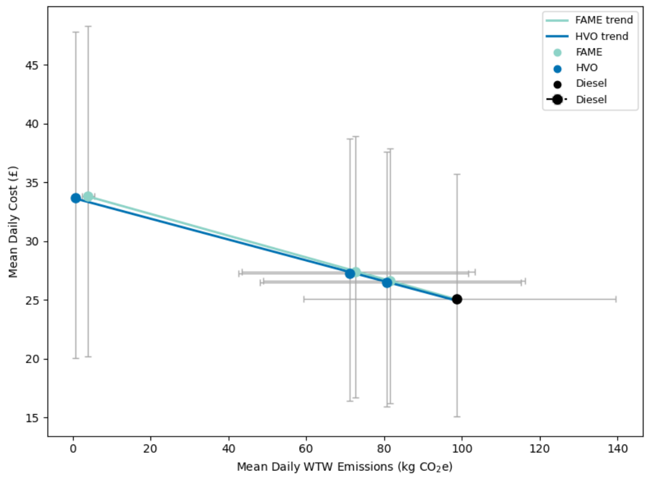


Figure 3: Mean daily cost plotted against mean WTW emissions for all fuel scenarios. Blends with higher biofuel content (B100, H100) appear at the lower-emission end of the plot, followed by B30/H30 and B20/H20, with diesel exhibiting the highest emissions. Error bars represent 95% confidence intervals, indicating uncertainty in both cost and emissions. Linear trend lines are included for FAME and HVO blends, showing the cost–emissions relationship for each biofuel.

3.4 Operational Considerations

Within this report, we have not looked at the operational considerations of using biofuels, such as vehicle compatibility, fuel availability, or storage requirements.

Both FAME and HVO require lower injection pressures than diesel [23], potentially requiring vehicle changes for higher blends. However, issues are minimal at lower blend ratios ($\leq 30\%$), where biofuels function as drop-in substitutes.

We found that the availability of biofuels in the UK is not yet ideal. In 2025 the UK Government reported that only 7.3% of total road and non-road mobile machinery fuel was renewable [24]. This is not encouraging. However, we are able to identify suppliers offering HVO at the pump within Northern Ireland at 47 different locations [8]. This is hopeful, as it provides evidence that HVO blends can be sourced directly from suppliers in Northern Ireland.

Under current conditions, the use of biofuels would potentially require FCT to order and store fuel, adding costs that are not in our model. This could, however, allow for hedging against the highly volatile nature of biofuel prices, and fuel prices more generally.

We also acknowledge that the assumptions underlying the pricing of both HVO and FAME are relatively weak. As discussed in Subsection 2.1, limited available data forced these assumptions. With increased fuel availability, a more accurate model of both costs and emissions could be developed.

More generally, the model excludes several considerations, such as weather and seasonal effects, vehicle age and condition, air pollutants other than CO_{2e} such as NO_x, and variable passenger demand. These limitations offer areas where further modeling could improve the report.

4 Conclusion

The conclusion of this report is that, with appropriate financial support or internal budget reallocation, Fermanagh Community Transport depending on the exact nature of their financial situation could feasibly use low biofuel blends such as HVO20 or HVO30 as an interim solution. Low blends were found to offer WTW emissions reductions in the range of 18.3–27.8% at a cost increase of 5.7–8.8%. Based on the operational considerations discussed in Subsection 3.4, particularly the availability of HVO from suppliers operating in Northern Ireland, an interim transition to low HVO blends seems possible and effective.

This report excluded a number of topics most notably, non-CO_{2e} pollutant emissions, weather and seasonal effects, and passenger demand variability. These represent opportunities for further work. Future work involving these factors, with improved data on biofuel pricing, would allow a more complete study of the financial and environmental implications of biofuel use for providers such as FCT.

References

[1] Fermanagh Community Transport. (accessed 10 November 2025). fermanaghcommunitytransport.com.

[2] Department of Agriculture, Environment and Rural Affairs (DAERA), *Northern Ireland Greenhouse Gas Statistics 1990–2023 Released*, (2024). daera-ni.gov.uk.

[3] Northern Ireland Assembly, *Climate Change Act (Northern Ireland) 2022*, legislation.gov.uk.

