EG UK Computer Graphics & Visual Computing (2025)
Y. Sheng and A. Slingsby (Editors)

# Interactive Visual Analytics for Local Decarbonisation Planning: Empowering Policy-Aligned Scenario Exploration

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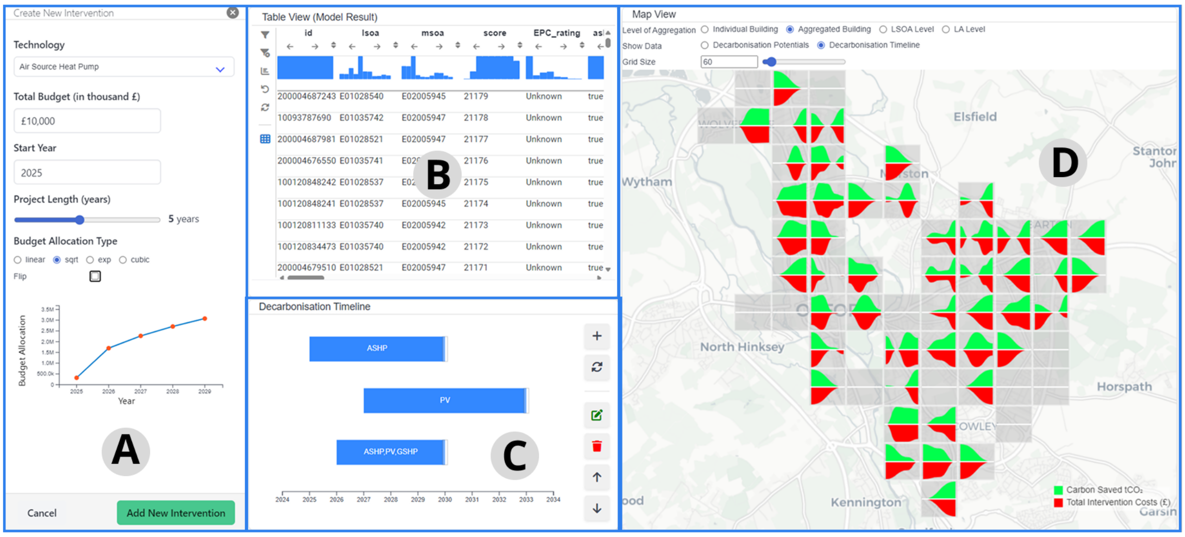


**Figure 1:** ***The Decarbonisation Planner Dashboard.*** *In New Intervention Panel (A), users define a granular decarbonisation intervention technology, targeted to specific buildings selected based on socio-demographic considerations, decarbonisation potential, and the geospatial parameters in Table (B) and Map (D) View. The Timeline View (C) allows users to refine modular interventions and adjust scenarios. Finally, (D) shows both multivariate decarbonisation potential and output timelines as glyph maps at different aggregation levels (`https://decarb-vis.netlify.app`).*

## Abstract

*Developing equitable and effective decarbonisation plans is a critical challenge for UK local authorities, who must balance complex technical, social, and economic factors. While computational models can propose optimal solutions based on a single objective, they often fail to account for the nuanced trade-offs and competing priorities inherent in public policy. We address this with a visual analytics system designed to support a human-in-the-loop planning process. Our primary contributions are threefold: (i) a modular, component-based planning paradigm that makes the construction of complex, multi-objective strategies cognitively manageable; (ii) a multi-scale visualisation framework that uses a model-driven glyph design to represent multivariate and temporal data uniformly across geographic scales, enabling fair and just assessment; and (iii) a tightly-integrated workflow that allows planners to iteratively explore data, compose interventions, simulate outcomes, and refine their strategies in real-time. We demonstrate through an application scenario how our system empowers planners to move beyond monolithic optimisation and engage in a transparent, evidence-based dialogue with their data, ultimately supporting the creation of more robust and equitable decarbonisation plans.*

### CCS Concepts

• ***Human-centered computing*** → ***Geographic visualization; Visual analytics;***

## 1. Introduction

The transition to net-zero emissions presents UK local authorities with a multifaceted policy challenge. Frameworks such as Local Area Energy Plans (LAEPs) require a holistic approach that accounts for carbon reduction potential, installation and operational costs, local energy demand, building efficiency, and crucial socio-demographic dimensions such as fuel poverty and housing inequality [CW23, GOC*21].

