Digital Twin Development for Solar-Powered Refrigeration Systems Integrated with EVs for Cooling Transportation in Clean Air Zones

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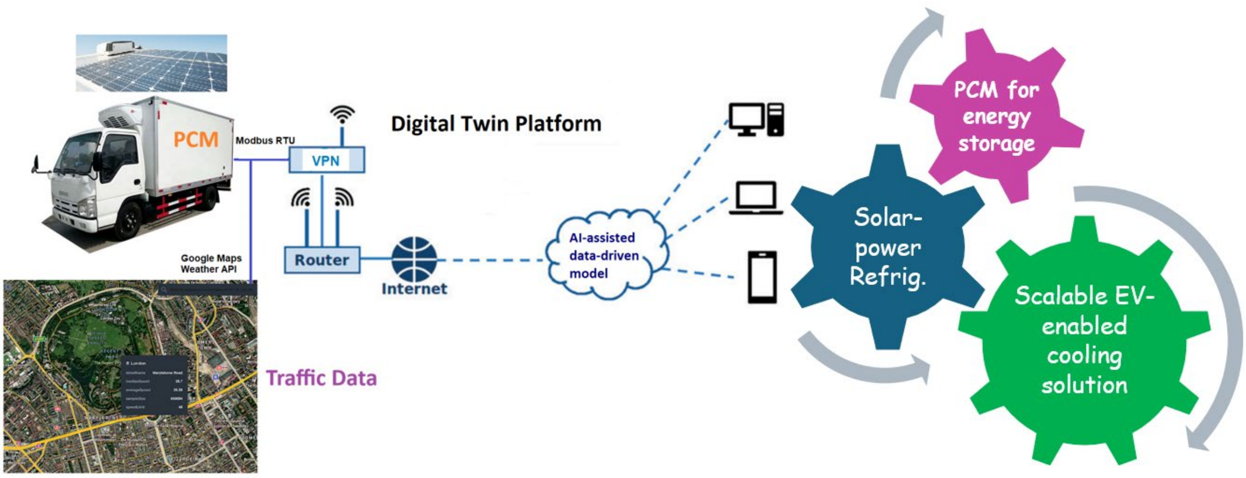

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REnewable Energy for Future UK Net-Zero Cooling (Reef-UKC) Network, EP/Z533129/1

Indicative summary

This final report synthesises the entire progress with the technical, market and policy outcomes achieved by the end of the award. The project delivered a high-fidelity digital twin (DT) of a solar-assisted, phase-change-material (PCM) buffered refrigerated van, together with an AI-assisted supervisory layer for energy-aware temperature control. The DT generated structured datasets for training a Random Forest model capable of predicting short-horizon battery state-of-charge (SOC) with a mean accuracy of approximately 96% across representative delivery scenarios. In operational terms, this capacity enables pre-trip feasibility assessments and, during duty, anticipatory actions, such as pre-cool timing and compressor speed modulation, that reduce temperature excursions without compromising energy autonomy. Complementing the technical programme, stakeholder engagement and a 29-response retailer survey informed a pragmatic business model and canvas, while a policy framework and recommendations were developed to align pilots and scaling with the F-gas phase-down, the UK ZEV mandate, and CAZ/ULEZ regimes.

Scope and Objectives

The project's overarching objective was to de-risk clean cold deployments on electric vans by integrating a system-level digital twin with a tractable AI-assisted control concept. Specifically, we sought to (i) construct a Modelica-based representation of the refrigeration loop, insulated enclosure, rooftop photovoltaics and battery subsystem under realistic urban logistics missions; (ii) generate and curate simulation data to train a Random Forest model that supports short-horizon SOC prediction and temperature-relevant load anticipation; (iii) engage market actors to validate pain points and refine a credible traction pathway from pilot to scale; and (iv) map the UK regulatory landscape and propose near- and long-term policy measures that reduce adoption risk whilst ensuring safety, data stewardship and interoperability.

Methodology

1. Digital Twin Architecture

The digital twin was developed in Modelica to capture the thermo-fluid dynamics of a vapour-compression cycle (compressor, condenser, expansion device and evaporator) coupled to an insulated enclosure subject to transient heat loads from transmission, infiltration, solar gains and product handling (Fig .1). The energy subsystem models a ~1 kW class rooftop PV array routed through appropriate DC–DC conversion into a Li-ion battery store decoupled from traction. Control is represented at two levels: a fast PI/PID layer for temperature regulation and a supervisory layer that shapes compressor speed and cabinet set-points in anticipation of upcoming load. Scenario blocks formalise ambient climate (EPW→MOS), route duration and stop density, door-opening cadence and product temperature classes (chilled and frozen). Refrigerant options were reviewed with a sustained emphasis on low-GWP fluids; whilst early internal references examined a hydrocarbon baseline, the narrative and policy alignment ultimately foreground R1234yf, with final choice contingent on supplier certification for pilot vehicles.

