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Economic, Climate Change, and Air Quality Analysis of Distributed Energy Resource Systems

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Abstract
This paper presents an optimisation model and cost-benefit analysis framework for the quantification of the economic, climate change, and air quality impacts of the installation of a distributed energy resource system in the area surrounding Paddington train station in London, England. A mixed integer linear programming model, called the Distributed Energy Network Optimisation (DENO) model, is employed to design the optimal energy system for the district. DENO is then integrated into a cost-benefit analysis framework that determines the resulting monetised climate change and air quality impacts of the optimal energy systems for different technology scenarios in order to determine their overall economic and environmental impacts.

Keywords: Distributed Energy Resource Systems, MILP, Air Quality, Optimisation

1 Introduction

The United Kingdom is committed to achieving an 80% reduction in national greenhouse gas emissions by 2050. To do so will likely require the utilisation of a significant amount of renewable resources and the adoption of distributed energy resource (DER) systems. Therefore there is a need to develop optimisation models that facilitate the design of cost-effective, low carbon DER systems by temporally matching energy generation with demand at fine time resolutions, i.e. time intervals of 1 hour or less, over long time horizons. However, it is incomplete to limit the performance analysis of DER systems to just economic cost and CO_2 emissions. It is also necessary to evaluate the impact that distributed energy systems have on the air quality in the areas in which they are installed.

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Epidemiological research suggests that there is a positive correlation between ambient concentrations of fine particulate matter (i.e. $PM_{2.5}$), which can occur as a result of fuel combustion, and the risk of premature mortality due to lung and cardiovascular cancer (Laden et al, 2006). Therefore, the integration of an air quality assessment with the economic and CO_2 emissions analyses facilitates the design of cost effective DER systems that are able to achieve the required CO_2 emissions reductions without negatively impacting the health of the local population.

An increasing number of studies have attempted to include this air quality analysis in their assessment of the impact of DER systems. Genon et al (2009) conducted a study of the energetic and environmental impact of a new district heating CHP system. In addition to calculating CO_2, NO_x, SO_x, and PM emissions from the CHP system, they also employed an air quality model to analyse the dispersion of these pollutants into the local environment, and the resulting ambient concentrations. However, they did not convert the environmental impact, i.e. the change in environmental quality, of energy generation into the resulting environmental externality, i.e. the social cost or benefit of the impact of that environmental quality change on the population. To address this externality issue, 50 research teams in more than 20 countries worked together on the ExternE project that aimed to quantify the external costs of energy production so that they could be taken into account during energy planning. The ExternE project utilised an impact pathway methodology which traces the emissions from their source, to the change in ambient concentrations, to the resulting impact on receptors, and finally to the monetary valuation of that impact (Roos, 2010). However, even though the ExternE project created a framework for monetising the impact of energy production, few DER planning studies actually carry out air quality modeling in order to determine the additional social costs of the distributed energy systems. Instead, these studies, like Holmgren and Amiri (2007), employ aggregated local heath impact data from the literature, mainly social cost outputs from the ExternE project, which do not take into account the sub-national site-specific characteristics (i.e. population density, meteorology, etc.) of the areas that they are studying. The integration of a DER system optimisation model and an air quality model into the impact pathway approach that is presented in this paper aims to fill this research gap by creating a cost-benefit analysis framework that results in a more comprehensive assessment of the economic, climate change, and air quality impact of a distributed energy system.

2 Methodology

Figure 1 outlines the process for the integrated cost-benefit analysis framework, which is composed of five distinct modules. 1) The Distributed Energy Network Optimisation (DENO) Model, 2) the Air Pollution Dispersion (APD) Model, 3) the Air Quality Impact Assessment (AQIA) Model, 4) the Climate Change Impact Assessment (CCIA) Model, and 5) a final module that is used to compare and analyse the outputs from each of the four aforementioned models.

