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Sustainable refrigeration technology selection: An innovative DEA-TOPSIS hybrid model

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ABSTRACT

This study proposes a novel multiple criteria decision making (MCDM) framework aimed at selecting refrigeration technologies that are both carbon- and energy-efficient, aligning with the UK’s net-zero policies and the UN’s Sustainable Development Goals (SDGs). Addressing the challenge of a limited number of competing technologies and the need to incorporate diverse stakeholders’ perspectives, we design a hybrid DEA-TOPSIS approach utilizing the Feasible Super-Efficiency Slacks-Based Algorithm (FSESBA). FSESBA proves invaluable, especially in scenarios involving super-efficiency or efficiency trend measurement, where addressing undesirable factors may lead to the well-known infeasibility problem. While we establish the theoretical soundness of the DEA-TOPSIS model, we validate the efficacy of our proposed approach through comparative analysis with conventional methods. Subsequently, we evaluate the choices of present and upcoming refrigeration technologies at a leading UK supermarket. Our findings reveal a shift from prevalent HFO-based technologies in 2020 to CO2-based technologies by 2050, attributed to their lower energy usage and GHG emissions. In addition, maintaining current refrigeration systems could contribute to achieving international and national targets to decrease F-Gas refrigerant usage, although net-zero targets will remain out of reach. In summary, our research findings underscore the potential of the introduced model to reinforce the adoption of novel refrigeration system technology, offering valuable support for the UK SDGs taskforces and net-zero policy formulation.

1. Introduction

The UK’s commitment to achieving net zero by 2050 signifies a significant milestone, positioning the nation as a global leader in sustainability. This ambitious goal is underpinned by a comprehensive strategy outlined by the Department for Business, Energy, and Industrial Strategy (BEIS) in 2021. This strategy emphasizes emission reduction, creation of green economic opportunities, and promotion of increased private sector investment (BEIS, 2021).2 This commitment is in accordance with the UK’s SDG13, particularly focusing on SDG13.2, which emphasizes the integration of climate change measures into national policies, strategies, and planning. This integration involves thoughtful consideration of total greenhouse gas (GHG) emissions annually.3

Furthermore, the UK has played a pivotal role in adopting the 2030 Agenda for Sustainable Development and the SDGs since 2015. This commitment is evident in the UK’s inaugural Voluntary National Review,4 which highlights efforts across all 17 Goals. Notably, the UK

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1 We are grateful to all project academics and industrial partners for the valuable comments they provided to this study. Bing Xu acknowledges the UK Energy Research Centre (UKERC) project “Sustainable food cold-chains”, UK Research and Innovation funding of the project “Zero Emission Cold-chain (ZECC)” (EP/V042548/1). Mehdi Toloo acknowledges REFRESH - Research Excellence For REgion Sustainability and High-tech Industries [CZ.10.03.01/00/22_003/0000048 via the Operational Programme Just Transition]. The standard disclaimer applies.
3 https://sdgdata.gov.uk/13/#;--text=Take%20urgent%20action%20to%20combat%20climate%20change%20and%20its%20impacts&text=With%20particular%20focus%20on%20natural%20disasters.

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remains committed to spending 0.7% of Gross National Income (GNI) on Official Development Assistance to support international goals. While the report highlights progress in crucial areas such as healthcare, education, employment, climate, and equality, it also identifies challenges in addressing climate issues and supporting a growing population. In addition, it outlines the UK’s strategic initiatives, manifested through various taskforces, aimed at advancing specific SDGs, such as increase sustainability, productivity and resilience in agriculture, fishing, food, and drink sectors (SDG2 and SDG12), unleashing innovation and accelerating science and technology nationwide to enhance productivity and amplify the UK’s global influence.

The optimization of cold chain stands as a cornerstone of the UK’s sustainability endeavours, playing a crucial role in safeguarding perishable products, prolonging their shelf life, and reducing food waste and loss. However, current estimations reveal concerning levels of emissions associated with refrigerant leakage, diesel fuel used by transport refrigeration units (TRUs), and electricity consumption (Foster et al., 2023). These emissions total an estimated 14.1 million tonnes of carbon dioxide equivalent (CO₂e) annually, representing 3.5% of the UK’s total annual territorial GHG emissions. Additionally, the energy consumption attributed to the food cold chain contributes to 2–4% of UK’s overall GHG emissions (Cold-Chain-Federation, 2022a).

Notably, refrigeration systems within UK supermarkets consume approximately 1% of the nation’s electricity, while accounting for 30–60% of the energy consumed by the supermarkets (Filta, 2019).

The UK is committed to reducing HydroFluoroCarbon (HFC) emissions by 85% by 2036, in accordance with the Kigali Amendment to the UN Montreal Protocol (DEFFRA, 2017), highlights the necessity for rapid and transformative action. Given that the UK food and beverage cold chain produced 6.204 MtCO₂e of F-Gas in 2017, adhering to business-as-usual (BAU) practices would impede the UK’s ability to meet its obligations and environmental targets. To address these challenges, the UK government has dedicated £75 million in funding towards Research & Development (R&D) projects aimed at achieving net-zero utilization of natural resources, waste, and F-gases by the year 2037. This funding represents a significant portion of total national and climate fund (~10%), underlining the importance of improving food and food refrigeration technology in the UK. Therefore, the food and drink industry must prioritize environmentally conscious business decisions, with the adoption of sustainable refrigeration systems emerging as a viable approach.

Significant advancements have been made in food refrigeration systems, addressing various aspects to enhance energy efficiency and refrigerant management. These advancements include automation, compressor controls, energy storage (thermal and electrical), evaporative and adiabatic condensers, heat exchangers, the use of low global warming potential (GWP) refrigerants, temperature control, among others (Daly, 2006; Evans, 2009). Emerging energy-efficient technologies, such as hydrate-based refrigeration systems, are being introduced to the market (Matsuura et al., 2021). Technological advancements have led to the development of alternatives to high GWP refrigerants (e.g., HFC) with the lower GWP options such as Hydrofluoro-Olefins (HFO), CO₂, and natural refrigerants (Choudhari and Sapalli, 2017; Girotto et al., 2004; Minor and Spatz, 2008). Recently, Hua et al. (2022) assessed the carbon dioxide hydrate-based vapor compression refrigeration system, considering technical aspects separately. However, the food and drink sector encounters considerable hurdles as it strives to balance emissions reduction, cost reduction, and meeting customer demands. Hence, there is an urgent need to support businesses in navigating these challenges by assisting them in selecting the most suitable low carbon equipment, improving the efficiency of existing equipment, and transitioning away from high GWP refrigerants5 (Cold-Chain-Federation, 2022b).

5 https://www.coldchainfederation.org.uk/download/cold-chain-report-23/

1.1. Motivation

Many studies assessing refrigeration technologies have typically focused on singular aspects or examined different dimensions separately. For instance, Sharma et al. (2014) analysed various CO₂ configurations in supermarket refrigeration systems in the US while primarily considering the operation criteria. Similarly, Cui et al. (2020) conducted a feasibility analysis of CO₂ booster refrigeration systems in China, but evaluated energetic, economic, and environmental aspects independently. Yet, there is limited research that integrates all dimensions of sustainability—economic, environmental, and social—into the selection process for current and future cold-chain technologies, especially refrigeration systems. Furthermore, addressing the need for sustainable refrigeration technologies requires considering stakeholders’ viewpoints across short, mid, and long-term horizons. Therefore, employing multiple criteria/attribute decision analysis (MCDM) models become crucial, as businesses are more inclined to embrace and scale-up the adoption of novel technologies that align with economic, environmental, and social objectives simultaneously (Kersten et al., 2015).