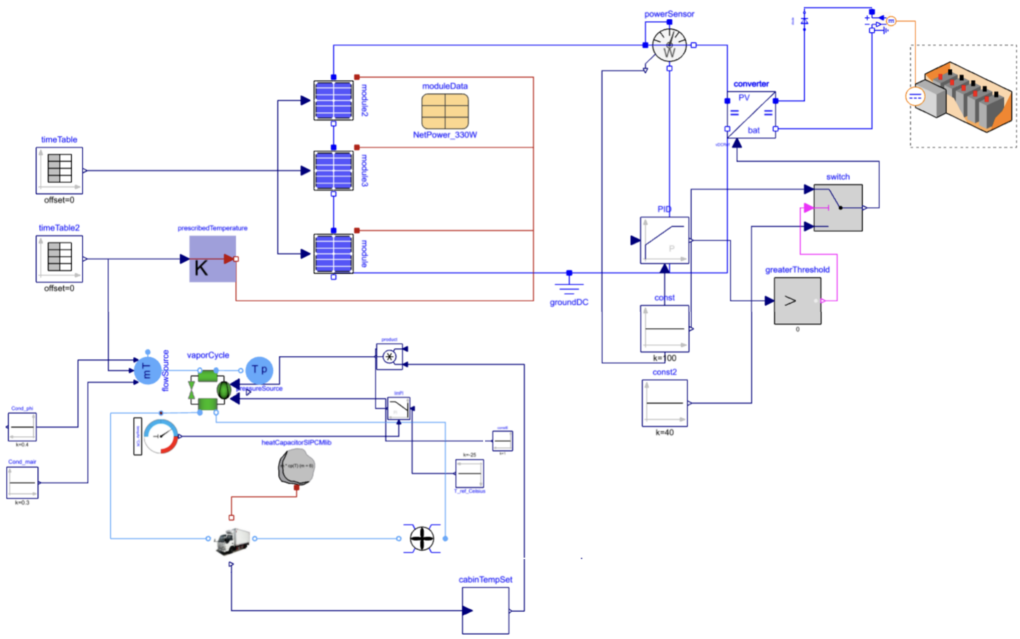

Figure 1: Digital Twin architecture and integration layout (Modelon platform)

2. Data Pipeline for AI

A deterministic pipeline was established to transform simulation outputs into machine-learning-ready feature and target matrices. Principal features comprise solar irradiance, ambient temperature, route duration, inter-stop spacing, door events, evaporator temperature, compressor current and a proxy for battery SOC derived from voltage/current traces. To capture duty severity and dwell, the pipeline integrates contextual variables from Google APIs, including traffic-informed travel times. The pipeline performs timestamp harmonisation, normalisation and labelling by scenario family, with train/validation partitions designed to test generalisation across duty patterns rather than memorising specific traces.

The two below diagrams represent different but complementary phases in the development of an AI-assisted digital twin. At the current stage of the project, the simulation phase (first diagram) has been implemented (Fig. 2). In this phase, the digital twin is constructed upon mathematical equations that emulate the behaviour of the physical system. External inputs such as traffic data and irradiance data, obtained through Google APIs, are incorporated to generate system-relevant parameters, most notably the cooling demand. The outputs of these equations are subsequently used to train machine learning models, with Random Forest algorithms playing a central role in predicting rotor speed signals and the state of charge of the battery system. The final step of the workflow involves estimating battery tolerance, which is crucial for assessing system reliability and long-term performance. This phase, therefore, emphasizes model training, evaluation, and validation in a controlled environment, with predictive accuracy measured using indicators such as RMSE and R^2. By doing so, the digital twin achieves methodological robustness before advancing to real-world deployment.

The second framework (real-world phase) is presented as a conceptual diagram that guides the future direction of the project (Fig. 3). Unlike the simulation phase, which relies on mathematical equations to generate synthetic data, the real-world phase incorporates live sensor inputs and is structured around the interaction between a physical layer and a digital layer. For example, cabin temperature, measured directly from the physical system, is used alongside other contextual information to feed into the AI model. This model, trained in the simulation phase, replaces the earlier mathematical formulations and directly estimates cooling demand under operational conditions. The workflow then proceeds in a similar manner, with Random Forest models predicting rotor speed and state of charge and ultimately supporting battery tolerance estimation. This conceptual design highlights the envisioned transition from theoretical modeling to practical implementation, enabling the digital twin to operate as a real-time, data-driven mirror of the physical system.

Taken together, the two diagrams reflect a phased approach to digital twin development. The first, already implemented, provides a validated foundation based on simulation that ensures the feasibility and reliability of the AI models. The second, as a conceptual framework, outlines the planned evolution towards a fully operational digital twin capable of continuous synchronization between physical measurements and digital predictions.

From an academic standpoint, this progression illustrates the strength of a hybrid approach, where physics-based modeling ensures reliability in early stages, while data-driven methods provide adaptability in real-world deployment. Nonetheless, transitioning from simulation to real-world data introduces challenges, including potential discrepancies between synthetic and sensor data distributions, which may necessitate techniques such as transfer learning or continuous retraining. Despite these challenges, the proposed two-phase framework constitutes a rigorous methodology for bridging the gap between controlled model validation and practical application in complex, data-intensive environments.

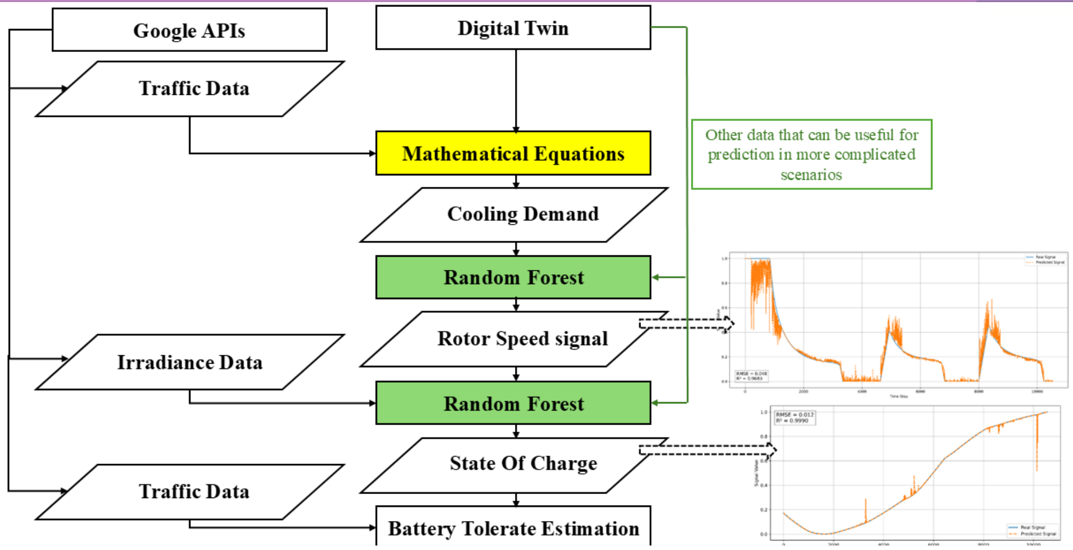

Figure 2: AI-Assisted Digital Twin (Simulation phase)