Firstly, the DENO model developed by Omu et al (2013) is used to determine the optimal energy system for the district that minimises economic cost, subject to constraints on energy generation, CO_2 emissions, energy demand, etc. DENO produces three outputs for the optimal energy system in the final year of the time horizon, 1) the annual CO_2 emissions, 2) the annual economic cost, and 3) the annual fuel consumption which is converted into the average hourly fuel consumption of each fuel type over the entire year. The annual CO_2 emissions are an input into CCIA, which uses the social cost of carbon (SCC) to determine the social cost of climate change for the optimal energy system designed by DENO. The average hourly fuel consumption is converted into average hourly $PM_{2.5}$ emissions, and is inputted into APD. APD employs a Gaussian dispersion model to calculate the resulting change in the ambient concentration of $PM_{2.5}$, which is then used as an input into AQIA. AQIA uses the population density, $PM_{2.5}$ concentration-response function, and the value of a statistical life (VSL) to quantify and monetise the impact that the change in ambient $PM_{2.5}$ concentrations has on the health of local population by calculating the social cost of air quality. The final module of the cost-benefit analysis framework takes in the annual social cost of climate change from CCIA, the annual economic cost from DENO, and the annual social cost of air quality from AQIA in order to determine the net impact cost of the distributed energy system that was designed by DENO.

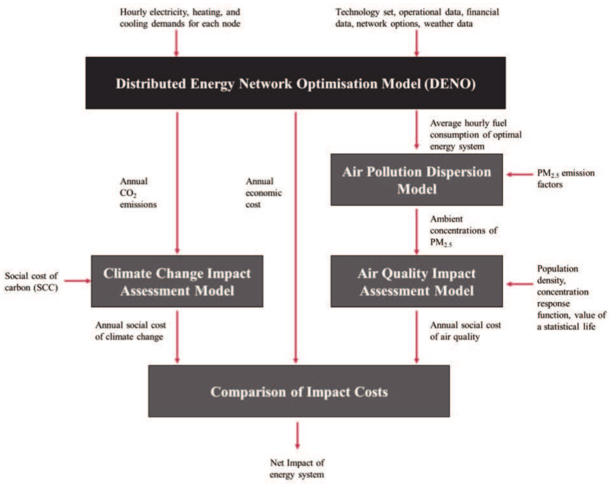

Figure 1: Process flow of the cost-benefit analysis framework

3 Case Study: Paddington Area

The cost-benefit assessment framework is used to analyse distributed energy system options for the area surrounding Paddington station in London, England. 75 buildings were identified in the area in the immediate vicinity of the station, bounded by the A40 motorway, Westbourne Terrace and the A4209. The different building uses in the Paddington area are shown in the left of Figure 2, with Paddington station and all the surrounding roads shown in grey.

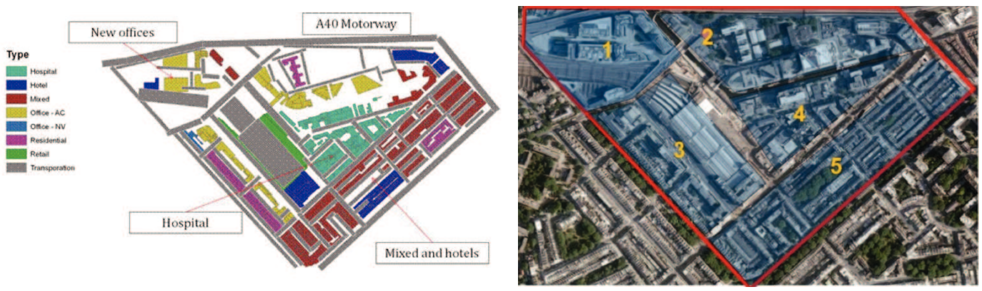

Figure 2: Building use in Paddington Area (left) and identification of the clusters (right)

The area is going through a period of rapid redevelopment, with new buildings being constructed and old infrastructure due to be razed and rebuilt in the coming years. There is interest in the adoption of distributed energy resource systems in the area, as illustrated by the recent installation of series of Combined Cooling, Heating, and Power (CCHP) systems in the Paddington Basin site indicated by the group of air conditioned office buildings near the centre of the map shown on the left in Figure 2.

DENO was therefore used to analyse the distributed energy system options for a 19 year time horizon between 2012 and 2030. This time horizon was divided into three phases, a three-year phase from the start of 2012 to the end of 2014, a five-year phase from the start of 2015 to the end of 2019, and an eleven-year phase between the start of 2020 and the end of 2030. Each year was composed of 4 typical days, one each for winter, spring, summer, and autumn, and each typical day was divided into 24 1-hour time intervals. Table 1 summarises the model characteristics for the DENO implementation of the Paddington case study.

