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The development of a carbon roadmap investment strategy for carbon intensive food retail industries

A.N. Ayoub*, A. Gaigneux, N. Le Brun, S. Acha, R. Lambert, N. Shah

Department of Chemical Engineering, Imperial College London, South Kesington, London, SW7 2AZ, United Kingdom

Abstract

The COP21 has accelerated a global transition to a low-carbon economy in all markets and sectors. Commercial organizations are required to meet science-based targets that are in line with the level of decarbonisation required by the Paris Agreement. The challenge in pursuing the low-carbon targets typically lies in implementing the strategies cost-effectively. This work presents an approach to develop an innovative decarbonisation investment strategy framework for carbon intensive UK industries by using statistical analysis and optimisation modelling. The case study focuses on taking a representative sample of retail buildings and assesses the financial viability of installing low-carbon Combined Heat and Power units (CHPs) and Photovoltaic Solar Panels (PVs) across a portfolio of buildings. Simulation of each building are initially conducted, and the results generate a set of regression coefficients, via a multivariate adaptive regression splines (MARS), which are inputted into a Mixed Integer Linear Programming (MILP) problem. Solving the MILP yields the optimal decarbonisation investment strategy for the case study up to 2050, considering market trends such as electricity prices, gas prices and policy incentives. Results indicate the level of investment required per year, the operational and carbon savings associated, and a program for such investments. This method is reiterated for several scenarios where different parameters such as utility prices, capital costs and grid carbon factors are forecasted up to 2050 (following the Future Energy Scenarios from National Grid). This work shows how a clear mathematical framework can assist decision-makers in commercial organizations to reduce their carbon footprint cost-effectively and thus reach science-based targets.

Keywords: Carbon roadmap, decarbonisation; food retail industry; investment strategy; science based targets.

* Corresponding author: Alexandre Ayoub. *E-mail address:* alexandre.ayoub14@imperial.ac.uk

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1. Introduction

In 2015, 195 countries of the world signed the Paris agreement (COP21), aiming to limit the temperature increase to 2°C compared with pre-industrial temperatures. The COP21 has accelerated the transition to a low-carbon economy happening globally over all markets and sectors. More than 300 companies have already committed to science-based targets to be in line with the transformation of the economy. *"Science-based targets are in line with the level of decarbonisation required to keep global temperature increase below 2°C compared to pre- industrial temperatures, as described in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5)"* [1].

The advantages of setting ambitious environmental targets imply companies will lead innovation, will have a better influence on new policies and will stay ahead of potentially handicapping regulations in the future. Hence, it will ensure competitiveness in a future where resources will become scarce and expensive. This work looks at a modelling framework that can address the science-based targets food retailers need to meet by 2050.

The food retail industry is large and complex and represented £179 billion in sales in 2016 [2]. Furthermore, food retailing accounts for approximately 1.9% of total UK greenhouse gas emissions [3]. Indirect emissions from using the electricity grid is the single most important contributor to total greenhouse gas emissions as it represents 56% [4]. The carbon breakdown in the food retail industry is shown on Table 1.

Table 1: Food retail industry emissions breakdown.

Source	Percentage of total emissions
Electricity from the grid	56%
Refrigerants	18%
Logistics	10%
Natural gas	9%
Waste, employees travels, etc.	7%

Carbon roadmaps consist of qualitative trend-based studies and technology deterministic studies, often operating within a 'back-casting' framework. It permits the identification of the decisions and actions that must be taken at critical points in time if the objective is to be achieved [5].

Research has been published on understanding the factors influencing carbon emissions in the food retail sector as well as methods to tackle them. Spyrou et al. [6] investigated the electricity and gas demand drivers in large food retail buildings. The paper outlines the method used to create multiple linear regression models that predict energy and gas demand of a food retail store based on several variables.

After understanding what drives energy demand, it is paramount to look at means of reducing carbon emissions. Several technologies enable the production of clean sustainable energy such as but not limited to combined heat and power (CHP), photovoltaic cells (PV), biomass boilers and organic Rankine cycle units. Compelling research has been conducted to create models which optimize the use of those technologies to maximize efficiency, carbon savings and cost reduction. Cedillos, Acha, Shah and Markides [7] developed a technology selection operation (TSO) optimisation model that provide decision makers with insight on distributed technologies covering many systems [8] and [9].

Finally, Y. Bentley [10] investigated the supply chain decarbonisation strategies of 15 large UK companies. The most important barriers to the implementation of carbon reduction scheme according to the companies reviewed included a lack of resources, the risk associated with investing in technologies that are not yet settled as well as the lack in a well-thought-out investment strategy for their decarbonisation program.