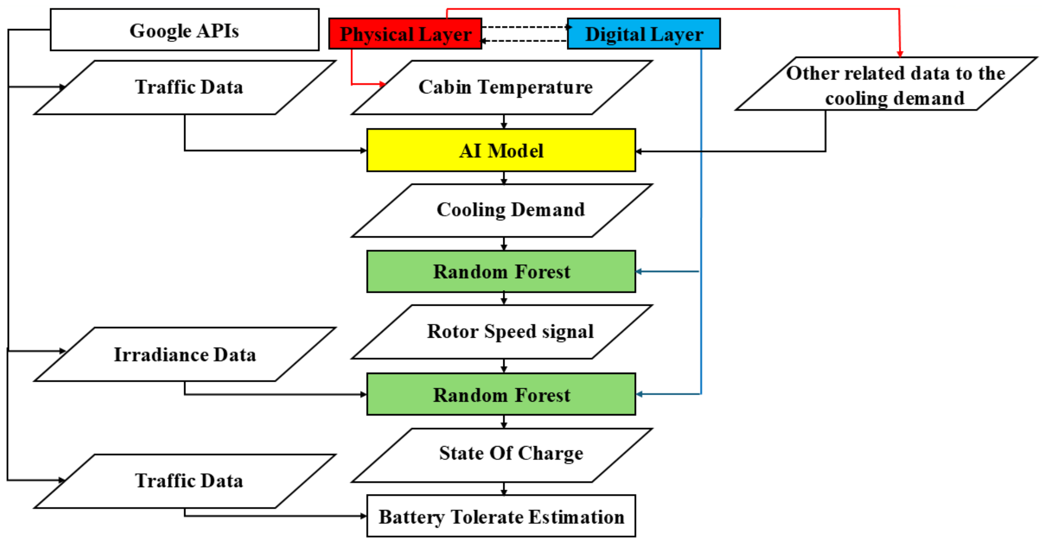

Figure 3: AI-Assisted Digital Twin (real-world phase)

3. Machine Learning & Control Concept

We employed a Random Forest regressor to predict short-horizon SOC and to expose assistive signals to the supervisory controller. The concept of operations is threefold. Pre-trip, the model offers a feasibility assessment that, when risk is indicated, proposes a pre-cool window or alternative route timing. During operation, the supervisory layer adjusts compressor speed and set-points proportionally to predicted load and SOC trajectory, thereby preserving thermal integrity under door events without exhausting energy reserves. Post-trip, telemetry is uploaded to the cloud to support periodic retraining and fleet-level analytics. This architecture balances on-edge responsiveness with cloud-based continuous improvement.

4. Validation Approach & Assumptions

Model performance was assessed using k-fold validation across distinct scenario families to avoid leakage between train and validation sets. Feature-importance diagnostics were used to verify physical plausibility, irradiance, compressor current, evaporator temperature and route timing consistently ranked highly. Assumptions included representative weather years for the operating region, realistic urban delivery patterns derived from the survey, and the availability of core sensors. The principal limitations at this stage are the use of simulated rather than on-road datasets for training, and the reliance on an SOC proxy pending integration with calibrated battery management data during pilots.

Stakeholder Engagement

1. Evidence from Retailer Survey

The outcome of survey from 30 retailers at Birmingham Whole Sale Market indicates that they frequently manage mixed product classes, approximately three-quarters fruit and vegetables, with a non-trivial share of meat/fish and frozen goods, necessitating careful set-point discipline. The present fleet composition remains heavily diesel-biased, suggesting substantial decarbonisation potential through off-engine electric refrigeration. Many routes exceed two hours and cluster between 08:00 and 12:00, which fortuitously overlaps with the solar resource for part of the year. Destinations skew towards city centres, markets, and the hospitality trade, reinforcing the need for low-emission operations under CAZ/ULEZ restrictions.

2. Business Model and Traction Path

The business model targets primary segments in food distribution (fresh and frozen) and pharmaceutical wholesale/courier services, with secondary opportunities in catering and hospitality SME fleets operating in clean-air zones. The value proposition combines zero tailpipe emissions and low-GWP refrigerants with modelled lifecycle cost reductions and prospective spoilage avoidance through fewer temperature excursions. Relationships are built around direct sale or lease, retrofit partners and pilots with service-level agreements, all instrumented through a cloud portal for analytics and compliance reporting. Revenue is diversified across hardware margin, refrigeration-as-a-service, and SaaS analytics, with incremental value from compliance automation and carbon instruments as relevant. The traction pathway envisages a 2025–26 pilot, a 2026–28 seed phase with an OEM option-pack (order-of-hundreds vehicles), and subsequent national scaling as the approach is operationally demonstrated and policy-aligned.

3. Indicative Unit Economics and Operational Benefits

Preliminary analysis suggests energy savings relative to engine-driven refrigeration owing to electrification and PV offset during daytime deliveries, augmented by AI-guided pre-cool that reduces peak compressor energy. Operationally, improved temperature conformity reduces spoilage risk and returns, whilst automated audit trails lower administrative burden for HACCP/GDP compliance. Financing structures, capex sale, lease, or blended service models, can be matched to the risk appetite of adopters.