The 75 buildings in the Paddington area were divided into 5 clusters (identified on the right of Figure 2), based on geographic proximity, and the individual energy demand profiles for each building within a cluster were aggregated to create five demand nodes for DENO to analyse. Annual energy demand density was found to be the highest in building cluster 1, which is the location of a conglomeration of high-rise air-conditioned offices, and lowest in cluster 5, which is mainly composed of low rise residential buildings. Clusters 1 and 2 were found to have the highest electricity and cooling demands, and cluster 5 has the lowest electricity and cooling demands. While, clusters 2 and 4 have the highest heating demands, and cluster 1 has the lowest heating demand.

Model Characteristics	
Spatial scale	75 buildings
Spatial Resolution	Clusters of 10 – 20 buildings
Number of Demand Nodes	5
Time Horizon	19 years
Number of Phases	3
Number of Seasons	4
Total Time Intervals	288
Energy End Uses	Electricity, Heating, and Cooling
Number of Variables [Integer]	63,409 [11,560]
Number of Constraints	97,974

Table 1: Characteristics of the DENO model implementation for the Paddington case study

3.1 Scenario Development

The assessment of the distributed energy system options in the Paddington area employs the cost-benefit analysis framework in order to analyse the economic, climate change, and air quality impacts of various distributed technology options. This analysis is valuable when assessing electrified heating versus cogeneration scenarios, as they have been found to have opposing impacts on local air quality. Namely, the electrification of heating redistributes air pollutant emissions to national grid power stations that are further away from populations, while cogeneration brings air pollutant emissions closer to populations. However, the different technology options mean that the economic and climate change impacts of these systems are not as easy to understand without first optimising their design using DENO. There are three technology retrofit scenarios in this case study that create a set of options that range from complete electrified heating to complete combustion heating. Note that the cogeneration scenario has been expanded to encompass all technologies that combust fuel locally, i.e. CHPs and boilers. The intermediate scenario reflects the projected deployment of electrification technologies obtained from a Greater London Authority report on the economic analysis of the deployment of distributed generation technologies in London by 2030 (GLA, 2011).

A business as usual (BAU) scenario was used to indicate the reference case in which all the currently installed energy generation technologies in the Paddington buildings are kept. The BAU scenario also assumes that the change in energy demand between 2012 and 2030 progresses along its current trajectory. However, for the three technology retrofit scenarios, the projected changes in energy demand are modelled, and heat demand in 2030 is reduced through 100% penetration of cavity wall insulation, loft insulation, double glazing, and draught proofing in residential buildings. For non-domestic buildings, energy demands are reduced through the improvement of windows and wall u-values to 2002 Part L standards, and reduction of infiltration to 0.3 ACH. Thus, the four scenarios that are employed in this case study are:

1. **BAU**: Energy is supplied using the technology choices that are currently installed at each building.
2. **Only Electric**: Only heat pumps, electric chillers, electric heaters, PV, and solar thermal systems can be installed in the Paddington area, and the on-site combustion of fuel is not allowed. Furthermore, each building cluster in the Paddington area operates autonomously, with no distribution of energy between clusters.
3. **Mixed**: The adoption level of electricity-driven heat technologies is limited to the GLA's expected technology penetration for London by 2030, i.e. 8% of heat generated by GSHP and 4% of heat generated by ASHP. Furthermore there is no distribution of energy between clusters.
4. **District CHP**: No heat pumps, electric chillers, electric heaters, or solar thermal can be installed in the Paddington area. Only combustion technologies and PV are allowed. The space requirements of a district scale CHP system mean that only one district energy plant can be installed, and this plant is allowed to supply energy to all of the clusters in the Paddington area.

3.2 Climate Change Impact Assessment (CCIA) Model

The climate impact of the CO_2 emissions was determined by multiplying the annual CO_2 emissions by the global social cost of carbon (SCC). The global SCC, calculated by the Interagency Working Group on the Social Cost of Carbon, is an average of the SCC determined by FUND, DICE, and PAGE, which are the three most common integrated assessment models (IAMs) used for analysing the SCC, and have been employed in the Intergovernmental Panel on Climate Change (IPCC) assessments. All three IAMs convert annual CO_2 emission into changes in atmospheric CO_2 concentrations, determine the resulting change in temperature, and finally calculate the global economic damage that occurs as a result of the temperature change. The SCC employed in this study was £14.27/tonne CO_2, which corresponds to the average FUND, DICE, and PAGE SCC at a discount rate of 3% (IWG, 2010).