Given the extensive array of criteria, solutions and technologies involved, MCDM has gained its importance in Technology Assessment/Technology Selection (TA/TS). Kozłowska (2022) conducted a systematic literature review on the MCDM models and applications, highlighting their prominent role in assessing the importance of technologies in energy intensive industries across various dimensions of criteria. Stojic et al. (2019), Badi et al. (2023), Huang et al. (2023) and Banadkouki (2023), and Ding et al. (2023) highlighted that TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) remains one of the most popular MCDM model. Additionally, outranking methods such as ELECTRE (Roy, 1968), and PROMETHEE (Jean-Pierre, 1982) are also widely used in practice, albeit each with its own set of flaws and limitations (Anand and Kodalii, 2008; Del Vasto-Terrientes et al., 2015; Rogers et al., 2013; Zandi and Roghanian, 2013). For example, one of the key shortcomings for TOPSIS is the use of hypothetical ideal and anti-ideals. Furthermore, the three of TOPSIS, ELECTRE and PROMETHEE rely on predefined relative importance (weights) for the criteria, which may not suitable in our case, as the relative importance may vary depending on the state of the technological development (Pohekar and Ramachandran, 2004). Last, but not least, although, TOPSIS aims to identify both an ideal and an anti-ideal solution, representing the best and worst values across all criteria, respectively, from the theory of trade-offs in operations management perspective, in a real market, rivals (competing firms), in short term, cannot improve in different production dimensions simultaneously, especially when they are working on or close to the production frontier (Sousa et al., 2023). Hence, TOPSIS’ ideal and anti-ideal points are often regarded as unattainable benchmarks for the alternatives, diminishing the reliability of this model.

Another widely used methodology in TA/TS studies is DEA model. However, conventional DEA models are criticized for their low discrimination power, particularly when the number of alternatives is low relative to the number of criteria (Chen, 2004; Jahanshahlo et al., 2005). In such cases, it is recommended to employ super efficiency alterations of the models to enhance their discrimination power (Andersen and Petersen, 1993). Nonetheless, in presence of undesirable factors such as emission, DEA super-efficiency and efficiency trend measurement models such as Directional Distance Function (DDF) or Slacks-Based Model (SBM) face a prevalent infeasibility problem when incorporating undesirable criteria (Arabi et al., 2015; Färe et al., 2001).

In this study, our primary objective is to propose a reliable MCDM framework capable of simultaneously incorporating multiple criteria, including undesirable factors (e.g., emissions), while evaluating a small number of competing alternative technologies. Additionally, we aim to demonstrate how our proposed model in sustainable refrigeration system TA/TS can aid in the execution of UK SDG taskforces.
1.2. Contribution

The innovation of this research lies in leveraging the novel DEA-TOPSIS model to tackle the challenges posed by the presence of undesirable variables, offering a robust and offering a robust and infeasibility-free framework with significant discrimination power, particularly when the number of alternatives (refrigeration technologies) is relatively low. Our major contributions can be summarized as follows. First, we introduce FSESBA, a novel approach that expands the scope of applications by addressing challenges in measuring super-efficiency, particularly in scenarios involving undesirable criteria. Note that FSESBA not only overcomes the infeasibility problem commonly encountered in such cases but also enhances the infeasibility-free algorithm proposed by Arabi et al. (2015) for evaluating the Malmquist-Luenberger Index (MLI). Secondly, the proposal of the DEA-TOPSIS approach employing FSESBA to effectively evaluates efficiency scores and ranks alternatives, especially valuable with a small number of alternatives relative to the criteria combined with undesirable criteria. Furthermore, our UK case studies provides a real-world context for evaluation, offering practical implications and relevance to the refrigeration industry in the country. This approach enhances the credibility and applicability of the findings that align with sustainable practices making them more practical for industry professionals, policymakers, and other stakeholders. The framework’s adaptability and versatility ensure that it can be extended to other regions and industries facing similar challenges, broadening the impact and significance of this research beyond the confines of the UK refrigeration sector.

1.3. Outline

The rest of the paper is organized as follows. Section 2 presents a review of the literature on TA/TS method, with a particular focus on refrigeration system technologies. Section 3 outlines our research framework, including the case study, criteria selection processes, and scenario developments. Section 4 shows our proposed methodology for evaluating competing refrigeration systems and empirical results. Then in Section 5 we discuss the empirical and methodological implications and future studies, suggest policies, and strategies following the UK net zero policies framework. Section 6 offers concluding remarks and pinpoints potential avenues for future studies.

2. Literature review

Technology assessment/selection plays a pivotal role in facilitating the acquisition of novel knowledge, components, and systems, thereby empowering companies to develop more competitive products and services, streamline processes effectively, and foster the creation of innovative solutions. (Houseman et al., 2004). It is widely acknowledged that each technology comes with its own set of advantages and drawbacks, influencing the TA/TS process (Hamzeh and Xu, 2019). Note that TA/TS is a multifaceted process that involves considering multiple criteria and attributes, which may encompass qualitative, quantitative, or mixed category types (Saen, 2006). Additionally, decision support system should consider not only internal but also external factors, such as the technology’s impact on employment, to facilitate optimal TA (Elahi et al. 2011).

In this section, we first examine the relevant prior studies around TA/TS that have utilised MCDM methods. Next, we delve into an analysis of sustainable cold chain technology studies. Lastly, we discuss key supermarket refrigeration technologies within the UK context.

2.1. Prior studies around TA/TS

2.1.1. Employing SDGs as Key Criteria for TA/TS

Following the declaration of SDGs, numerous sustainability assessment studies have integrated these goals into the models. For instance, Allen et al. (2019) utilized a series of MCDM models to evaluate the ‘level of urgency’, ‘systemic impact’, and ‘policy gap’ in achieving SDGs across 22 Arab countries. Similarly, Olabi et al. (2022) conducted a comprehensive study on re-combustion, a promising carbon capture technology, analysing its impact on SDGs across economic, environmental, and social aspects of sustainable development. While such studies demonstrate the significant contributions of certain technologies to SDGs, Janousková et al. (2018) emphasized the importance of a well-designed, conceptual indicator framework for selecting and/or designing criteria to assess the SDGs. The absence of such framework could lead to ambiguous results, hindering the accuracy in evaluating progress towards SDGs.

In one line of research, DEA models have demonstrated substantial promise in assessing progress towards achieving the SDGs. For instance, Koçak et al. (2021) examined the environmental efficiency of R&D expenditures across various energy-related domains (e.g., energy efficiency, renewable energy, power and storage technologies) in OECD countries, employing DEA. Pereira et al. (2021) investigated convergence in productivity across World Health Organisation (WHO) member states, analysing performance in achieving the UN’s SDG3 (Good health and well-being) using DEA, finding varying levels of convergence and divergence across WHO regions. Pereira and Marques (2021) examined the progress of low- and middle-income UN Member States towards achieving SDG 6 (Water and sanitation) and proposed policy implications. Recently, Soltanifar et al. (2023) introduced an integrated framework combining multi-attribute decision-making and DEA models to address heterogeneous attribute problems, applied to evaluate European countries’ fulfilment of SDG, offering minimized computational complexity and independence from expert-defined weights for ranking determination, with comparisons to standard MCDM techniques.

2.1.2. Applications of MCDM Models

A diverse array of MCDM models have been developed and applied in the assessment of TA/TS. Streimikiene et al. (2013), for instance, utilized an interval TOPSIS approach to rank order competing road transport technologies based on private costs and atmospheric emissions. Recently, Yang et al. (2023) utilized a stakeholder participation-based q-rung orthopair linguistic multi-criteria framework in order to identify the best alternative low-carbon fuels technologies. Mehdiabadi et al. (2013) augmented DEA with TOPSIS to address the limitations of DEA’s alternative efficient units. Lofti et al. (2011) employed TOPSIS following a DEA ranking model to obtain a comprehensive ranking of efficient Decision-Making Units (DMUs). Wang and Luo (2006) introduced a DEA-TOPSIS model incorporating a virtual DMU, critiqued for its utilization of a non-real (virtual) DMU. Later, a DEA-TOPSIS approach that uses the best and worst practice model to identify TOPSIS’s ideal and anti-ideal introduced by Venkata Subbaiah et al. (2014), yet, they did not address the issue of alternative best and worst practices common in DEA models with few DMUs.