Risks & Mitigations

The principal risks concern representativeness of the survey sample and the absence of on-road data in the present training set. These are mitigated by broadening engagement and, critically, by instrumented pilots that will generate telemetry for retraining and validation. Supplier dependency and refrigerant certification risks are addressed through early NDAs, dual-sourcing critical components and confirming refrigerant choices against standards prior to procurement. Edge compute constraints are mitigated by parameterised models on-vehicle and cloud-based retraining with measured, signed OTA promotion. Cybersecurity and data governance are managed via encryption, role-based access controls and adoption of the proposed Connected Refrigeration Code. Finally, performance variability across routes and seasons is handled by explicit inclusion of irradiance and traffic features and by instituting continuous learning from deployed fleets.

ECR Involvement

Two Early Career Researchers (ECRs) were formally engaged in the project team: **Mr Armin Esmaeilzadeh** and **Mr Mohammad Keramati Feyz Abadi** (Aston University).
Through hands-on involvement, the ECRs gained applied experience in: physics-based digital-twin modelling, simulation experiment design (mission profiles and door-opening cadence), ML dataset engineering and validation practice, and system integration concepts for IoT-enabled "real-world phase" progression (sensor suite, edge inference, and telemetry for retraining). These activities position them to contribute to the pilot phase and subsequent publications, and to carry transferable skills into future net-zero cooling and cold-chain decarbonisation projects.

Project Outcome

The project concluded with a coherent, pilot-ready package that integrates (i) a Modelica-based digital twin for a solar-assisted, PCM-buffered refrigerated van, (ii) an AI/ML layer (Random Forest) demonstrating ~96% mean short-horizon battery SOC prediction accuracy across representative duty scenarios, and (iii) a complementary set of business model/canvas and policy recommendations to support adoption in CAZ/ULEZ operating contexts.
Critically, the outcome was not only technical: stakeholder engagement and survey evidence anchored assumptions in operational reality, and the final meeting on 29 August 2025 presented the digital twin, ML results, business model, and policy recommendations, securing consensus that the project is ready to proceed to a contained pilot (with the final presentation referenced as supporting evidence).

Project outputs

1. System-Level Behaviour and Mission Profiles

The integrated twin demonstrates the expected coupling between ambient conditions, PV yield, compressor duty and SOC trajectory under urban delivery patterns. Temperature integrity during stop-dense missions is materially enhanced when the controller acts anticipatorily-bringing the cabinet to a deeper pre-cool prior to clusters of door events and momentarily permitting a slightly lower compressor speed once the predicted load subsides. Across representative morning routes, the PV contribution helps offset compressor energy during the most solar-aligned part of the day, modestly flattening the SOC decline without introducing operational complexity.

Fig. 4 shows the compressor rotor speed from the start to the end of the journey for the 3 kg PCM case in the 15th month for February, May, January, and November. It is observed that, at the beginning of the journey the compressor operates at maximum speed to reduce the cabin temperature to the lower set point (−18 °C), which is shown in Fig. 5 as the solid green line. Then, the PI controller, considering the refrigerated enclosure temperature and the set point, regulates the compressor speed, reducing it to an off-load level. As the temperature approaches the upper set point, the controller increases the compressor speed again to maintain the cabin temperature within the desired set-point range.

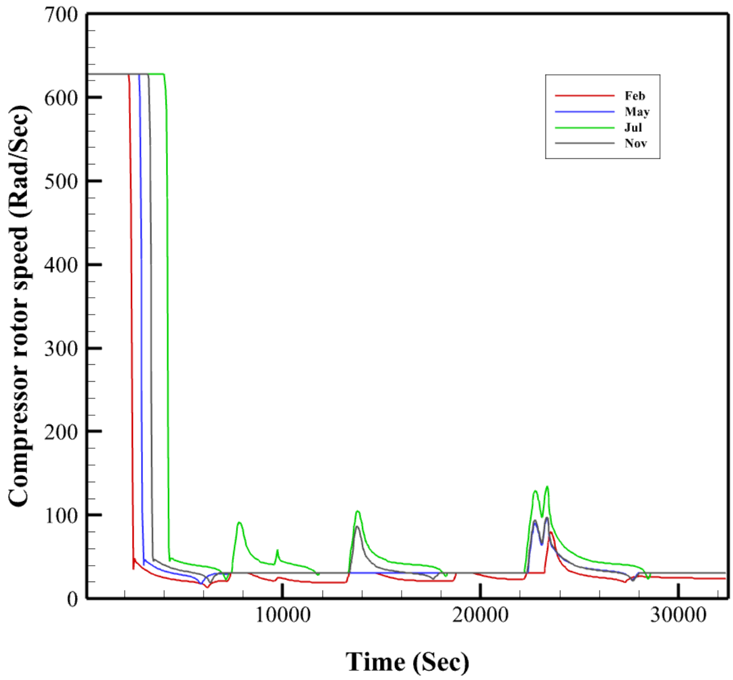

Figure 4: The compressor rotor speed during the journey on 15th desired months.