From the literature review, it is apparent firms lack a strategic global approach to decarbonise their operations. Extensive research has been performed at a micro-scale, looking at decarbonising individual buildings. The challenge in this case lies in the overall problem of decarbonising an entire operation composed of a large property portfolio (for example the food retail industry). The approach taken here is applied on a macro scale, looking at a representative set of stores, taking its learnings and applying it to make broad assumptions across a large multi-site organisation.

This paper aims at detailing a decarbonisation investment strategy tailored to the current market and to future scenarios which consider different yearly variations of utility costs, capital costs and electricity grid carbon factors. The key research question trying to be addressed is an optimization problem aiming to minimize capital expenditure and operating costs while reaching a carbon reduction target. This is done by considering a range of technology types and sizes, resulting in various investment strategies from 2020 to 2050 for different future scenarios.

This paper is structured in six sections. The current section has provided the background and purpose of this work as well as the scope of the problem. The second section describes the methodology and mathematical formulation of the problem. The third section provides the results from the regression model, while the fourth section describes the results applied to the case study. The fifth section displays a summary of key findings and limitations. Lastly, the final section provides concluding remarks.

2. Methodology

2.1 High-level description

The aim of this paper is the development of an optimal decarbonisation investment strategy for large industries minimizing annual capital expenditure (CAPEX) while maximizing operational cost savings (OPEX) and achieving carbon saving targets.

With estates of large magnitude such as the food retail industry, it is convenient to start by clustering stores to understand what parameters affect carbon emissions. Three sub-categories are present: Convenience stores, Supermarkets and Distribution Centres. Any of those sub-categories could potentially be clustered, however for this research only supermarkets are considered. Once distinct clusters are determined, the installation and operation of a range of capacities of all types of technologies are simulated on each store to evaluate the resulting carbon emissions and operating costs. For this work, the analysis was centered around CHP technologies and PVs. However, different technologies could be added to the model such as: biomass boilers, Organic Rankine cycle (ORC) units, etc.

Consequently, from the data gathered through simulations, three sets of plots are generated for each store showing all outcomes of installing different combinations of technologies. In this case study where only two technologies are considered, the independent variables are the CHP sizes and the number of PV panels which are plotted against key performance indicators (CAPEX, OPEX or carbon savings). The next step is to approximate the calculated data points with a linear regression model to generate a set of regression coefficients which are used as inputs in a Mixed Integer Linear Programming (MILP) problem. To obtain linear coefficients which fit this nonlinear data, a multivariate adaptive regression splines (MARS) analysis is performed by splitting the data into 4 domains which results in 4 sets of linear coefficients for each key performance indicator of each store.

After solving the MILP, an optimized yearly investment plan is found showing which technology type and size to install each year, where to install them and their resulting capital costs, annual carbon and operating savings. This method is reiterated for different scenarios where different parameters such as the utility prices, technology capital costs and electricity grid carbon factor are forecasted up to 2050, following the Future Energy Scenarios devised by the National Grid [11]. Finally, the MILP problem is modified to allow for variable yearly capital investments to investigate the importance of having a flexible investment budget.

2.2 Modelling tools

To create an accurate model, a great amount of data is required. The case study's data sources contain half hourly energy consumption information of commercial building as well as their characteristics such as age, location and sales surface area. Taking the electricity and gas consumption data in half hourly intervals for various years for several stores represent an exceptional amount of data. Thus, these datasets were compiled into an SQL database for convenience. Python, a programming language, is then used to connect to the specific database, retrieve the information requested and process it according to the user's needs. Those tools enabled the creation of three models: a business as usual model (BAU), a model incorporating CHP technology and one incorporating PV panels. The BAU model represents the operation of a store without any installed technology, based on the half hourly energy consumption data collected for 2016. Once the simulations are done and the regression coefficient are generated, GAMS is used to solve a MILP problem (see Figure 1). The solution to this optimization is the investment strategy.

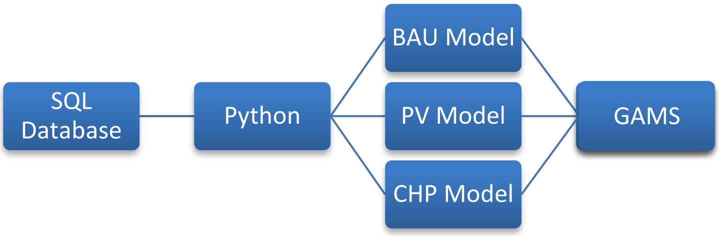

Figure 1: Processing data and modelling tools schematic.