Incorporating undesirable factors in efficiency measurement presents a variation in DEA studies. Some approaches use theoretical developments such as the hyperbolic efficiency model (Boyd and McClelland, 1999), SBM (Tone, 2001), range adjusted measure (RAM) model (Zhou et al., 2006) and directional distance function (Faure and Grosskopf, 2000, 2010a; Faure et al., 2007; Picaio-Tadeo et al., 2005; Sahoo et al., 2011). Despite their popularity, DDF and SBM are known to face an infeasibility problem, particularly in efficiency trend measurement studies to calculate the MLI (Chung et al., 1997; Faure et al., 2001). The infeasibility problem can occur in mixed period models as well as super-efficiency measurement problems, when a DMU is located beyond the frontier. Arabi et al. (2015) introduced an algorithm to calculate efficiency trends using MLI by applying a SBM model. Recently, Tone et al. (2020) modified the SBM model to measure SBM-efficiency score of inefficient units and super SBM-efficiency score of strong efficient units, simultaneously.
2.2. TA/TS in food and cold-chain industry

One strand of the literature focused on evaluating refrigeration systems. Chadderton et al. (2017), for example, introduced a model for selecting an appropriate food waste management technology. Islam et al. (2021) proposed a hybrid fuzzy AHP (Analytic Hierarchy Process) -TOPSIS for selecting the most sustainable food supply chains. Qian et al. (2022) developed a monitoring system using sensing information to collect and analyse whole cold chain data to improve the equipment efficiency. However, Kozlovska (2022) highlighted that despite energy, renewable energy, sustainable technologies, and waste management being among the top industries employing MCDM models for TA/TS, the food and food cold-chain have not effectively employed these methods.

Despite the importance of making informed decisions around technology upgrade/change/replacement on cold stores or refrigeration systems, there are limited studies in the literature (Cold-Chain-Federation, 2022b). For instance, Sharma et al. (2014) studied various CO₂ configurations in the US supermarket refrigeration systems based on operational criteria, while Savalha et al. (2017) compared HFC refrigeration systems with CO₂ trans-critical refrigeration systems in Sweden also included operation criteria only. Alrwashdeh and Ammari (2019) evaluated the life cycle analysis of two different refrigeration systems powered by solar energy considering cost variables. More recently, Sleiti et al. (2020) explored innovative thermo-mechanical refrigeration systems using low-grade heat, primarily from a technical perspective. Cui et al. (2020) conducted energetic, economic, and environmental analyses separately to identify the best CO₂ booster refrigeration systems in China.

While some research projects address the performance and priorities of single technology from a single dimension, there is a lack of comprehensive studies on refrigeration systems in the UK market. For example, Efstratiadi et al. (2019) conducted a pre-feasibility study investigating the impacts of using a water-cooled configuration rejecting heat to the soil on the overall cooling performance of commercial refrigeration systems against air-cooled designs, considering both technical and economic aspects. Maouris et al. (2020) assessed the performance of a refrigeration integrated heating and cooling system installation with thermal storage in a UK supermarket using technical and economic criteria. Hua et al. (2022) evaluated a CO₂ hydrate-based vapor compression refrigeration system from technological (thermodynamics) and economics aspects by using load shifting controls in summer. The reader is referred to Appendix A Table A1 for a summary of models and criteria been applied in TA/TS.

2.3. Refrigeration system in the retail sector

Appendix A Table A2 provides a summary of new refrigeration systems that are currently being deployed by supermarkets worldwide, which encompass two types of refrigeration systems: those based on specific refrigerants and those focused on technologies regardless of the refrigerants used. In section R.3.1, we offer a more detailed discussion of the direct expansion and single temperature range unit technologies.

CO₂ serves as an excellent refrigerant due to its highly favourable heat transfer coefficient. It remains relatively unaffected by pressure losses, boasting an exceptionally low viscosity. Additionally, it stands as an appealing choice with zero ozone depletion potential (ODP) and a GWP of just 1. Numerous studies have emphasized the superior properties of CO₂ as a refrigerant compared to HFO/HFC, considering both energy efficiency and environmental factors (Arami-Niya et al., 2020; Karampour and Sawalha, 2019).

The direct expansion system has been experiencing rapid growth due to its ability to eliminate much of the ductwork and piping. The popularity of this system stems from the simplified installation process, consequently reducing the overall system cost. In the Direct Expansion (DX) System, the evaporator is placed in the space to be refrigerated. As the refrigerant in the evaporator coil expands, it cools the space by absorbing the heat from it (Llopis et al., 2017).

The single temperature range unit is a cooling technology that can be configured in various sizes and formats. This technology finds applications in refrigeration, freezer, air conditioner or even heat pump. The units are easily upgradable, with air as secondary refrigerant, and can be adapted for use in medium temperature display cases and cold rooms. Single temperature range unit refrigeration technology offers several advantages, including simplistic design, direct connection to drains, minimum air spillage from the display cases, and compatibility with any refrigerants (Hsu et al., 2013).

Hydrocarbons (HC) refrigerants have attracted attention due to their zero GWP, high efficiency, reduced charge sizes, and other favourable properties (Corberan et al., 2008). Despite their flammability, HC refrigerants offer benefits such as low lower compressor discharge temperatures and improved heat transfer within heat exchangers. In addition, more studies have focused on identifying channels to enhance the refrigeration cabinets’ efficiency via cabinet lighting controls and increased cabinet set points, and fitting doors on open-fronted cabinets, all of which contribute to significant energy savings (e.g., Mouss et al., 2014) (Lindberg, 2020; de Fries et al., 2020; Rolfsman et al., 2014).

In summary, our paper contributes theoretical advancements and practical insights to the field of TA/TS. First, we introduce an advanced MCDM framework that tackles the challenges of alternative ideal and anti-ideals while incorporating novel SBM super-efficiency DEA models with desirables, thus overcoming prevalent infeasibility problem. Additionally, our study provides practical insights into the adoption of refrigeration systems that align with sustainable practices and contribute to a greener future.

3. Research framework

Following the Design Science Research Methodology (DSRM) approach introduced by Peffers et al. (2007), our study presents a novel framework designed to evaluating the attractiveness of competing refrigeration technologies and devising a decision-support system to aid stakeholders in making well-informed decisions (see Table 1 and Table 2).

The use of the DSRM in conjunction with DEA has gained significant traction in recent years. For instance, Charles et al. (2019) employed DSRM in their research to address the issue of dimensionality in DMUs within a DEA model. Following this, Tsolas et al. (2020) utilized DSRM for the performance assessment of bank branches through a DEA-Artificial Neural Network (DEA-ANN) approach. In another notable study, Antunes et al. (2024) applied DSRM and DEA to evaluate the cost efficiency of Chinese banks using Multi-Layer Perceptron with Symmetrical Synthetic Relevance Plotting (MLP-SSRP) analysis. Zhu et al. (2022) implemented a DEA-DSRM method to assess the environmental efficiency of the EU, focusing on fixed cost allocation and various decision goals. Additionally, Omran et al. (2023) developed a research methodology using DSRM to evaluate bank branches within a DEA model under discrete scenarios. Most recently, Ma and Li (2024) introduced a novel parallel framework algorithm for solving large-scale DEA models using a DSRM approach. We draw insights from the DEA-DSRM literature and construct our research framework using the DSRM approach, as outlined in Table 1.

3.1. Case study development

Concurrently, the Cold Chain Federation, acknowledging the pressing challenges at hand, emphasizes actions to: 1) curb emissions; 2) reduce costs; and 3) meet customer demands within temperature-controlled logistics businesses. These actions include strategic investments in low-carbon, low energy equipment, optimizing the energy efficiency of existing equipment, and phasing out high GWP refrigerants.