3.3 Air Pollutant Dispersion (APD) Model

Local scale dispersion modeling is applied to estimate $PM_{2.5}$ concentrations at a 10 m resolution using AERMOD, a steady-state plume model recommended by the US Environmental Protection Agency (Cimorelli et al., 2004). Meteorological data including upper sounding (UK Meteorological Office, 2006a) and surface meteorological data (UK Meteorological Office, 2006b) were obtained from the NCAS British Atmospheric Data Centre and UK Meteorological Office and pre-processed using AERMET (USEPA, 2012). Calculated local concentrations are sensitive to the chosen surface roughness length, z_0. This was calculated using the formula from Britter and Hanna (2003) as 15% of the average building height in the Paddington area. An average building height of 10.75 m was calculated from building data that was collected for the Paddington area, resulting in z_0 = 1.6 m. An albedo of 0.2 was taken to be representative of Greater London (Kolokotroni and Giridharan, 2008). The Paddington area was represented by a gridded square, and the annual average emission rate of $PM_{2.5}$, in $kg_{PM2.5}$ per second, from each grid square was inputted into AEROMOD.

3.4 Air Quality Impact Assessment (AQIA) Model

Once the ambient pollutant concentrations were determined, population data, concentration-response functions (CRF), and the value of a statistical life (VSL) were used to quantify and monetise the resulting air-quality derived health impacts. Firstly, receptors were identified by mapping population densities onto the grid squares. The ambient $PM_{2.5}$ concentrations from the air quality modelling and the population density data were then used to calculate population weighted $PM_{2.5}$

concentrations, which indicate the concentration of $PM_{2.5}$ that the average person is exposed to. Next, the resulting damage to human health was calculated using a CRF for $PM_{2.5}$. CRFs quantify the change in the risk of premature mortality that occurs due to the change in $PM_{2.5}$ exposure. Cooke et al (2007) and USEPA (2011) determined that there is a 1% decrease in all-cause deaths per decrease in average $PM_{2.5}$ exposure. Since the mortality impact of $PM_{2.5}$ is dominant over all other impacts and can account for around 80% of the social costs of air pollution (Andersen et al, 2008; Yim and Barrett, 2012), $PM_{2.5}$-attributable premature mortality was the only damage that was monetised. Monetisation was carried out using the VSL metric, which is calculated by determining how much people are willing to pay in order to reduce their risk of premature death. The mean UK VSL of £3 million per life (Yim and Barrett, 2012) was used. Finally, the social cost of air quality was calculated by multiplying the VSL by the number of premature deaths for each scenario.