2.3 Technology installation at individual sites

2.3.1 Technology optimisation

To estimate the optimal technology sizes for CHP and PV units, half-hourly data for 2016 was inputted for a total of 60 supermarkets among a group of hundreds. This subset is chosen to be representative of all supermarkets by ensuring a wide range of store properties (Energy demand, area, age and location). The code is comprised of a CHP model and a PV model which are both divided into two sections: an optimization model to find the optimal size of CHP or PV for a store, and a simulation model which calculates KPIs for a specified technology size. For each property, the optimal technology sizes and types were found by using the Python code described below; thus, deriving the investment strategy. From the half-hourly data, the Business as Usual (BAU) scenario is calculated, which represents the operation of each store when no technology is installed. Then, the code runs through all 20 technologies listed in Appendix A.1 for the CHP model and through a set of 4 types of panels (Appendix A.2) taking all available roof space for the PV model and selecting the technology; thus reducing the discounted OPEX against the BAU model.

The model output returns the best technology size and/or type, financial indicators (e.g. payback, ROI, CAPEX, cumulative discounted cash flow) and carbon emission reduction. The model's key equations are shown below:

$$Discounted\ BAU\ operating\ costs = \sum_{t=0}^{M} \frac{BAU\ operating\ costs_t}{(1 + discount\ rate)^t}$$
$$where, t\ is\ the\ time\ period\ in\ years\ and\ M\ is\ the\ number\ of\ time\ periods \quad (1)$$

$$Discounted\ tech\ costs\ = \sum_{t=0}^{M} \frac{(tech\ operating\ cost + Fixed\ Periodic\ Payment)_t}{(1 + discount\ rate)^t} \quad (2)$$

$$where\ :\ Fixed\ Periodic\ Payment\ = \frac{discount\ rate \times Total\ investment}{1 - (1 + discount\ rate)^{-tech\ lifetime}} \quad (3)$$

$$Operating\ cost\ savings = Discounted\ BAU\ operating\ cost - Discounted\ tech\ costs \quad (4)$$

2.3.2 Simulation of technology size combinations

The second section of the model is the simulation of the installation of a specified amount of PV panels and size of CHP unit on each store. The objective is to generate results for all combinations of technologies to input into a MILP optimisation. To do so, PV panel installations are simulated first. From the optimisation described in section 2.5, the best PV type was found to be the Monocrystalline Silicon (Mono-Si) and is therefore used in the simulation, only varying the number of panels installed.

2.3.2.1 PV panels

The photovoltaic model simulates how adding panels on supermarkets' roofs impact OPEX and carbon savings. To do so, the power output of PV panels is calculated using the following equation:

$$Power\ (kWh) = Irradiance(kJ/m^2) \times efficiency \times N_{panels} \times Area_{panel}(m^2)/3{,}600 \quad (5)$$

The irradiance data for each store is determined by retrieving the hourly data collected in 2015 from the closest weather station. It is assumed that the irradiance maintains a similar behavior from year to year. The efficiency is a technology dependent specification which indicates the portion of energy in the form of sunlight that can be converted via photovoltaics into electricity. The number of panels (N_{panels}) is limited by the available roof space on each store. It is assumed that each rooftop is the same surface as the sales area of the supermarket and that only 60% of this surface is suitable for the installation of panels (leaving space for installation, maintenance and shadings). Additional constraints such as the roof maximum weight capacity was added to make sure of the feasibility of the installations.

The model also calculates the CAPEX necessary to install a PV panel. This accounts for the price of the PV panel but also all Balance-of-System components which can include the inverter, wiring, switches, a mounting system, a battery bank and battery charger.

$$CAPEX\ (£) = N_{panels} \times Nominal\ Power(Wp) \times (Panel\ Price\ \left(\frac{£}{Wp}\right) + BOS\left(\frac{£}{Wp}\right)) \quad (6)$$

Additionally, to make the model the most accurate as possible feed-in tariffs (FIT) were considered into the OPEX savings calculations. The FIT value was chosen for capacities above 1 MW [12].

2.3.2.2 CHP units

After the installation of PV panels have been simulated, the CHP model calculates the additional OPEX and carbon reduction incurred when a CHP unit is installed. The model finds the optimal part load for the operation of the unit from the store's energy demand, which has been reduced by the amount covered by the previously installed PV electricity production. If the CHP unit is not large enough to meet the demand of the whole store, electricity grid is used. If the CHP is too large, the excess electricity produced is exported and sold. These dynamics are modelled through the following equations:

$$Electricity\ production = a_{fuel} \times part\_load + b_{fuel} \quad (7)$$

$$Heat\ production = a_{th} \times part\_load + b_{th} \quad (8)$$

$$OPEX = \left(CHP\ gas\ consumption + \frac{Thermal\ demand - Heat\ production}{Boiler_{eff}}\right) \times Price_{gas} + (Electricity\ demand - Electricity\ production) \times Price_{elec} \quad (9)$$