In our evaluation of alternative refrigeration technologies, we have selected five sustainable options for consideration: DX HFO; HFO-Single...
Table 1

<table>
<thead>
<tr>
<th>DSRM Activities</th>
<th>Description</th>
<th>Knowledge Base</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Problem Identification &amp; Motivation</strong></td>
<td>- We identify issues with TOPSIS in ranking competing refrigeration technologies.</td>
<td>- Literature review. - Preliminary analysis of the current research case.</td>
</tr>
<tr>
<td></td>
<td>- Conventional DEA models face challenges in providing complete rankings, especially with limited number of alternatives or include undesirable criteria.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- DDF-SBM-DEA models encounter potential infeasibility issue in presence of undesirable factors.</td>
<td></td>
</tr>
<tr>
<td><strong>Define the Objectives</strong></td>
<td>- Developing a DEA-TOPSIS approach to enhance TOPSIS’s result by utilizing DEA approach.</td>
<td>- Pinpoint TOPSIS &amp; conventional DEA models’ drawbacks.</td>
</tr>
<tr>
<td><strong>Design &amp; Development</strong></td>
<td>- Developing the FSESBA algorithm and associated DEA models to identify the ideal and anti-ideal solutions using TOPSIS.</td>
<td>- Understanding the challenges in sustainable refrigeration system TA/TS.</td>
</tr>
<tr>
<td></td>
<td>- The DEA-TOPSIS approach is introduced to achieve a complete ranking.</td>
<td></td>
</tr>
<tr>
<td><strong>Demonstration</strong></td>
<td>- Application of the DEA-TOPSIS approach for refrigeration systems TA/TS using the developed scenarios in the UK.</td>
<td>- Utilising the model/approach introduced.</td>
</tr>
<tr>
<td><strong>Evaluation</strong></td>
<td>- Discussions and robustness check. - Deriving policy implication.</td>
<td>- Understanding of current solution &amp; its advantages.</td>
</tr>
</tbody>
</table>

Table 2

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Definition &amp; measures</th>
<th>Inputs/ Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Energy</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy Demand (E_D)</td>
<td>Energy Demand (ED) by implementing the new refrigerant system is computed as follows: [ ED = PE \times UEP ]</td>
<td>Input</td>
</tr>
<tr>
<td>Environmental Emission (AE)</td>
<td>This measures the total annual emission (AE) of each refrigeration system including both direct annual emissions (AE_d) and indirect annual emissions (AE_i) and is calculated as follows: [ AE = AE_d + AE_i ] where [ AE_i = PE \times UEP \times \frac{1,000,000}{GDF} ] and GDF is the grid emission factor.</td>
<td>Undesirable Output</td>
</tr>
<tr>
<td><strong>Economical</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investment cost (CAPEX)</td>
<td>The capital investment required to implement an intervention over a BAU scenario.</td>
<td>Input</td>
</tr>
<tr>
<td>Operating Costs (OPEX)</td>
<td>This criterion consists of ongoing costs required over the intervention period such as additional costs of maintenance to ensure system safety and avoid any system failures as well as the carbon tax.</td>
<td>Input</td>
</tr>
</tbody>
</table>

3.2. Scenario development

The pathways of refrigeration technologies toward the net-zero 2050 target are influenced by several key factors, which we consider in constructing our scenarios. These scenarios are built upon three foundational pillars: 1) supermarket BAU and information; 2) UK policies and plans; and 3) future forecasts.

Moreover, assuming that the CAPEX and OPEX will remain unchanged over 2020–2050 period, we identify supermarket refrigerant leakage, UK grid emissions, and carbon tax/price variables as the most important drivers of the economic and environmental variables of technology selection over the long term in shaping the scenarios:

- **Supermarket Refrigerant Leakage**: Our assessment of under-reported supermarket data reveals that refrigerant leakage was at a 10% level in 2020. The UK has committed to significant reductions in HFCs, as mandated by EU and Montreal Protocol obligations. In

fact, the UK must halve the refrigerants’ emissions from 40 MtCO₂e in 2020–20 MtCO₂e by 2035 and later cut all the refrigerants emissions by 2050 (BEIS, 2021). To align with UK government policies and stakeholders’ preferences, we develop the refrigerant reduction scenarios, as indicated in Fig. 1.

- **UK Grid Emissions**: despite extensive research has examined UK grid emissions, Energy and Emission Projection (EEP) reports serving as reliable sources for past, present and future projections. Leveraging data from on EEP2017 and EEP2018, Inter-seasonal Heat Transfer, ICAX, estimates the UK grid emission for every year in 2018–2035 period. Then, ICAX extends this estimation to 2050 by considering SAP10 and SAP2012 reports.

- **Carbon Tax/Price**: carbon tax/price is a critical sub-criterion of OPEX and obtaining reliable data is essential for our analysis. While various sources offer such data, it is important to ensure that is aligns with our objectives and timeframe. We have chosen to utilized data from the “Future of Carbon Pricing in the UK study and Carbon Pricing Leadership Coalition” (CLPC) to develop our scenarios (Vivid-Economics-Limited, 2019) Table 3.

Given the data of the under-assessment supermarket is from 2020, in the end, we opt to employ the data provided by the 2020, 2035, and 2050 Scenarios. Our scenarios, based on the Cold-Chain-Federation (2020) report, we take the BAU as the baseline as the main references to put forward the following scenarios: (Table 3)

The reader is referred to Appendix A Table A3 for the normalised dataset.

4. **Methodology**

In this section, we present an innovative DEA-TOPSIS hybrid model to select alternative sustainable refrigeration technologies.

4.1. **TOPSIS**

Conventional TOPSIS, based on the idea of measuring the best rank of a chosen alternative among the other that can be measured by its distance to the ideal and anti-ideal (Hwang and Yoon, 1981). The alternative closest to the ideal or farthest from the anti-idea is considered the best within the group. This evaluation applies to a set of homogenous alternatives with identical criteria set. The ideal represents a hypothetical alternative achieving the highest measures across all criteria, while the anti-ideal represents one with the lowest measures. The key merits of TOPSIS relays its simplicity to use and generate ranking efficiently, regardless the number of alternatives and criteria.

4.2. **DEA**

DEA stands as one of the prominent methodologies for evaluating efficiency of DMUs, employing a non-parametric frontier mathematical programming approach. The concept behind DEA is measuring efficiency using a technical production frontier as initiated in Farrell (1957), and later extended to cases with multiple-inputs multiple-outputs by Charnes et al. (1978), after which many theoretical and empirical studies followed this idea (Cook and Seiford, 2009; Emrouznejad et al., 2008; Seiford, 1996).

4.2.1. **Proposed Approach**

Our aim is to introduce a tailored TA/TS model suitable for scenarios with a limited number of alternatives. As discussed in Section r1.1, TOPSIS has areas for improvement, and Section r5.1, will highlight how TOPSIS inadequately responds to the designed scenarios. Hence, we enhance the TOPSIS model by initially identifying its ideal and anti-ideal through the application of DEA as it is indicated in Fig. 2.

Recall that the discriminatory power of the conventional DEA model diminishes significantly when the number of alternatives (DMU’s) is low relative to the number of inputs and outputs, as is the case in our study.
Moreover, incorporating an undesirable output in the model necessitates calculating a SBM score of inefficiency, incorporating undesirable outputs as productivity measures. Arabi et al. (2015) presented Model (1) for calculating a SBM score of inefficiency, incorporating undesirable outputs as follows:

\[
\bar{D}_O(x, y, b) = \max \beta_1 + \cdots + \beta_j + y_1 + \cdots + y_K 
\]

subject to:

\[
\sum_{n=1}^{N} z_n x_{in} \leq x_{ii}; \ i = 1, \ldots, I 
\]

\[
\sum_{n=1}^{N} z_n y_{jn} \geq y_{jo} + \gamma_j; \ j = 1, \ldots, J 
\]

\[
\sum_{n=1}^{N} z_n b_{kn} = b_{ko} - y_k; \ k = 1, \ldots, K 
\]

\[z_n \geq 0, \gamma_j \geq 0; \beta_j \geq 0; \ n = 1, \ldots, N; \ j = 1, \ldots, J; k = 1, \ldots, K\]

Then, we can write the production possibility set (PPS) of Model (1) as:

\[
P_1(x, y, b) = \{ (x, y, b) | \sum_{n=1}^{N} z_n x_{in} \leq x_{ii}, \sum_{n=1}^{N} z_n y_{jn} \geq y_{jo} + \gamma_j, \sum_{n=1}^{N} z_n b_{kn} = b_{ko} - y_k \}
\]

where, \( x \in \mathbb{P}^I, \ y \in \mathbb{P}^J \) and \( b \in \mathbb{P}^K \) are inputs, outputs and bad outputs of DMUs, and \( j \) denotes the expansion or contraction ratio of good and bad outputs and \( D_o \) expands good outputs and contracts bad outputs simultaneously as much as feasible. \( a_1, \ldots, a_I, \beta_1, \ldots, \beta_J \) and \( y_1, \ldots, y_K \) are variable.