[4] Fermanagh Community Transport, *Response to the DfI Budget 2023–24 Equality Impact Assessment*, (2023).

[5] K. Q. Lian and G. A. Tribello, *An Elementary Approach to the Vehicle Routing Problem via Python and Google API*, American Journal of Operations Research, 14(6) (2024). doi:10.4236/ajor.2024.146009.

[6] Confederation of Passenger Transport, *Delivering Zero Emission Bus Services to Rural Areas (Rural Zero Emission Bus Taskforce Report)*, (2024).

[7] D. Dreier, S. Silveira, D. Khatiwada, K. V. O. Fonseca, R. Nieweglowski, and R. Schepanski, *Well-to-Wheel Analysis of Fossil Energy Use and Greenhouse Gas Emissions for Conventional, Hybrid-Electric and Plug-in Hybrid-Electric City Buses in the BRT System in Curitiba, Brazil*, Transportation Research Part D: Transport and Environment, 58 (2018). doi:10.1016/j.trd.2017.10.015.

[8] FleetMaxx Solutions, *HVO Fuel Is Now Available to UK Fuels Fuel Card Customers*, (2025). (accessed 14 November 2025). fleetmaxxsolutions.co.uk.

[9] Pure Biodiesel Ltd, *Mail Order Biodiesel*, (2025). (accessed 14 November 2025). purebiodiesel.co.uk.

[10] 123 Oil, *FAME Biodiesel*, (2025). (accessed 14 November 2025). 123oil.co.uk.

[11] Department for Infrastructure (DfI), *Transport Strategy 2035: Consultation Draft*, (2025). (accessed 14 December 2025). infrastructure-ni.gov.uk.

[12] S. Mustika and W. W. Purwanto, *Multi-Objective Optimization of Blending Strategy of FAME, HVO, and Petroleum Diesel*, IOP Conference Series: Materials Science and Engineering, 1143 (2021). doi:10.1088/1757-899X/1143/1/012046.

[13] Northern Ireland Statistics and Research Agency (NISRA), *Census*, (2023). (accessed 14 November 2025). nisra.gov.uk.

[14] Google, *Distance Matrix API*, (2025). (accessed 14 November 2025). developers.google.com.

[15] C. Brucato, *The Traveling Salesman Problem*, M.S. Thesis, Department of Mathematics, University of Pittsburgh (2013). mathematics.pitt.edu.

[16] Mercedes-Benz Vans UK Ltd, *The Mercedes-Benz Sprinter: Panel Van Models, Technical Data and Pricing Guide*, Mercedes-Benz AG (2025). (accessed 14 November 2025).

[17] Department for Energy Security and Net Zero (DESNZ), *Weekly Road Fuel Prices – Unleaded Diesel (ULSD)*, (2025). (accessed 10 November 2025). gov.uk.

[18] Prema Energy Ltd, *How Much Does HVO Fuel Cost Compared to Fossil Diesel?*, (2025). (accessed 13 November 2025). premaenergy.co.uk.

[19] M. Gustafsson, *Well-to-Wheel Greenhouse Gas Emissions of Heavy-Duty Vehicles*, Energy Policy, 154, (2021). sciencedirect.com.

[20] C. Malins (Cerulogy), *Alternative Fuels in Aviation: Part 1 – Life Cycle Assessment*, Aviation Environment Federation (2023). aef.org.uk.

[21] Department for Energy Security and Net Zero (DESNZ), *UK Government GHG Conversion Factors for Company Reporting 2024 – Well-to-Tank (WTT) Biofuel Emission Factors*, (2024). gov.uk.

[22] REN21, *Renewables 2020 Global Status Report – Units & Conversion Factors*, (2020). (accessed 14 November 2025). ren21.net.

[23] J. Hunicz, P. Krzaczek, A. Tazerout, and A. Teodorczyk, *Comparative Study of Combustion and Emissions of a Diesel Engine Fuelled with FAME and HVO*, Fuel, 304, (2021). researchgate.net.

[24] UK Government, *Renewable Fuel Statistics 2025 – Final Report*, (2025). (accessed 14 November 2025). gov.uk.