This model also assumes that the installation of the CHP equipment will incur additional costs to the price of the technology itself. They are referred to as hidden costs and are taken to be equal to an average installation cost of £200k plus a factor to account for dependence on store area. Additionally, the Enhanced Capital Allowance (ECA) is considered which results in a 26% reduction in the CAPEX of the technology. The CHP model assumes that the fuel used is biomethane which has a lower carbon factor than the natural gas used in the BAU model (0.00538 $kgCO_2/kWh$ and 0.184 $kgCO_2/kWh$; respectively). The grid electricity carbon factor for 2017 was 0.351 $kgCO_2/kWh$ [13].

2.4 Regression method

The PV and CHP models (sections 2.3.2) have simulated the installation of a range of sizes of these technologies and their combination in a representative subset of 60 stores. Therefore, data for CAPEX, OPEX savings and carbon savings for each technology size combination has been calculated. To input this data into a MILP to find the optimal sequence of investments in each store, it needs to be approximated using linear regression. However, it is observed that the data set for carbon savings and for OPEX savings are not correlated linearly to the CHP unit size.

To generate linear regression coefficients on nonlinear data points, a MARS analysis was used to minimise the prediction error. The MARS analysis splits the data into four domains and generates a regression model for each one of those datasets. It calculates the prediction error and reiterates using different bounds for the domains generated randomly. After a set number of iterations, the model outputs the regression coefficients and the bounds which minimises the residual sum of the squares, therefore giving the best fit.

The dependent variables for this case study are the number of PV panels and the CHP unit size which are plotted against either CAPEX, OPEX savings or carbon savings. In each domain, the coefficients calculated fit the data according to the following linear regression model:

$$Y = a \times x_1 + b \times x_2 + c \tag{10}$$

Where a, b, c are the parameters adjusted to fit the data, x_1 and x_2 are two independent variables and Y is a dependent variable. In the domain containing the point (0,0), meaning that no PV panels or CHP units have been installed, here the c parameter is forced to zero to avoid calculating savings even when no technologies are installed.

2.5 MILP optimisation

The regression coefficients calculated using the MARS analysis and linear regression for all stores and years until 2050 are input into a MILP model to calculate the carbon and OPEX reduction.

2.5.1 Objective function

The optimisation model minimises the sum of the investments necessary to install low carbon technologies and the sum of the resulting operating costs after their installation in 60 buildings over the selected time frame of 30 years. The results provide insight on the optimal size (*s*) and combination of technology (*t*) to install in each store and on what year to do so. The objective function is shown in equation (11):

$$\begin{gathered} \min f = \sum_t Yearly\ investment(t) - \sum_t \sum_s OPEX\ savings(t,s) \\ where\ t\ the\ combination\ of\ technology\ and\ s\ is\ the\ optimal\ size \end{gathered} \tag{11}$$

2.5.2 Operating costs and carbon emissions calculation

Like mentioned above, the annual OPEX and CO_2 savings are calculated through the regression coefficients inputted into the model. These coefficients correspond to a certain store *s*, for a certain time *t*, technology *tech* and domain of regression *d*. The following equations (12-16) enable the calculation of these values. The binary variable IO_cons_i assures that the correct coefficients (K_i) are associated with the correct technology size (x) range between the lower and upper bound of the domain of regression. The sum of IO_cons_i over the domain set d (equation 16) ensures that the savings are not double counted. The parameter M is a large number to allow for an MILP formulation and is equal to 10^6.

$$g_1: savings_i(t,s) > \sum_{tech} K_i(d,tech,t,s) \times x(tech,t,s) - (1 - IO\_cons_i(d,t,s)) * \mathrm{M} \tag{12}$$

$$g_2: savings_i(t,s) < \sum_{tech} K_i(d,tech,t,s) \times x(tech,t,s) + (1 - IO\_cons_i(d,t,s)) * \mathrm{M} \tag{13}$$

$$g_3: x(tech,t,s) > x\_limit\_bottom_i(d,tech,t,s) - IO\_cons_i(d,t,s)) * \mathrm{M} \tag{14}$$

$$g_4: \quad x(tech,t,s) < x\_limit\_top_i(d,tech,t,s) - IO\_cons_i(d,t,s)) * \mathrm{M} \tag{15}$$

$$\begin{gathered} h_1: \sum_d (IO\_cons_i(d,t,s)) = 1 \\ where\ i = \{OPEX, CO2\} \end{gathered} \tag{16}$$