4.2.2. SBM score of inefficiency

The SBM score of inefficiency, introduced by Tone (2001), is one of the most prominent models in DEA literature. Tone (2010) further expanded this concept, developing variations to measure various productivity measures. Arabi et al. (2015) presented Model (1) for calculating a SBM score of inefficiency, incorporating undesirable outputs as follows:

\[
\bar{D}_O(x, y, b) = \max \beta_1 + \cdots + \beta_j + y_1 + \cdots + y_K 
\]

subject to:

\[
\sum_{n=1}^{N} z_n x_{in} \leq x_{ii}; \ i = 1, \ldots, I 
\]

\[
\sum_{n=1}^{N} z_n y_{jn} \geq y_{jo} + \gamma_j; \ j = 1, \ldots, J 
\]

\[
\sum_{n=1}^{N} z_n b_{kn} = b_{ko} - y_k; \ k = 1, \ldots, K 
\]

\[z_n \geq 0, \gamma_j \geq 0; \beta_j \geq 0; \ n = 1, \ldots, N; \ j = 1, \ldots, J; k = 1, \ldots, K\]

4.2.3. Infeasibility Problem in Presence of Undesirables

Arabi et al. (2015) highlighted the issue of infeasibility in situations of super efficiency, particularly when a DMU is located beyond the efficiency frontier. This challenge has been documented in various studies such as Färe et al. (2001); Chung et al. (1997); and Oh (2010). Similarly, the calculation of super efficiency using DDF DEA models can also encounter this infeasibility problem. It is important to note that non-radial DDF with undesirable outputs is vulnerable to this infeasibility problem, especially when applied to measure the MLI, as discussed by Wang et al. (2013).

To address this problem, several strategies have been proposed. Arabi et al. (2015) extensively discussed the strengths and weaknesses of these strategies and proposed an algorithm to tackle the infeasibility problem.

4.2.4. Adopting Arabi et al. (2015) approach to eliminate the infeasibility problem in Super-Efficiency Measurement

We reformulate model (1) for the DMUs located above the frontier as follows:

\[
\overline{D}_o(x, y, b) = \min \beta_1 + \cdots + \beta_j + y_1 + \cdots + y_K 
\]

subject to:

\[
\sum_{n=1}^{N} z_n x_{in} \leq x_{ii}; \ i = 1, \ldots, I 
\]

\[
\sum_{n=1}^{N} z_n y_{jn} \geq y_{jo} - \beta_j; \ j = 1, \ldots, J 
\]

\[
\sum_{n=1}^{N} z_n b_{kn} = b_{ko} - y_k; \ k = 1, \ldots, K 
\]

\[z_n \geq 0, \gamma_j \geq 0; \beta_j \geq 0; \ n = 1, \ldots, N; \ j = 1, \ldots, J; k = 1, \ldots, K\]

where \( a = (\beta_1, \ldots, \beta_J, y_1, \ldots, y_K) \). Model (3), unlike Model (1), seeks for the nearest direction toward frontier, since the DMUs below and above the frontier follow different paradigms.

Now we put forward the following axioms:
Axion 1: For the DMUs located below the frontier, those closer to the frontier are evaluated as being more efficient.

Axion 2: For the DMUs located above the frontier those closer to the frontier regarded as being less efficient.

In other words, in this case, the DMU located furthest away from the frontier, is the most efficient. Aiming at the super-efficiency measurement we rewrite Model (3) as below:

\[
\overline{D}_O(x, y, b) = \max \beta_1 + \cdots + \beta_J + \gamma_1 + \cdots + \gamma_K
\]

subject to:

\[
\sum_{n=1}^{N} z_n x_{in} \leq x_{0n}; \ i = 1, \ldots, I
\]

\[
\sum_{n=1}^{N} z_n y_{jn} \geq y_{jn} - \beta_j; \ j = 1, \ldots, J
\]

\[
\sum_{n=1}^{N} \bar{z}_n b_{kn} = b_{kn} - \bar{y}_k; \ k = 1, \ldots, K
\]

\[z_n \geq 0; \ \beta_j \geq 0; \ n = 1, \ldots, N; \ j = 1, \ldots, J; \ k = 1, \ldots, K\]

And the PPS corresponding to Model (6) can be written as below:

\[
P_6(x, y, b) = \left\{ (x, y, b) \left| \sum_{n=1}^{N} z_n x_{in} \leq x_{0n}, \sum_{n=1}^{N} z_n y_{jn} \geq y_{jn} + I_y \beta_j, \sum_{n=1}^{N} \bar{z}_n b_{kn} = b_{kn} - \bar{y}_k \right\} \right.
\]

where: \( I_y \in IY = \left\{ I_y \left| j = 2^i, 2^i - 1, \ldots, 2^0; I_y \left| j \in \{1, -1\}\right. \right. \}, \ I_y \in IB = \left\{ I_y \left| k = 2^i, 2^i - 1, \ldots, 2^0; I_y \left| k \in \{1, -1\}\right. \right. \}, \ i = 1,2,\ldots, 2^k\). In other words, \( IY \) is the set of all permutations of 1 and -1 in a J-dimension vector. Or equivalently, \( IB \) is the set of all permutations of 1 and -1 in a K-dimension vector.

Therefore, \( |IY| = 2^J, |IB| = 2^K \). If \( J = 2^k \) and \( K = 1 \), for example, then we obtain \( IY = \left\{ \left[ \begin{array}{c} 1 \\
-1 \\
-1 \\
1 \\
-1 \\
-1 \end{array} \right] \right\}, \ I_y = \left\{ \left[ \begin{array}{c} 1 \\
-1 \end{array} \right] \right\} \), \( IB = \left\{ \left[ \begin{array}{c} 1 \ \\
-1 \end{array} \right] \right\} \), and \( I_y \in IB \).

Theorem 1: \( P_1 \subseteq P_6 \).

Proof: first we assume:

\[
P_6(x, y, b) = \left\{ (x, y, b) \left| \sum_{n=1}^{N} z_n x_{in} \leq x_{0n}, \sum_{n=1}^{N} z_n y_{jn} \geq y_{jn} + I_y \beta_j, \sum_{n=1}^{N} \bar{z}_n b_{kn} = b_{kn} - \bar{y}_k \right\} \right.
\]

If we put: \( I_y \in \{1\} \rightarrow I_y = 1, I_y \in \{-1\} \rightarrow b_{k1} = b_{k1} \). Then we obtain:

\[
P_6(x, y, b) = \left\{ (x, y, b) \left| \sum_{n=1}^{N} z_n x_{in} \leq x_{0n}, \sum_{n=1}^{N} z_n y_{jn} \geq y_{jn} \right\} \right. \subseteq P_6(x, y, b)
\]

Therefore, we obtain \( P_1 \subseteq P_6 \).

Corollary 1: Theorem 1 implies that if \( D_{O1}(x, y, b) \) presents the optimum objective function value of Model (6) and \( D_{O1}(x, y, b) \) is the optimum objective function value of Model (1) for DMU, then \( D_{O1} \leq D_{O1} \). Consequently, according to Axion 2, it can be inferred that Model (6) offers superior solutions compared to Model (1).