4 Results and Discussion

4.1 Distributed Energy System

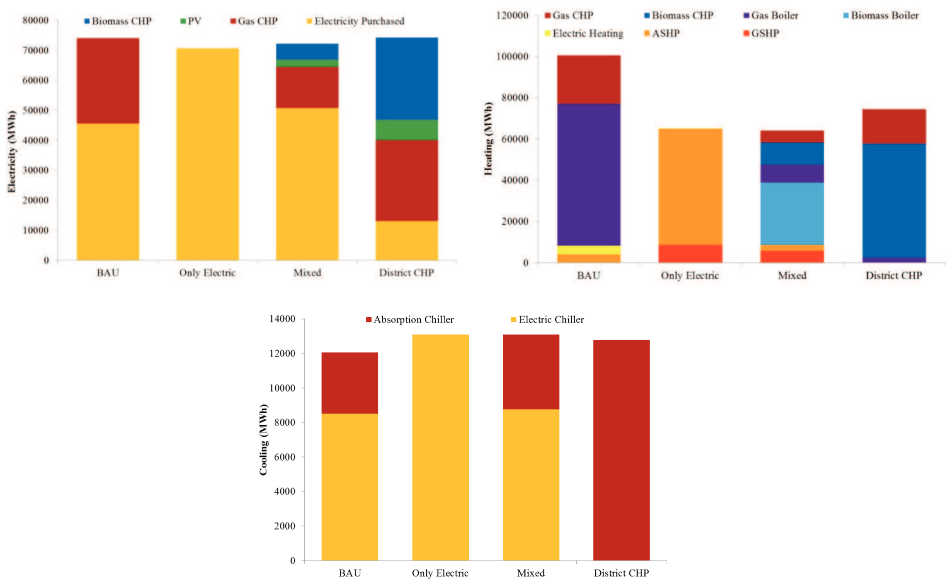

Figure 3: Comparison of electricity, heating, and cooling generation from technologies in each scenario

The DENO model results for the four scenarios are presented in Table 2 and Figure 3. Table 2 shows the optimal technology set in the final year of each scenario, while Figure 3 shows the quantities of electricity, heating, and cooling generated by each technology in each of the four scenarios in 2030. The BAU scenario is characterised by a reliance on electricity purchased from the national grid or generated by the 5.2 MWs of gas CHPs that are already installed in cluster 2. Heat is mainly supplied by building-scale gas boilers, with only 8% of the heat is provided by ASHP and electric heaters. In cluster 2, cooling is supplied by 2.3 MWs of absorption chillers, while in all other clusters it is supplied by electric chillers. In the Only Electric scenario all electricity is purchased from the grid and all cooling is supplied by electric chillers. A 1.5 MW GSHP is installed to supply heating to cluster 3. ASHP are used to supply the majority of the heating demand, however, electric heaters are also installed in all the clusters to meet peak demands. In the Mixed scenario, 12% of the heat generated is by heat pumps and 11% of the electricity generated is by PV. Furthermore, in comparison to the BAU scenario, there is a decrease in the utilisation of gas CHPs and boilers, and an increase in the amount of heat that is generated by biomass boilers. Finally, in the District CHP scenario, instead of installing additional biomass boilers, gas boilers, or gas CHP units to compensate for the displacement of the heat pumps and electric heaters, 4.6 MWs of biomass CHPs are installed. This is likely due to the technology's high heat to power ratio. 2 kWh of heat are generated for every 1 kWh of electricity generated, therefore the biomass CHP produces more heat than the three other combustion technologies for every kWh of fuel consumed. This means that there is also more heat available for the absorption chiller, and therefore no electric chillers are required.

Scenario	Total Installed Capacity	Scenario	Total Installed Capacity
BAU	Absorption Chillers: 2.3 MW ASHP: 500 kW Electric Chillers: 6.2 MW Electric Heaters: 1.2 MW Gas Engine CHP: 5.2 MW Natural Gas Boiler: 25.8 MW	**Mixed**	Absorption Chillers: 2.3 MW ASHP: 400 kW Biomass Boiler: 5.1 MW Biomass CHP: 800 kW Electric Chillers: 6.2 MW Gas Engine CHP: 2.7 MW GSHP: 700 kW Natural Gas Boiler: 20.7 MW PV: 16,277 m^2
Only Electric	ASHP: 18.2 MW Electric Chiller: 8.5 MW Electric Heater: 11.4 MW GSHP: 1.5 MW	**District CHP**	Absorption Chillers: 8.2 MW Biomass CHP: 4.6 MW Gas Engine CHP: 5.3 MW Natural Gas Boiler: 14,1 MW PV: 46,396 m^2

Table 2: Optimal technology set for each scenario

Table 3 presents the economic, CO_2, and $PM_{2.5}$ results for the four scenarios. The BAU scenario has the lowest annual economic cost, but the highest annual CO_2 emissions in 2030. For the Only Electric and Mixed scenarios, the increase in the annual economic cost is marginal, only 5%. However, the installation of the biomass CHPs means that the District CHP scenario has an annual economic cost that is 33% greater than the BAU scenario. Furthermore, while the District CHP scenario leads to lower annual CO_2 emissions than the Only Electric scenario, the trend is reversed for the annual local $PM_{2.5}$ emissions, illustrating the climate change and air quality trade-off between combustion technologies and electrification technologies. While electrified heating technologies reduce local $PM_{2.5}$ emissions by shifting combustion to national grid power stations that are far away from the consumers, the carbon intensity of the national grid is almost twice the gas CHP CO_2 emission factor, and more than twenty times greater than the CHP biomass emission factor.