2.5.3 Capital investment calculation

After the savings are calculated, the CAPEX needed to install the technologies has to be calculated. The calculation is the sum of all investments made on all sites and is made of two parts. The first is valid for modular technologies like PV panels. The regression coefficient is timed by the difference between the total amount installed on year t and the amount previous installed the year before $(t-1)$. Indeed, there is no need to reinstall all panels for every increase in size. However, it is the case for CHP units which is not a modular technology and its capex is calculated as $non\_modular\_capex$ as shown in equation (17).

$$h_2:\ capex(t,s) = \sum_{tech} K1_{CAPEX}(tech,t) \times (x(tech,t,s) - x(tech,t-1,s)) + non\_modular\_capex(tech,t,s) \quad (17)$$

The CAPEX for CHP units is calculated using the regression coefficients input into the model and using a binary variable $IO\_install$.

$$g_5: non\_modular\_capex(tech,t,s) > K0_{CAPEX}(tech,t) + K1_{CAPEX}(tech,t) \times x(tech,t,s) - (1 - IO\_install(tech,t,s) \times 100000 \quad (18)$$

$$g_6: IO\_install(tech,t,s) > x(tech,t,s) - x(tech,t-1,s) \times 0.0001 - IO\_modular(tech) * 100000 \quad (19)$$

If a technology is modular $(IO\_modular = 1)$ or a larger technology is not installed between $(t-1)$ and t, $IO\_install$ is driven to 0 in equation (19) and this results in a null $non\_modular\_capex$ in equation (18). In the opposite scenario where a technology is modular, and a larger technology is installed then the following equation applies:

$$\begin{aligned} &IO\_install = 1 \\ &non\_modular\_capex(tech,t,s) = K0_{CAPEX}(tech,t) + K1_{CAPEX}(tech,t) \times x(tech,t,s) \end{aligned} \quad (20)$$

2.5.4 Problem constraints

The following constraints have been applied to the model. Equation (21) fixes the CAPEX to sum up to the same value for each year to avoid having all the investments made at the beginning of the 30 years. It was assumed to be necessary as it would be more practical for a business to spread out the investments over the time horizon. Equation (22) ensures that the size of the technology can only be increased as time progresses because it would be unwise to uninstall technologies in practice. Finally, equation (23) sets a minimum carbon reduction target per year.

$$g_7: \sum_s capex(t,s) < Yearly\ investments(t) \quad (21)$$

$$g_8: \quad x(tech,t,s) > x(tech,t-1,s) \quad (22)$$

$$g_9: \sum_s savings_{CO2}(t,s) > CO2\_savings\_target(t) \quad (23)$$

2.5.5 Time value of money constraints

To build on the model, add complexity and provide more powerful insights, it was decided to add two additional constraints which adds some flexibility to the investments made. They enable the yearly investments to vary from year to year by a factor of $(1-\alpha)$ to $(1+\alpha)$ where $0 < \alpha < 1$. For this case study a variation of 30% was chosen.

3. Regression Results

After calculating the Key Performance Indicators (KPIs) for each store and a range of technology types and sizes, it is necessary to approximate this data using linear regression to compute an optimised solution in a MILP.

3.1 Capital cost regression

The CAPEX coefficients only depend on the time horizon analysed, as it was assumed that the price of each technology would be decreasing overtime due to technological innovation and costs of installation decreases. It is calculated individually for each technology and therefore a simple linear regression is fitted to each set of data according to the following equations:

$$CHP\ CAPEX\ (£) = 587 \times x_1 + 108{,}000 \quad (24)$$

$$PV\ CAPEX\ (£) = 128 \times x_1 \quad (25)$$

Where x_1 is the technology size

3.2 Carbon and operational cost savings regression

The data calculated for annual carbon and OPEX savings is not correlated linearly to CHP size. Indeed, they increase almost linearly until a certain point and then plateau or even slightly decrease. This change in behaviour happens at the point where the CHP unit size is large enough to cover most of the demand of a store and the imports from the grid tend to 0. As CHP units can only operate at a part load greater than 60%, adding a larger unit would be inefficient and will only increase the biomethane consumption and thus the operating costs and emissions. To minimise the prediction error, MARS analysis was used to approximate the data on different domains.

The fit and error has been calculated for the regression models of all 60 stores to evaluate the accuracy of the prediction. It was found that the OPEX saving is well predicted with an average R^2 of 0.95 and mean relative error of 2.4% whereas the carbon savings prediction is not as good with a lower mean R^2 of 0.71 and a mean relative error of 7.6%. This is explained by the fact that the regression models were forced to 0 at the origin, to enforce the fact that no carbon or OPEX savings must be calculated if no technology is installed. It is observed that the calculated operating costs are reduced linearly from 0 as technologies are installed, while carbon savings go from null to significant savings once a CHP unit is installed and then increase at a slower rate when the size of the unit is increased. Forcing the regression to go through the origin therefore increases errors for the carbon savings regression model.