We also introduce the following model to find the super worst practice DMU:

\[
\overline{D}_O(x, y, b) = \min \beta_1 + \cdots + \beta_J + \gamma_1 + \cdots + \gamma_K
\]

subject to:

\[
\sum_{n=1}^{N} z_n x_{in} \geq x_{0n}; \ i = 1, \ldots, I
\]

\[
\sum_{n=1}^{N} z_n y_{jn} \leq y_{jn} - I_y \beta_j; \ j = 1, \ldots, J
\]

\[
\sum_{n=1}^{N} \bar{z}_n b_{kn} = b_{kn} + I_k \gamma_k; \ k = 1, \ldots, K
\]

\[z_n \geq 0; \ \gamma_k \geq 0; \ n = 1, \ldots, N; \ j = 1, \ldots, J; \ k = 1, \ldots, K\]

Thus, the following new algorithm is proposed to improve the algorithm introduced in Arabi et al. (2015):

1. Examine if there are DMU’s that are located beyond the efficiency frontier.
2. If so, for every \( l=1, \ldots, 2^k \), deploy Model (6) to calculate \( D^l_0(x^l, y^l, b^l) \) and \( D^l_0(x^l, y^l, b^l) \) for the same DMUs put:
\[
D^l_0(x^l, y^l, b^l) = \min \{ D^l_0(x^l, y^l, b^l) \mid l=1, \ldots, 2^k \}
\]
and \( D^l_0(x^l, y^l, b^l) = \min \{ D^l_0(x^l, y^l, b^l) \mid l=1, \ldots, 2^k \} \).

3. Otherwise deploy Model (1) to compute \( D^0_0(x, y, b) \), \( D^0_0(x, y, b) \), \( D^0_0(x, y, b) \), and \( D^0_0(x, y, b) \) for all DMUs.

In the rest of this paper, we refer to this algorithm as FSEA (Feasible Super Efficiency Algorithm).

Here, we illustrate this case with a very simple example of single input and two outputs – one good and one bad. Here efficiency score is (1 - D).

In this example we have \( IY = \{1, -1\} \) and \( IB = \{1, -1\} \), then \( I = 1, 2, \ldots, 2^1 = 1, 2 \), therefore if we employ FSEA we need to run Model (4) four times using all permutations of \( I_1 = 1, I_2 = -1, I_3 = 1, \) and \( I_2 = -1 \).

Fig. 3 is a graphical presentation of Table 4, where \( P(x) \) is the production possibility set, in period \( t. DV_{t:1,0,2} \) is the shortest direction vector toward the frontier achieved by solving Model (4) for \( DMU_0 \), where \( I_1 = -1 \) and \( I_0 = 1 \), and \( D^0_2(x, y, b) = 0.375 \). In addition, \( DV_{t:1,0,4,6} \) is the shortest direction vector toward the frontier achieved by solving Model (3) for \( DMU_0 \) where \( I_1 = -1 \) and \( I_0 = 1 \) and \( D^0_6(x, y, b) = 0.5 \). Obviously, \( DV_{t:1,0,6} \) and \( DV_{t:1,0,6} \) do not intersect the frontier, therefore \( D^t_{1,6}(x, y, b) = \infty \) and \( D^t_{1,6}(x, y, b) = \infty \) and \( D^t_{1,6}(x, y, b) < D^t_{1,6}(x, y, b) \).

As can be seen from Table 4 and Fig. 3, by using FSEA, not only the infeasibility problem is tackled but also gives a solution than the one introduced by Arabi et al. (2015).

4.3. A super-efficiency slacks-based DEA algorithm for the problems with undesirable factors

In the previous sections, we discussed a situation in ML calculation that a DMU is located beyond the frontier. A similar situation will occur when the objective is super-efficiency measurement, especially when undesirables are included in the model. In this section we improve FSEA to introduce an algorithm for the SBM models that include undesirable factors as below:

1. Employ Model (4) -Model (5) for the best and worst practice measurement to examine if there are DMU’s that are located beyond the efficiency frontier.\(^9\)

2. If so, for every \( l=1 \ldots 2^k / l \), deploy Model (6) Model (8) to calculate \( D^l_0(x, y, b) \) for the same DMUs put:
\[
D^l_0(x, y, b) = \min \{ D^l_0(x, y, b) \mid l=1, \ldots, 2^k \}
\]
and \( D^l_0(x, y, b) = \min \{ D^l_0(x, y, b) \mid l=1, \ldots, 2^k \} \).

3. Otherwise deploy Model (4) and Model (5) to compute \( D^l_0(x, y, b) \) and \( D^l_0(x, y, b) \) for all DMUs.

From now on in this paper we call the above algorithm as Feasible Super-Efficiency Slacks-Based Algorithm (FSESBA).

4.4. DEA-TOPSIS model

Fig. 4 provides a visual representation of the essential steps involved in implementing our proposed DEA-TOPSIS framework.

Table A3, with electricity demand and economic factors as two inputs, and total emission as an undesirable output. Note that AIMMS 4.9, the academic version, is employed for mathematical modelling and programming purposes. The assumption is made that the unity is the output for all technologies. The DEA-TOPSIS approach is utilised to rank the technologies, as presented in Fig. 4 based on the different scenarios.

5. Empirical results and discussions

After running the FSESBA and giving the rank to each technology based on the TOPSIS distance measure, SBM inefficiency scores, and newly introduced DEA-TOPSIS model distance measure, we obtain Fig. 5.

Figs. 5-A and 5-B illustrate that both the ideal and anti-ideal TOPSIS methods exhibit similar rank orders. To be more specific, we have seen a consistent preference for HFO-based technologies over CO2-based technologies across various periods. However, Fig. 5-C and Fig. 5-D demonstrate that conventional DEA (SBM) models produce divergent results and fail to capture the impact of criteria changes on CO2 Single temperature range systems from 2020 to 2050, despite similar trends in economic, energy, and environmental criteria changes for both CO2 Single temperature range unit and DX-CO2. Furthermore, Fig. 5-E and Fig. 5-F, stemming from our novel DEA-TOPSIS model, highlight the sustainability of HFO-based technologies over the next decade. This suggests that simply adopting new technologies may not offer the most effective strategy for reducing carbon emissions or costs. Instead, supermarkets should prioritize investments in enhancing energy efficiency, intensifying monitoring, and training workers to reduce F-Gas leakage.

We depict the relationship between total emission and refrigeration technologies rank order in Fig. 6. The thickness of the ribbons and labels on them represent the total emissions of respective technologies. Notably, the advantages of utilizing CO2 as a refrigerant, such as improved energy efficiency and reduced impact on global warming, are highlighted. Despite initial higher costs associated with CO2-based refrigeration systems, our new model, predicts a narrowing cost difference over time. As total emissions increase, CO2-based technologies are projected to become increasingly competitive compared to their HFO-based counterparts. This finding underscores the significance of our model’s analysis, particularly as the world transitions towards a more sustainable future aligned with goals of reducing carbon footprint and

\(^9\) Note that, in super-efficiency measurement, DMU’s that are located on the frontier using a conventional DEA model, are located on or beyond the frontier when corresponding super-efficiency model is employed.
mitigating climate change.

5.1. Robustness check

In the realm of decision-making, a robustness check serves as a critical assessment of the stability, reliability, and sensitivity of our findings. Typically, this involves systematically altering one or more variables across a spectrum of scenarios to gauge their impact on the outcomes. Through such evaluations, we can uncover both the strengths and weaknesses inherent in our model, offering valuable insights into its validity and applicability.

Expanding upon Section 3.2, we have developed scenarios for 2020, 2035, and 2050 to conduct the refrigeration system TA/TS in the UK. Leveraging these scenarios, integral to our study, we aim to assess the robustness of our newly introduced model. Subsequently, we compare it with the conventional model to underscore the merits of our approach.