Scenario	Annual Economic Cost (£ millions)	Annual CO_2 Emissions (ktonnes)	Average $PM_{2.5}$ Emissions Rate (kg/s)
BAU	13.4	63.5	1.10×10^{-4}
Only Electric	14.2	54.1	0
Mixed	14.1	41.5	2.55×10^{-4}
District CHP	17.9	25.2	4.94×10^{-4}

Table 3: Energy supply modeling results for 2030

4.2 Air Pollutant Dispersion Model and Impact Costs

Figures 4 (a-c) show the spatial variation of the annual $PM_{2.5}$ concentration above background levels for the three scenarios that have energy systems that emit $PM_{2.5}$. In Figure 4a, the annual $PM_{2.5}$ concentrations for the BAU scenario shows that peak pollutant concentrations occur in cluster 2, where the gas CHPs are located. While in Figure 4b, the peak $PM_{2.5}$ concentrations in the Mixed scenario are located in clusters 2 and 5. In cluster 2, the peak concentration is due to the CHP units, while the peak in cluster 5 is more spread out, and is a result of emissions from a large number of biomass boiler units. Finally, in Figure 4c, the peak ambient $PM_{2.5}$ concentration in the District CHP scenario is located in cluster 2, where the district biomass CHP plant is sited. As all the biomass combustion in the area is now confined to a single location, the $PM_{2.5}$ concentrations around this point source is 3 times higher than the $PM_{2.5}$ concentrations in the other scenarios. However, because the majority of the fuel combustion is located in cluster 2, the change in $PM_{2.5}$ concentrations in all other parts of the Paddington area, particularly cluster 5, is lower than it is in the Mixed scenarios.

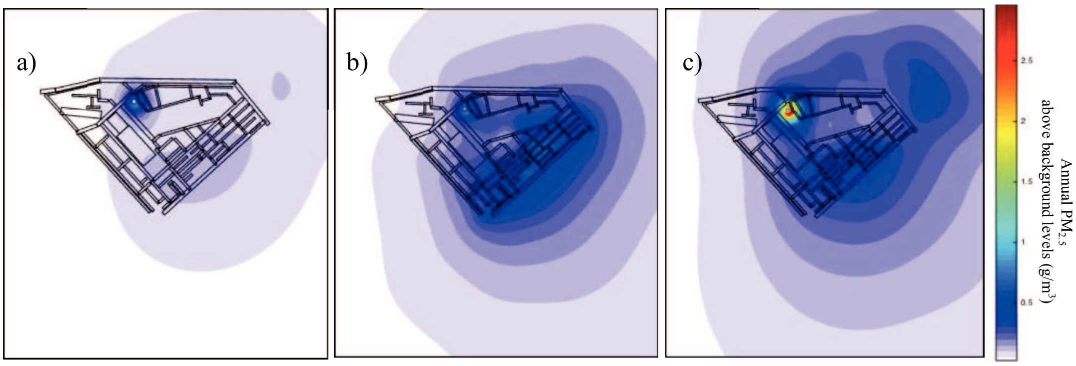

Figure 4: Spatial map of annual $PM_{2.5}$ concentrations (μg/m3) in a) BAU, b) Mixed, and c) District CHP scenarios.

For each scenario, the population-weighted ambient $PM_{2.5}$ concentrations above the background level are given in Table 4, alongside the average $PM_{2.5}$ emissions rate from Table 3. Although, the District CHP scenario has the highest $PM_{2.5}$ emissions rate, those emissions do not result in the highest population-weighted $PM_{2.5}$ concentrations. Instead, the highest population-weighted $PM_{2.5}$ concentrations occur in the Mixed scenario. This is likely due to the location of the emissions in these two scenarios. In the District CHP scenario, the majority of the $PM_{2.5}$ is primarily emitted at one point, the district biomass CHP plant, which has a high release height (i.e. flue stack level) that enables the pollutants to be dispersed further away from the area. Conversely, in the Mixed scenario, the $PM_{2.5}$ emissions are primarily from individual biomass boilers that are located throughout cluster 5, and the release height is much lower (i.e. building level). Therefore, the pollutants remain in the area and the local population is exposed to higher ambient concentrations. Furthermore, although a comparison of the spatial map of the $PM_{2.5}$ concentrations in both scenarios (Figures 4b and 4c) shows that the District CHP scenario has the highest ambient $PM_{2.5}$ concentration out of all scenarios. This elevated concentration is restricted to a relatively small area, which is why the average change in the population-weighted concentration is still lower than that of the Mixed scenario. The number of premature mortalities and the resulting social cost of air quality for each scenario are also presented in Table 4. As these values are functions of the population-weighted $PM_{2.5}$ concentrations, they follow the same trend. Therefore, the Mixed scenario has the highest social cost of air quality and the Only Electric scenario has the lowest social cost of air quality, as there are no local $PM_{2.5}$ emissions.