Table 2: MARS fit and errors

Measures		Operational costs	Carbon emissions
R^2 score	Mean	0.95	0.71
	Standard deviation	0.11	0.32
Relative error	Mean	2.4%	7.6%
	Standard deviation	1.7	6.7

4. Investment Strategy Results

The investment strategy relates to the implementation of the results discussed above. Because investments are not made in all stores every year, a clear roadmap can be defined depending on the scenario most adapted to the decision maker. The benefit of this model is it can be refined every year as investments are made and market externalities vary to update the results constantly.

4.1 Scenarios overview

When devising an investment strategy out to 2050, it is important to consider that external factors are unlikely to remain unchanged for the length of the project. For instance, important technological advances are being delivered constantly such as battery storage or electric vehicles and as such are driving change in the UK's energy landscape. It is therefore required to make informed decisions regarding future trends of external parameters.

Each year, the National Grid gathers impartial information from stakeholders across the energy industry in the *Future Energy Scenarios* publication to support decision making for organizations. The set of four credible pathways proposed by National Grid are "Steady State", "Two Degrees", "Slow Progression", and "Consumer Power" [11].

Each one of these scenarios consider the energy trilemma, consisting of the security of supply, affordability and sustainability of gas and electricity which in term would impact the energy industry and consumers.

- The **Steady State** scenario sees the slowest economic growth and is not environmentally ambitious.
- The **Two Degrees** scenario has the highest level of prosperity and will to decarbonize the economy.
- In the **Slow Progression** scenario, there is a collective will to decarbonize the economy however it is limited by a slow economic growth.
- The **Consumer Power** scenario has a high economic growth but limited ambition to become environmentally friendly.

4.1.1 Capital costs and technologies

The CAPEX required per year is plotted for each scenario. It was assumed a business would have a certain amount of money to invest every year and this will be the same until 2050. In section 4.2.3, this assumption was removed for the steady state scenario. Thus, for each scenario, the average amount spent every year is around £2.36 million for the 60 supermarkets considered. As it can be seen, the scenario requiring the least CAPEX is consumer power as in this scenario the focus is not on decarbonisation, whereas Two Degrees is the most optimistic which is correlated with the highest investments in green sources of energy.

Table 3: Yearly Capex for each Scenario

	Two Degrees	Consumer Power	Steady State	Slow Progression
Capex (£ millions)	2.70	1.90	2.30	2.55

The Capex is directly linked to the technologies installed in each store. In this case, the energy requirements are plotted yearly in kW. Interestingly, all four scenarios seem to follow the same trend and the results remain quite similar. This shows the robustness of this investment strategy as even if external factors vary.

As the curve increases, technologies are added in specific stores. However, as the curve flattens out for CHP most notably, it implies the existing technologies can cope with the demand. The model suggests adding CHPs in the first 10 years while investing continuously in PVs is the optimal strategy. It is important to note that while some scenarios might have the similar total capacity installed, the stores in which they are added are most probably different.

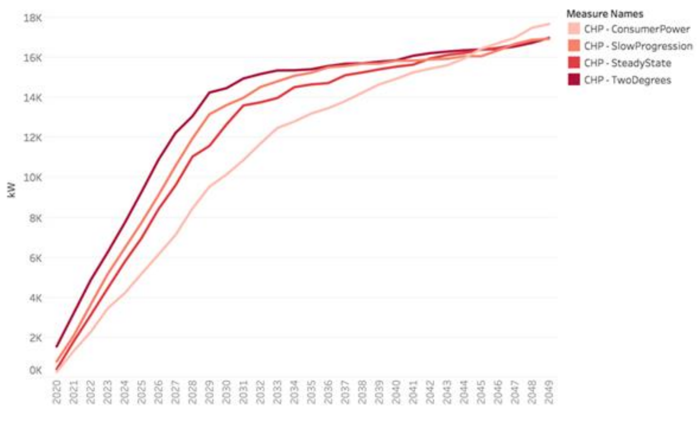

Figure 2: CHP Capacity installed per year for different scenarios.

4.2.2 Carbon Savings

By incorporating BAU emissions and carbon savings, it is possible to plot the carbon emissions roadmaps for each scenario and compare them with the target set by the Science Based approach. Two emissions targets are established: the goal is to reach 55% of reduction in 2030 and 98% in 2050.