Upon reviewing Fig. 5-A and Fig. 5-B, it becomes evident that although both ideal and anti-ideal TOPSIS portray identical rank orders, they fail to reveal the effects criteria changes along the horizons of 2035 and 2050, as HFO-based technologies remain in higher rank than the CO₂-based technologies. This indicates a lack of sensitivity in conventional TOPSIS models towards criteria change. In addition, conventional SBM models showcased in Fig. 5-C and Fig. 5-D reveal distinct outcomes for DEA best practices and DEA worst practices. This disparity underscores potential reliability concerns surrounding these models.

Furthermore, the accuracy of the FSESBA has already been rigorously tested, as substantiated by Corollary 1 and the comprehensive data...
provided in Table 4, Fig. 3, and the ensuing discussion. As previously discussed, the FSSEBA method demonstrates freedom from infeasibility issues and exhibits superior accuracy compared to previous approaches, particularly the one introduced by Arabi et al. (2015). Consequently, the model can be regarded as reliable. Note that Fig. 5-E and Fig. 5-F depict identical outcomes for the DEA-TOPSIS ideal and anti-ideal approaches.

Fig. 5. Comparison of Store Refrigeration System Rankings: TOPSIS vs. DEA (SBM) vs. DEA-TOPSIS across Scenarios for 2020, 2035, and 2050.

Fig. 6. Total Emission vs Refrigeration Technologies Rank Order.
The novel DEA-TOPSIS approach not only succeeds in uncovering the role of various criteria in the different horizons’ rank orders but also highlights the shift of CO$_2$-based technologies from the least to the most favourable positions from 2020 to 2050. Additionally, it yields consistent results irrespective of whether ideal and anti-ideal are chosen, indicating the stability of the model.

In summary, the new DEA-TOPSIS model, employing FSEBA, offers distinct advantages over conventional TOPSIS and DEA (SBM) models. These advantages include free from infeasibility issues (reliability; theoretically proven), remarkable discrimination power, perfect sensitivity to the change of criteria over time, and stability in ranking outcomes. These characteristics show the robustness of the DEA-TOPSIS model, paving the way for its application in guiding sustainable business practices in the refrigeration industry. Further discussion on the priorities of the DEA-TOPSIS model will be provided in Section 5.2.

5.2. Discussion

In the pursuit of the UK’s net-zero targets and alignment with SDGs, DEFRA (2022) projected the total F-Gas consumption across various scenarios. Even under the most ambitious scenarios, meeting Kigali Agreement and Montreal Protocol limits falls short of achieving the net-zero targets. Efforts to reduce food access levels (SDG2) and maintain food resilience (SDG12) (Khosla et al., 2021; DEFRA, 2023; Latter and Wentworth, 2023; The Food Foundation, 2023). Consequently, all sectors, including the food cold chain industry, particularly the retail sector, must adopt more ambitious economic, technical, and environmental strategies in the short, medium, and long term to phase out carbon production entirely.

Despite investments in new low-carbon technologies and improvements in the efficiency of existing equipment and operational processes, one of the most crucial steps for temperature-controlled logistics businesses in the UK to lower their carbon footprint is to reduce or entirely phase out the use of high GWP refrigerants (Cold-Chain-Federation, 2023). A promising trend is the adoption of CO$_2$-based refrigeration systems, with approximately 33% of newer systems (aged 0–5 years) now utilizing CO$_2$ while older primary refrigeration systems (aged 20 years or more) predominantly do not use CO$_2$ as a refrigerant. Recent research has evaluated the economic, technological and environmental aspects of novel CO$_2$ based systems (Dai et al., 2023; Tsimpoukis et al., 2023). In their recent study, Hua et al. (2022) examined a CO$_2$ hydrate-based vapor compression refrigeration system, finding that the utilization of more natural gas, such as CO$_2$, necessitates stronger compression systems, thereby leading to higher leakage rates. This, in turn, requires increased quantities of refrigerants, resulting in elevated capital and operational expenditures and potentially raising carbon costs. Hart et al. (2020) highlighted the need for significantly increased investment to transition to a net-zero target, suggesting a shift from HFC to CO$_2$ refrigerants. However, this transition requires substantial investment, with eight times the annual investment compared to switching to HFO gases, resulting in nearly nine times more CO$_2$ emissions produced.

The above discussion underscores the critical importance of transitioning to natural refrigerants within the UK food cold chain to align with the nation’s SDG13 and to meet the 2050 net-zero targets. However, while the implementation of CO$_2$-based technologies is anticipated to become more economically viable post-2035, it is evident that additional measures will be imperative to achieve the net-zero target, even with the assumption of zero UK grid emissions by 2050. Simultaneously, prioritizing food security through the reduction of food waste via well-managed temperature-controlled food supply chains remains paramount (Jeswani et al., 2021), effectively advancing the objectives of both SDG2 and SDG12. In the context of retailers, Moul et al. (2018) show the vital link between food waste, refrigeration practices, and carbon footprint in the UK, emphasizing the importance of addressing SDG2, SDG12, and SDG13 concurrently. By introducing a model to aid food industries in sustainable refrigeration TA/TS, our study contributes to enhancing food resilience and reducing carbon emissions simultaneously. This contribution aligns with the objectives of SDG2, SDG12, and SDG13, while supporting the UK’s net-zero policies.

The findings of this study, although tailored specifically to a UK supermarket, carry broader implications for both businesses and governmental bodies. They indicate that through the implementation of low-carbon policies and taxations, the adoption of CO$_2$-based refrigeration systems will not only be environmentally responsible but also economically feasible within a thirteen-year timeframe. These insights offer valuable guidance for decision-makers seeking to foster sustainability within their organizations and communities. Furthermore, a potential future study could encompass a wider array of current and future refrigeration systems would yield a deeper understanding of the potential of CO$_2$-based technologies and their overarching impact on the industry.

5.3. Theoretical implication

It is crucial to note, as discussed in Section 5.1, that traditional TOPSIS and DEA (SBM) methods fall short in effectively capturing essential information from the data. This highlights the limitations of conventional approaches and the need for alternative approaches, such as the one presented in our model, to reflect the economic and environmental realities of the refrigeration industry more accurately. As demonstrated, DEA-TOPSIS approach presents a significantly greater discrimination and sensitivity power than the conventional TOPSIS and DEA (SBM) models. Additionally, the introduction of the FSEBA algorithm addresses instances of infeasibility that may arise when a DMU is positioned beyond the efficiency frontier.

Our DEA-TOPSIS approach represents a pivotal and easily replicable tool for future TA/TS studies. Through its comprehensive and integrated evaluation, the DEA-TOPSIS method ensures that the TA/TS process encompasses a broader range of relevant factors, thereby providing more reliable results.

5.4. Policy implications

The existing net-zero regulations and policies towards reducing refrigerant emissions do not adequately support stakeholders in the refrigeration industry to reach zero emissions by 2050. Addressing this issue requires a multifaceted approach, including:

- **Targeted Taxation:** Introducing targeted taxation to incentivize the transition to low-carbon refrigeration systems in the food cold chain industry is crucial due to the substantial capital expenditure involved. Additionally, offering financial incentives can spur investment in these technologies.

- **Fugitive Emissions Regulation:** Recognizing the significant role of fugitive emissions, particularly from refrigerants, in the country’s overall emissions is essential and should be a priority highlighted in the UK’s Voluntary National Reviews. Tighter regulations in this area can foster a more concise and actionable model for emission reduction.

- **Transparency in Reporting:** While studies on sustainable refrigeration systems are typically undertaken by businesses, there is a notable scarcity of comprehensive reports available. Robust regulations mandating transparency in sustainability reporting are necessary to provide more reliable data.

- **Behavioural Change:** Encouraging behavioural change within the industry is crucial to prioritize the transition to low-carbon refrigeration. This involves developing and implementing training programs to educate decision-makers on the importance of sustainability.

- **Innovative Business Models:** Developing innovative business models that integrate alternative solutions, is vital for achieving the
SDGs and net-zero targets. Collaboration among government entities, research institutions, consulting firms, technology providers, and financial institutions can facilitate the creation and dissemination of these models, which can then be integrated into relevant regulatory frameworks.