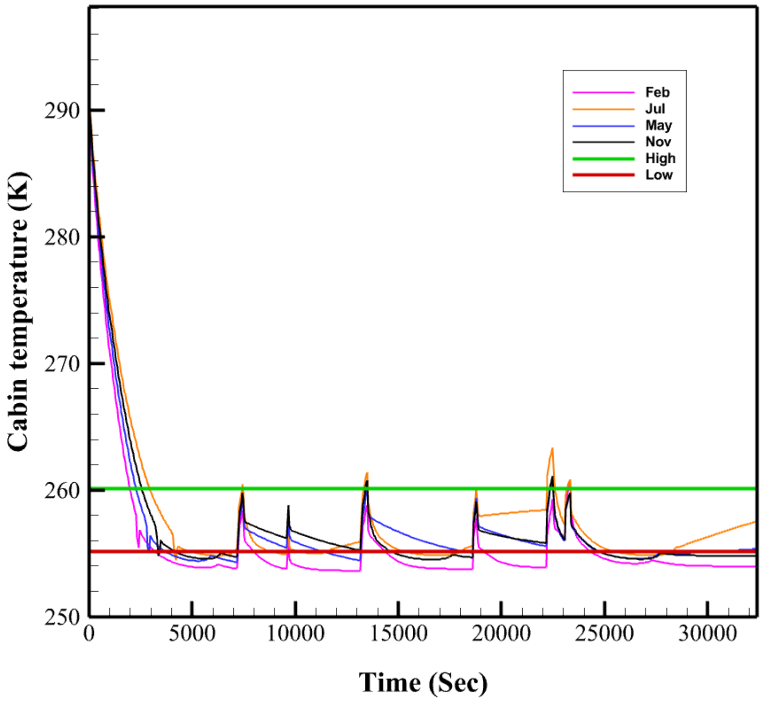

Figure 5: The refrigerated enclosure temperature change and the setpoints during the journey on 15th desired months.

2. PCM Effects and Operational Implications

Simulation results indicate that the inclusion of PCM reduces the amplitude of temperature excursions and shortens recovery when door openings are spaced sufficiently for the cabinet to settle. Conversely, for very frequent, short-interval openings, a higher apparent peak may emerge because the cabinet is repeatedly perturbed before re-establishing steady conditions. This behaviour suggests that there exists an optimum PCM mass conditioned by route topology and service pattern. Compressor shaft-power traces show a dominant initial ramp to attain the target set-point, with relatively modest energy differentials across PCM masses for certain missions. Practically, this points to route-specific tuning, particularly of pre-cool depth and compressor ramp timing, rather than a presumption that more PCM is always beneficial.

Fig. 6 shows the refrigerated enclosure temperature during the journey, starting from the point when the cabin temperature reaches the lower set point in the 8 kg phase change material (PCM) applied within the cabin. The cooling demand is calculated considering transmission heat load, product load, infiltration caused by one-sided ventilation during deliveries, and internal equipment heat sources such as fans and electrical components, with additional safety factors included for uncertainties.

The results show how the cabin temperature is affected by one-sided ventilation during door openings. As illustrated in the figure, in the cases where PCM is applied, the refrigerated enclosure temperature rises less than in the case without PCM. The temperature increase caused by door openings in the 8 kg PCM case is lower than in the 3 kg case because of the stronger buffering effect. When looking at the close peaks in the figure, which indicate frequent and shorter door-opening periods, the buffering effect of the PCM delays the enclosure's temperature release process after the door is closed. This delay causes the next door opening to result in a higher temperature peak in the PCM-applied case. This observation suggests that in scenarios where the electric vehicle (EV) operator makes frequent deliveries with short intervals, PCM application may become a disadvantage and introduce penalties. In other scenarios, however, applying PCM can maintain the temperature within the set-point range that is desired. As shown in Fig. 7, the rotor shaft power versus time indicates only one significant increase in power usage, caused by the compressor rotor speed rising to achieve the lower set point. Fig. 7 also shows 3% and 2.5% higher energy consumption compared with the 3 kg and 8 kg PCM cases, respectively. The energy consumption in the 8 kg case is higher than in the 3 kg case. These results indicate that when applying PCM for journeys with one-sided ventilation, careful consideration is required, and there may exist an optimum volume of PCM.

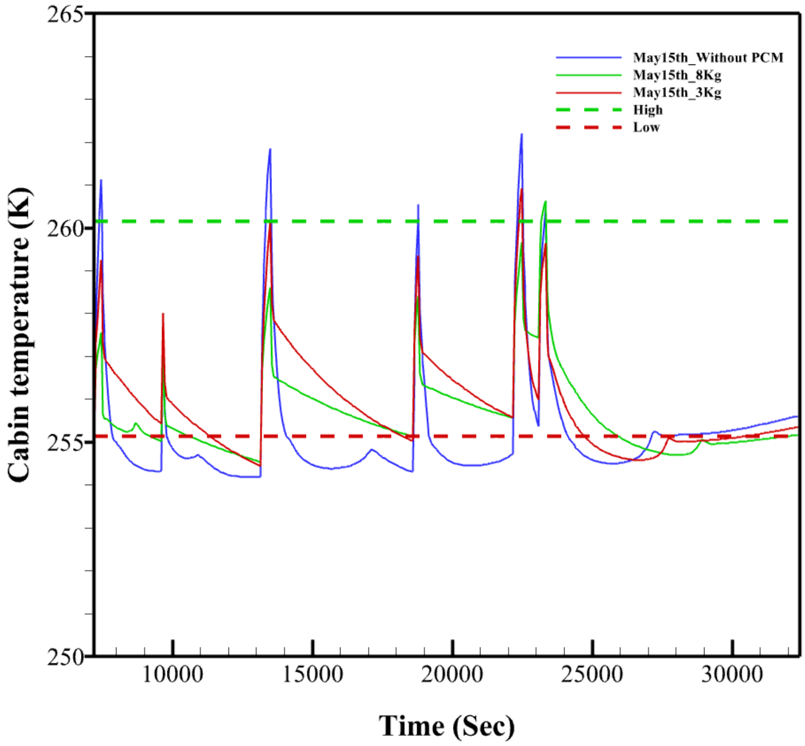

Figure 6: Temperature change during the journey within the refrigerated enclosure.