Scenario	Average $PM_{2.5}$ emissions rate (kg/s)	Ambient population-weighted $PM_{2.5}$ concentration above background levels ($\mu g/m^3$)	Premature Mortalities (deaths/year)	Social cost of air quality (£ thousands)
BAU	1.10×10^{-4}	0.00914	0.00191	5.73
Only Electric	0	0	0	0
Mixed	2.55×10^{-4}	0.325	0.0637	191
District CHP	4.94×10^{-4}	0.296	0.0596	179

Table 4: Mean $PM_{2.5}$ concentrations, premature mortalities, and social cost of air quality for all scenarios

4.3 Comparison of Impact Costs

Table 5 summaries the annual economic cost, social cost of climate change, and social cost of air quality for all four scenarios. The BAU scenario has the lowest economic cost, but the highest social cost of carbon, while the District CHP scenario has the highest economic cost but the lowest social cost of carbon, and the Only Electric scenario has the lowest air quality cost. When all three impact costs are added together, the BAU scenario has the lowest total impact cost. However, this result is driven by the relative magnitude of the annual economic cost, which is at least an order of magnitude larger than the social cost of climate change and the social cost of air quality. In comparison to the BAU scenario, all three retrofit scenarios increase the annual economic cost and decrease the annual social cost of carbon. However, while the Mixed and District CHP scenarios also increase the annual social cost of air quality, the Only Electric scenario decreases it because all local $PM_{2.5}$ emissions have been displaced to the national grid power stations. The net impact cost of each scenario is then calculated by summing the net economic, net climate change, and net air quality impact costs. Of the three scenarios, the Mixed scenario has the lowest net impact cost because although it has the highest social net air quality cost, it compensates by having the lowest net economic cost.

	£ thousand				
Scenario	**Annual Economic Cost**	**Annual Social Cost of Climate Change**	**Annual Social Cost of Air Quality**	**Total Impact Cost**	**Net Impact Cost**
BAU	13,400	906	5.72	14,312	NA
Only Electric	14,200	772	0	14,972	660
Mixed	14,100	593	191	14,884	572
District CHP	17,900	359	179	18,438	4,126

Table 5: Environmental impact assessment results for all the scenarios

However, the presentation of the impacts in monetary units and the straight summation of them to determine the net impact cost assumes that all three impacts are of equal importance. This may not necessarily be the case, as the context of the analysis may mean that particular impacts are deemed to be more significant. For example, if funding has already been secured for an energy system, then the air quality and climate change impacts may be more important than the economic impact. Therefore, the modular structure of the cost-benefit analysis framework is an advantage because the performance of each scenario can be calculated with respect to each impact or different combinations of the impacts.

5 Conclusion

In this paper an energy system analysis of the Paddington Area was used to illustrate how the energy planning optimisation model, DENO, can be integrated with the cost-benefit analysis framework in order to facilitate a more comprehensive analysis of distributed energy systems. One of the benefits of this integration is that the air quality impacts of an energy system can be determined, beyond just the calculation of emissions. As seen in Table 4, the magnitude of air pollutant emissions is not directly correlated to the resulting change in ambient concentrations and health impacts. Therefore, the modelling of pollutant dispersion is a vital step in the more rigorous quantification of environmental impacts. Ultimately, the magnitude of the economic costs in the Paddington area overshadowed both the climate change and air quality impact costs. However, the calculation of all three costs in monetary units enables the understanding of the interactions and trade-offs between the economic, climate change, and air quality impacts, which provides valuable information for decision making.

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