For every scenario, the 2030 target is reached ahead of schedule with the latest being in 2029. Regarding 2050 targets, they are reached in the "Two Degrees" and "Slow Progression" scenarios from 2041 onwards. Additionally, the "Steady State" scenario approaches the target very closely but does not quite reach it whereas in the case of "Consumer Power", the emission target in 2050 is far from being reached.

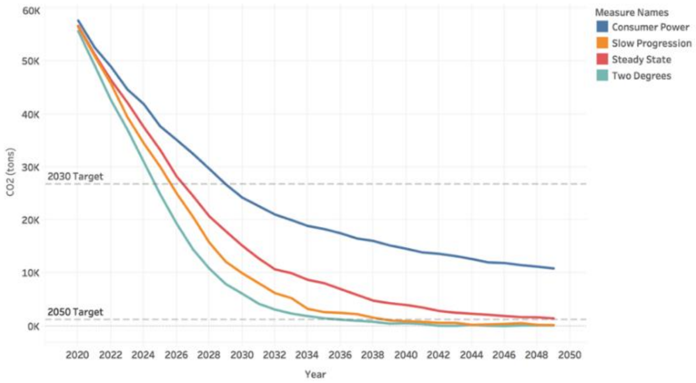

Figure 3: Carbon emissions trajectories for different scenarios.

4.2.3 Steady State Scenario

To have a better understanding of the case study it was decided to drill down in the steady state scenario. This scenario was chosen because it models what would happen if external factors remain the same as they have been behaving so far. Additionally, it was decided to question the assumption that the decision maker has a constant amount to invest every year thus in this case, the flexibility of yearly investments is considered.

4.2.4 CAPEX & Technologies

In this case, the spread of yearly investment is different to the previous section. As expected when the time value of money is considered, it is better to invest early on. The level of investment ranges from £7 million for the first few years and steadily decreases to about £1 million per year from 2030 onwards. The CAPEX is segmented into small, medium and large supermarkets. Because the sample of 60 stores has around the same number of stores of each category, the trends observed should be valid across the entire estate (composed of hundreds of properties). The large stores require more capex as they usually are the ones that emit the most carbon, followed by medium and then small.

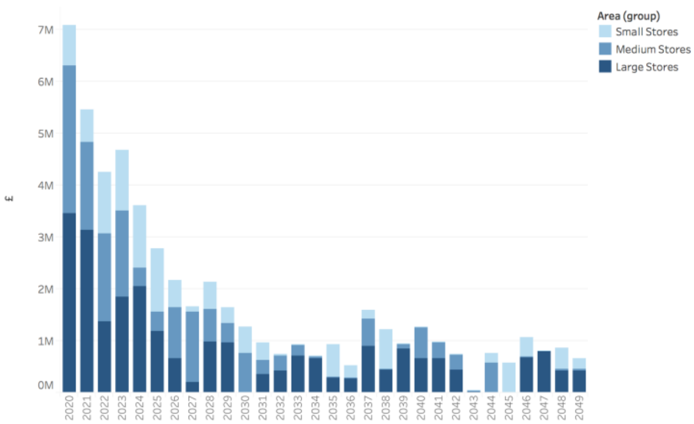

Figure 4: Steady State Capex with flexibility of amount invested

5. Key Findings and Discussion

5.1 Key findings

A broad spectrum of forecasted external factors till 2050 was evaluated by considering four different scenarios. It was found that the Two Degrees scenario was the most carbon efficient. The model suggests investing an average of £2.3 million per year to minimize CAPEX & OPEX. This amount would enable not only to install technologies in all 60 stores considered but also reach the Science Based target set for 2030 and for 2 of the 4 scenarios set for 2050.

Table 4: Results scenario summary.

Scenario	Yearly Capex (£)	Avg. Opex Savings (£)	Avg. Carbon Savings	Avg. Payback Time	2030 Targets	2050 Targets
Two Degrees	2.69 million	22.8 million	17,200 tons	2.02 years	✓	✓
Slow Progression	2.45 million	17.2 million	22,300 tons	2.36 years	✓	✓
Steady State	2.31 million	11.1 million	23,800 tons	3.13 years	✓	✗
Consumer Power	2.91 million	6.6 million	15,400 tons	4.46 years	✓	✗

The investment strategies analysed in this case study are based on assumptions which are necessary for the construction of the model and cause errors and deviations from the true optimal solution.

5.2 Uncertainties in inputs

The model depends strongly on the assumption of the prediction of future change in utility costs, electricity grid carbon factors and technology costs, which is highly uncertain. This can be limited by applying the strategy for the initial years and rerunning the optimisation each year as the investments are made. This would limit the prediction assumptions to 1 year in the future compared to 30 years predicted (as is the case in this study).