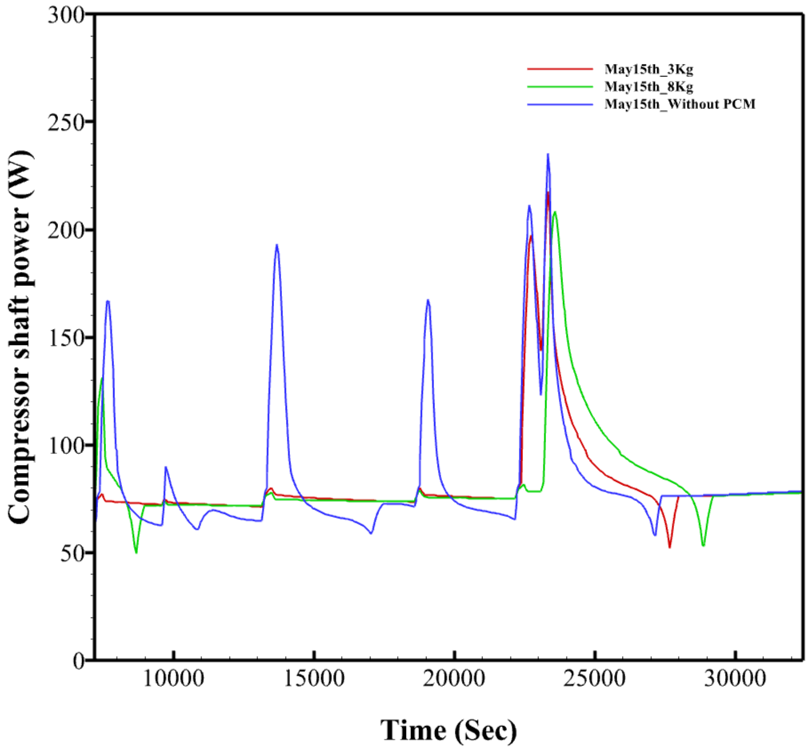

Figure 7: Compressor shaft power change during the journey

3. AI Performance and Supervisory Use

Across four scenario families the Random Forest achieved a mean SOC prediction accuracy of ~96%, with narrow dispersion across folds. Feature-importance patterns accord with engineering intuition: irradiance and compressor current dominate, followed by evaporator temperature and route timing/traffic descriptors. From an operational standpoint this accuracy enables three valuable functions: (i) pre-trip feasibility decisions with recommendations for pre-cool intervals; (ii) in-trip adjustment of compressor speed and set-point that preserves SOC whilst limiting temperature deviation; and (iii) post-trip learning, whereby model updates are prepared in shadow mode and promoted following performance checks.

Table 1 presents detailed information on the data collection conditions, including the frequency of door openings, duration, journey characteristics, start time, and related parameters.

Table 1: Data entry for case scenario development in machine learning model training stage

Date	Time	Door Opening Start Times [s]	Door Opening Durations [s]	t_total [s]	dt [s]	A_wall [m²]	x_e [m]	x_m [m]	x_i [m]	k_wall_e [W/m·K]	k_wall_m [W/m·K]	k_wall_i [W/m·K]	hi [W/m²·K]	ho [W/m²·K]	alpha_i	q_internal [kW]	A_door [m²]	v_inf [m/s]	h_i [kJ/kg]	h_r [kJ/kg]	rho [kg/m³]
15th February (set 9)	05:00 AM - 02:00 PM	[7200, 9600, 13200, 18600, 22200, 23100]	[270, 120, 300, 210, 300, 270]	32400	64.8	10	0.0007	0.006	0.0006	16.2	0.025	50	1.6	6	0.85	0.3	1.2	0.1	14.9	1.942	1.2
15th May (set 10)	05:00 AM - 02:00 PM	[7200, 9600, 13200, 18600, 22200, 23100]	[270, 120, 300, 210, 300, 270]	32400	64.8	10	0.0007	0.006	0.0006	16.2	0.025	50	1.6	6	0.85	0.3	1.2	0.1	14.9	1.942	1.2
15th July (set 11)	05:00 AM - 02:00 PM	[7200, 9600, 13200, 18600, 22200, 23100]	[270, 120, 300, 210, 300, 270]	32400	64.8	10	0.0007	0.006	0.0006	16.2	0.025	50	1.6	6	0.85	0.3	1.2	0.1	14.9	1.942	1.2
15th November (set 12)	05:00 AM - 02:00 PM	[7200, 9600, 13200, 18600, 22200, 23100]	[270, 120, 300, 210, 300, 270]	32400	64.8	10	0.0007	0.006	0.0006	16.2	0.025	50	1.6	6	0.85	0.3	1.2	0.1	14.9	1.942	1.2

4. Sensing, Control and Connectivity

The proposed sensing suite comprises battery voltage/current for an SOC proxy, compressor current, strategically placed temperature and pressure transducers, a door-state switch and an ambient probe. An accelerometer is included as an optional diagnostic channel to correlate shocks or vibrations with anomalies in temperature or compressor behaviour. On-vehicle control blends fast PI/PID loops with a supervisory inference module running on an edge gateway. Telemetry is buffered securely and transmitted opportunistically over LTE/Wi-Fi to a cloud environment that supports anonymised data ingestion, periodic model retraining, KPI dashboards (e.g., HACCP/GDP traceability, °C-minutes above threshold, kWh per route) and over-the-air (OTA) updates with appropriate signing.

The results for all four different scenarios are generated under varying conditions using the simulation environment. The collected data has been normalized and is illustrated as in Figure 8. These signals, irradiance, cooling demand, rotor speed, and evaporator temperature, are the ones available before the start of the journey, along with the target signal, the State of Charge (SOC), which we aim to predict.

Figure 9 represents Correlation Matrix that is the correlation between the signals, indicating which of them have a stronger effect on predicting the SOC. Figure 10 presents SOC prediction results, i.e. the outcomes of SOC prediction across different scenarios, with an average accuracy of approximately 96% for all generated cases.

The most important capability of the trained AI model is its ability to accurately predict the SOC of the battery during a journey under different conditions. By incorporating traffic data obtained from Google APIs, the Digital Twin will be able to estimate whether the battery can sustain the entire journey or not.