In summary, the government plays a pivotal role in fostering the sustainable expansion of the cold-chain industry (Cold-Chain-Federation, 2023; Latter and Wentworth, 2023). These interventions span various domains (e.g., formulation of new policies and strategies, taxation adjustments, provision of economic incentives) to ensure the achievement of the UK net-zero and SDG2 and SDG12 requirements.

6. Conclusion

In this paper, we propose an innovative approach to identifying the most sustainable refrigeration system technologies suitable for the UK. Our study begins with an analysis of the essential criteria for assessing refrigeration technologies, considering both cold-chain priorities and the SDGs. We introduce a practical set of sustainability assessment criteria to effectively assess both existing and upcoming refrigeration technologies. Subsequently, we conduct a comprehensive examination of prevalent MCDM methods used in TS and TA exercises. While acknowledging the widespread use of DEA and TOPSIS methods in TS/TAs, we pinpoint their limitations. To address these shortcomings, we introduce a hybrid DEA-TOPSIS model to tackle these shortcomings.

We then apply our new model to evaluate the technologies used by a major UK supermarket, including DX HFO, CO₂-Single temperature range unit, HFO/Single temperature range unit Blend, HFO-Single temperature range unit, and DX-CO₂. By developing net-zero scenarios aligned with stakeholders’ preferences and market parameters, we conduct robustness checks to validate the reliability of our results for policy and decision-making purposes. Furthermore, we showcase the superiority of our proposed model to conventional DEA and TOPSIS models. Interestingly, our analysis reveals a shift in preference towards CO₂-based technologies by 2050, despite their initial lower attractiveness compared to HFO-based technologies in 2020.

To accelerate the transition to net-zero, the UK government should officially recognize the importance of publishing sustainability data across various industries (e.g., F-Gas leakage rates). Access to such data not only enhances public awareness but also drives behavioural change in strategic investment decision-making. While the emphasis on SDGs and net-zero policies is increasing, there is a need for clearly specified long-term rules, regulations, and energy/carbon tariffs. Such clarity is crucial for data-intensive studies like ours and can provide a clearer roadmap for the UK food cold chain industries regarding their strategic investments in low carbon measures.

It is important to note that the reliability and predictability of performance, operation, and maintenance costs of new technologies are often not fully established during the initial commissioning phase. Many factors affecting technical availability and technical sustainability, particularly for emerging technologies, remain uncertain variables, despite their availability and adoption by industries.

Our study highlights the need for further research on examining the significant role of SDGs in target setting, both at the industry and firm levels. This includes developing criteria that align with the SDGs and introducing more SDG-specific assessment tools and models for various applications. Moreover, future studies should explore the potential of low GWP refrigerants (e.g., natural ones) and their associated technologies. The implementation of these zero-GWP refrigerants holds promise for significantly contributing to the achievement of the net-zero targets and enhancing sustainability efforts in the refrigeration industry.

Furthermore, the DEA-TOPSIS framework proposed in this study offers a robust foundation for the development of advanced market analysis tools. One promising direction for extension involves incorporating different functions to gain deeper insights. For instance, integrating cost, revenue, and allocative efficiency measurement models can provide investors with a comprehensive understanding of the costs and benefits associated with each refrigeration system. In addition, exploring dynamic models presents another avenue for enhancing our forecasting capabilities regarding future cost and financial developments. By incorporating dynamic elements into the analysis, stakeholders can better understand various factors may evolve over time, enabling them to make more strategic and adaptive decisions.

CRediT authorship contribution statement

Behrouz Arabi: Conceptualization, Data curation, Validation, Visualization, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. Mehdi Toloo: Funding acquisition, Conceptualization, Methodology, Validation, Visualization, Writing – review & editing. Zaoli Yang: Conceptualization, Methodology, Visualization, Writing – review & editing. Peihao Zhang: Conceptualization, Data curation, Investigation. Bing Xu: Funding acquisition, Project administration, Supervision, Conceptualization, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.
Table A1 (continued)

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<td>Multicriteria (MCDM) framework using AHP and q-ROLBMM operator</td>
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<td>• cost of the water make-up and blow-down</td>
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Table A2
List of Current and Future Refrigeration Technologies

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| 1. | • a vapor compression refrigeration system powered by a photovoltaic array.  
• a vapor absorption refrigeration system powered by a solar evacuated tubes thermal unit | Life cycle cost analysis of two different refrigeration systems powered by solar energy | (Alrwashdeh and Ammari, 2019) |
| 2. | Secondary loop and cascade system  
• CO2 Secondary Coolant (S.C) System  
• CO2 direct expansion cascade (DEC) system  
• Combined CO2 secondary/cascade (CSC) system  
• Combined glycol secondary/CO2 cascade (CSC-G) system  
Transcritical booster (CO2) systems  
• Standard transcritical booster system (STBS)  
• Transcritical booster system with upstream expansion valve (TBS-UX)  
• Transcritical booster system with bypass compressor (TBS-BC) | Comparative analysis of various CO2 configurations in supermarket refrigeration systems | (Sharma et al., 2014) |
| 3. | S-R404A DXRS consists of two R404A single-stage vapor compression refrigeration cycles at MT and LT, operating independently.  
• The HFCs/CO2 CRS is composed of two single-stage vapor compression refrigeration cycles, and the MT and LT cycles operate simultaneously.  
Thermo-mechanical refrigeration system and thermal-driven cooling technologies:  
• Electricity driven cooling (PV, TEC)  
• Absorption with heat source temperature: 85–220 °C  
• Absorption with heat source temperature: 60–165 °C  
• Desiccant with heat source temperature: 60–95 °C  
• Organic Rankine cycle ORC with heat source temperature: 100–300 °C  
• Ejector with heat source temperature: 60–160 °C  
• Thermal-Mechanical Refrigeration TMR with heat source temperature: 60–160 °C  
• NH3/LiNO3 absorption chiller cooled by H2O/ethylene glycol solution.  
• Air-cooled absorption cooling prototype working with an NH3/LiNO3 Absorber  
• Single-effect absorption chiller LiBr/H2O and NH3/LiNO3  
• Thermally driven solution pump for NH3/H2O heat pump  
• NH3/LiNO3 mechanical absorber and chiller  
• Aerofoil Energy’s Vortex future-fridge technology  
• Absorption and other heat driven cooling & heating equipment  
• Air-cooled condensing units  
• Automatic permanent refrigerant leak detection  
• Refrigeration system controls  
• Evaporative condensers  
• Packaged chillers  
• Refrigeration compressors  
• Air blast coolers  
• Hydrocarbon (HC)  
• Boreholes and Ground Sink Condensers  
• Carbon dioxide hydrate-based vapor compression refrigeration system | Preliminary study on the feasibility assessment of CO2 booster refrigeration systems for supermarket application in China: An energetic, economic, and environmental analysis | (Cui et al., 2020) |
| 4. | Review of innovative approaches of thermo-mechanical refrigeration systems using low grade heat | (Sleiti et al., 2020) |
| 5. | Absorption Refrigeration Systems Based on Ammonia as Refrigerant Using Different Absorbs: Review and Applications | (Lina et al., 2020) |
| 8. | Review of standards for the use of hydrocarbon refrigerants in A/C, heat pump and refrigeration equipment | (Corberán et al., 2008) |
| 9. | Feasibility of using ground-coupled condensers in A/C systems | (Said et al., 2010) |
| 10. | Thermodynamic analysis and economic assessment of a carbon dioxide hydrate-based vapor compression refrigeration system using load shifting controls in summer | (Hua et al., 2022) |
Table A3
Refrigeration System Technologies’ Data

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<tr>
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</table>

References


Cold-Chain-Federation. (2022a). Shaping the cold chain of the future: the road to net zero, Part one- Setting the scene. [https://www.coldchainfederation.org.uk/roa-1-to-net-zero/].