Also, the model is limited by the technologies incorporated in the study. The range of technologies used as inputs for the model is for the moment limited to CHP units and PV panels. For CHPs, conventional internal combustion engines are assumed. Moreover, the PV technology type in this work are poly-silicon panels. This reduced choice of technology is a limitation which can be remedied by finding the relevant data for additional technologies and adding them to the model. An additional uncertainty comes from the assumptions made for the energy generation efficiencies of the technologies which are estimated and, some discrepancies might appear due to technological improvements or irradiance variations for example.

5.3 Regression limitations

To input data into the MILP model, the following assumptions were made. Firstly, it was assumed that the technology sizes are continuous, however in reality only a discrete number of CHP units with their respective power capacities are available on the market. Additionally, PV technology is a modular technology which provides a total power capacity depending on the number of panels installed, a measure which is not continuous.

As mentioned in the regression method (section 2.4), the calculated data for OPEX and carbon reduction do not behave linearly with respect to technology size, however linear regression was used to approximate this data. Using the MARS analysis to divide the set of data in domains reduced the error, however this is not reduced entirely and still has an impact (especially for the carbon savings calculation).

5.4 Optimisation

For this case study presented here, the model has been tested for a range of 60 supermarkets and calculates yearly investments and savings for the next 30 years. This method is computationally intensive and time consuming and results in an effort time of 7 hours to determine each scenario. It would therefore be necessary to optimise the modelling framework to calculate data more efficiently for very large industries.

6. Conclusion and Recommendations

To be in line with the decarbonisation approach suggested by Science Based targets, businesses are keen to reduce its operations' carbon emission and thus align their environmental targets with the Paris Climate Accord. This work has presented a method to develop an innovative decarbonisation investment strategy framework for carbon intensive industries by using statistical analysis and optimisation modelling relying on big data. The example highlighted in this work concentrated on addressing food retail buildings emissions by analyzing the effect of installing low-carbon technologies such CHPs and PVs in these sites. The methodology creates a detailed annual investment strategy to decarbonise business's operations while maximising financial savings. The decarbonisation strategy outlines where, when, and what technology to add in each property. This is done by simulating the operation of a range of CHP and PV sizes over a set of 60 supermarkets to calculate the resulting CAPEX, OPEX and carbon reduction from 2020 to 2050 (under a different set of scenarios).

Results indicate that ambitious environmental milestones are feasible by 2030 if there is enough biomethane available. However, depending on the changing conditions of the energy market by 2050 it is not guaranteed carbon reduction targets can be met, as factors such as public policy, energy prices and technology developments are unclear. Nonetheless, the PV and CHP investments aside from their environmental benefits show they have also attractive returns, making it clear businesses can make sound investments and contribute to tackle climate change.

For future work, it is suggested to consider a wider range of low carbon technologies such as Organic Rankine cycle units and biomass boilers into the model. Additionally, a wider range of buildings should be investigated to understand the types of solutions suitable in these sites. However, adding new buildings to the model requires half hourly electricity and gas demand data and will necessitate more powerful processing power. Also, the maintenance costs, replacement of technologies after 20 years should be implemented to the model to increase the accuracy of the results. The model should be completed with the following constraints: Maximum acceptable investment payback and maximum biomethane consumption due to limited sourcing capacity.

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Appendix A. Technologies

A.1. CHP Sizes and Technologies

Table A1: Types of CHP

CHP unit name and size (kWe)	Price (£)
Unit 35	£94.2k
Unit 50	£115k
Unit 90	£159k
Unit 100	£169k
Unit 110	£178k
Unit 125	£189k
Unit 135	£199k
Unit 150	£211k
Unit 165	£223k
Unit 185	£238k
Unit 210	£255k
Unit 230	£268k
Unit 310	£317k
Unit 375	£352k
Unit 400M	£367k

Unit 425	£378k
Unit 500	£414k
Unit 530M	£428k
Unit E770	£527k
Unit 850	£556k

A.2. PV Technologies

Table A2: Different PV panels specifications

Type	Price per Module	Nominal Power (Wp)	Electrical Efficiency (100%)	Capex (£/Wp)	Module Area (m²)	Module Weight (kg)	Lifetime (years)
Mono-Si	£128	293	18.07%	£0.437	1.65	19.1	20
Poly-Si	£83	243	14.81%	£0.345	1.65	19.1	20
CIGS	£130	160	12.60%	£0.814	1.3	13.7	20
CdTe	£63	90	12.50%	£0.703	0.72	12.1	20

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