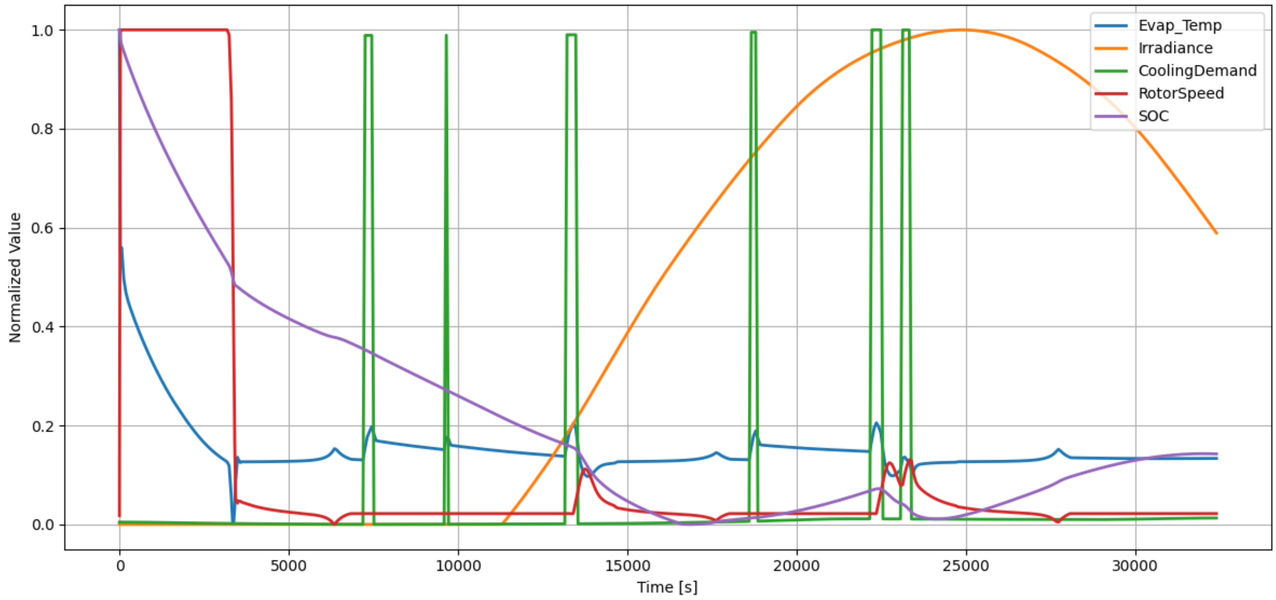

Figure 8: Normalized real-time trend of the main features contributed to ML model

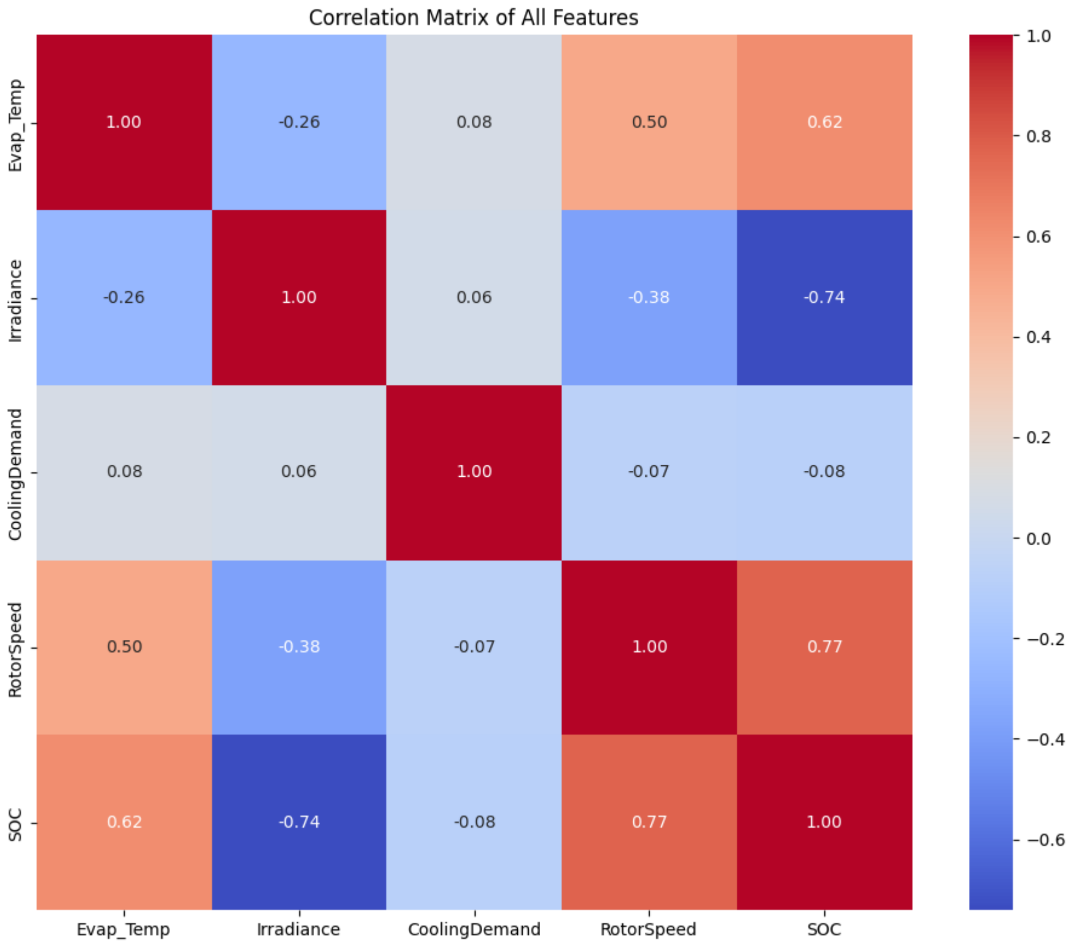

Figure 9: Correlation matrix of contributing features to ML model

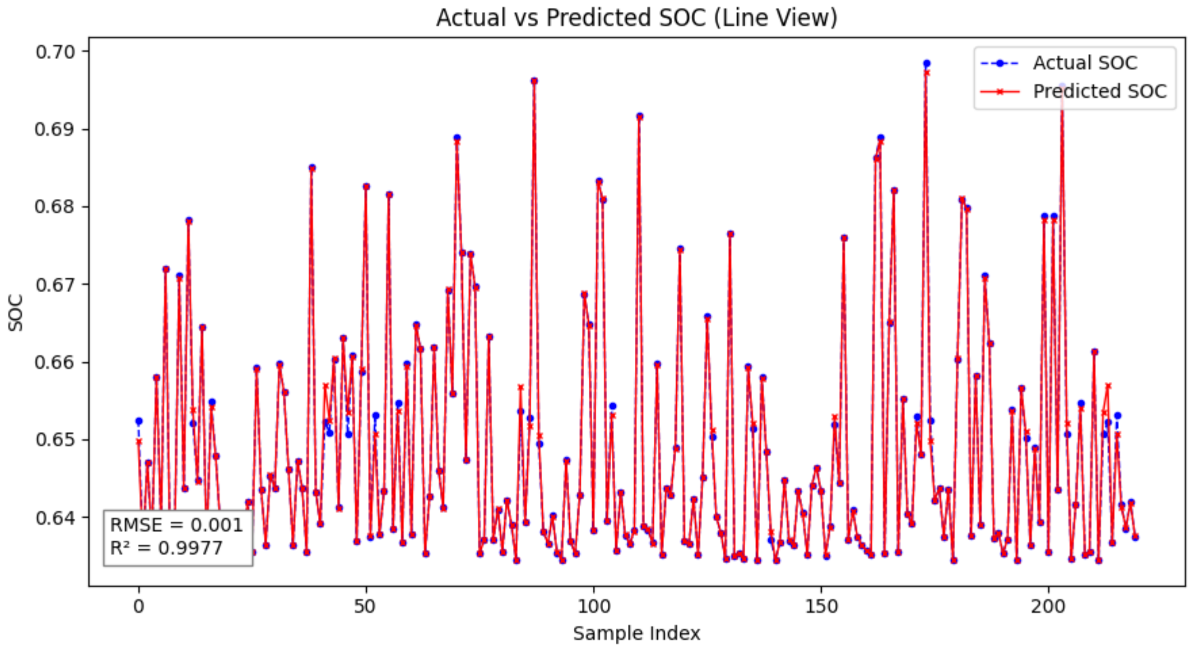

Figure 10: Validation of ML model performance in State of Charge of battery

Project Impacts and their realisation
Technical and innovation impact (de-risking clean cold on EV vans): The project delivered a high-fidelity, system-level Modelica digital twin of a solar-assisted, PCM-buffered refrigerated van, coupled with an AI-assisted supervisory layer for energy-aware temperature control. This directly addresses the core barrier to adoption in clean-air-zone logistics: maintaining temperature compliance without jeopardising operational energy autonomy. **Operational impact (predictive capability enabling better decisions):** The digital twin generated structured datasets used to train a Random Forest model that predicts short-horizon battery state of charge (SOC) with a mean accuracy of ~96% across representative delivery scenarios. This capability supports: (i) pre-trip feasibility checks and pre-cool planning; (ii) in-trip anticipatory control (compressor speed and setpoint shaping) to reduce temperature excursions; and (iii) a pathway to continuous improvement once telemetry is available from pilots. **Market-facing impact (evidence-led value proposition and traction plan):** Stakeholder engagement, including a ~30 retailer survey at Birmingham Wholesale Market, anchored modelling assumptions in real operational realities (mixed product classes, stop-dense morning routes, diesel-dominated fleets, and sensitivity to CAZ/ULEZ constraints). This evidence base informed the business model/canvas and a practical traction pathway from

pilot to scale, including service-led offerings (hardware + analytics) and compliance-oriented reporting potential.

Policy and regulatory impact (alignment and risk reduction): The work produced a policy framework to align pilots and scaling with UK regulatory drivers affecting clean cold and vehicle operations (e.g., low-GWP refrigerant direction of travel, ZEV mandate context, and CAZ/ULEZ operational constraints). This provides a clearer compliance narrative for adopters and de-risks implementation planning.

Realisation route and follow-on: Realisation is staged and credible. A final stakeholder meeting on 29 August 2025 confirmed readiness to proceed to a contained pilot; the defined next steps prioritise IoT deployment, pilot trials, and optimisation (solar+battery+PCM) with lifecycle cost/emissions assessment and expanded market data (food and pharma) through Impact Fund (RKE) provided by Aston University (Grant No. 21273).

Next Steps and outlook

a) **Deployment of the IoT module and trial tests of the integrated system in a pilot vehicle.**
b) **Optimisation** of integrated solar+battery+PCM for refrigerated transportation in terms of weight, life-cycle cost and life cycle emissions.
c) **Business model** for the new technology and inclusion of market assessment data in the pharmaceutical and food delivery sectors into the techno-economic optimisation
d) **Policy and regulation assessment** and recommendations for both DESNZ and DEFRA to not only explore the energy and sustainability related regulations related to cold transportation, but also food and pharmaceutical supply chain
e) A key **fast-paced issue** in refrigerated transportation is the increasing demand for same-day refrigerated delivery and the need to maintain strict temperature control during transit. This is driven by consumer expectations for speed and freshness, particularly for perishable goods. Does this technology address this challenge?
f) **CFD and experimental assessment** of State and state of charge estimation for the latent heat storage.

Acknowledgements

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