The task to build an effective decarbonisation plan without leaving anyone behind is complicated by two fundamental problems with existing decision-support tools: First, on the visualisation front, traditional GIS platforms rely on a map layer metaphor. This approach is inefficient for exploring multivariate data within the context of decision making, as it forces analysts to mentally integrate information from multiple, sequentially-viewed layers, increasing cognitive load and hindering the discovery of complex interrelationships [SR17, IF22]. Second, on the planning process front, decision-support systems often rely on optimisation models that produce a single, monolithic strategy based on a narrow set of constraints [SWW*21, SPBL24]. This rigidity fails to support the iterative, trade-off-based dialogue that is essential for developing publicly accountable and socially equitable policies [HV00].

To address these gaps, we present an interactive visual analytics dashboard that empowers UK local authorities to construct, simulate, and refine building-level decarbonisation plans. Our system makes three key contributions: **(i)** a multiscale visual framework using a model-driven glyph design to uniformly represent multivariate and temporal data across spatial hierarchies; **(ii)** a modular, component-based scenario builder that decomposes complex plan-building into manageable components aligned with specific policy goals; and **(iii)** a human-in-the-loop workflow that tightly integrates data exploration, simulation, and outcome analysis for real-time strategy refinement. Developed through interdisciplinary collaboration with a UK-based energy company, our platform reflects real-world policy workflows and aims to support the construction of equitable, transparent, and adaptable decarbonisation plans.

## 2. Related Work

This section situates our work within two key domains: decision-support systems for decarbonisation and geospatial visualisation for urban planning and the wider energy domain. We argue that while many tools address aspects of these domains, our system's contribution lies in its synergistic integration of a component-based planning paradigm with a multi-scale, glyph-based visual interface.

**Decision Support Systems for Decarbonisation**. A growing number of computational tools and Decision-Support Systems (DSS) have been developed to aid in the decarbonisation of building stock. These Energy System Analysis (ESA) and Modelling (ESM) aim to help decision makers to devise decarbonisation plans by applying computational model to determine what needs to be prioritised. These models are often complex in nature, balancing complex spatial, temporal, and multivariate statistical data of socio-demographic, renewable potential, grid structures and energy demand parameters [KNH*21, AARAA24]. A key issue with these models is the fact that they are mostly blackbox computational models, leading to a call for more transparent modelling process and outcomes to determine transition pathways [SWW*21].

Fundamentally, decarbonisation planning is a multi-objective optimisation (MOO) problem, requiring planners to navigate complex trade-offs between conflicting goals like minimising cost, maximising carbon savings, and ensuring social equity. A growing body of research in visual analytics is dedicated to supporting this process, often by providing interactive ways for users to explore the Pareto front of optimal solutions and understand the trade-offs between different objectives [HZJ*23, CWO*23, ZYCM24]. These systems empower users to identify desirable solutions from a set of pre-computed optimal outcomes. While our work shares the goal of supporting multi-objective decision-making, it differs in its approach. Rather than focusing on the exploration of a pre-computed solution space, our component-based paradigm focuses on the authoring process itself. This allows planners to build, layer, and simulate modular interventions, offering a more transparent and cognitively manageable way to engage with the multi-objective challenge.

Our system's primary methodological contribution is its component-based planning paradigm. By allowing planners to interactively build a complex strategy from smaller, layered, and independently defined components, we offer a more flexible and cognitively manageable approach. This departs from similar geospatial-based models [AARAA24, UAUFDAC*21] or geospatial multi-criteria decision support system [BB19]. Our component-based planning paradigm shifts the user's role from a passive observer of a model's output to an active author of the decarbonisation plan itself. This tight coupling of data-driven cohort selection, modular intervention design, and immediate visual feedback via an embedded simulation represents a novel workflow in the landscape of decision-support tools for building decarbonisation.

**Geospatial Visualisation in Urban and Energy Planning**. Geographic Information Systems (GIS) are foundational to urban planning, typically employing a map layer metaphor where thematic data are superimposed onto a basemap. GIS offers the technical means for decision-makers to grasp the connections among geographic, societal, and cultural elements when making choices [SD10]. While intuitive for showing individual spatial distributions, this approach has limitations for multivariate analysis. As users add more layers representing metrics like energy use, building age, and social factors, they face significant cognitive overhead in switching between them to understand interrelationships [SR17, KYM24]. This makes it difficult to answer complex questions that involve multiple datasets simultaneously. Furthermore, representing temporal change often requires cumbersome time-sliders or animations that hinder direct comparison across time points [SR17].

To address this "layer-overload," researchers in geovisualisation and visual analytics have explored more integrated representations. One powerful alternative is the use of glyphs: small, data-driven graphical symbols that can encode multiple variables [BKC*13]. Glyph-maps have been effectively used to explore spatio-temporal patterns in diverse domains [Sli18, BDHL21a, KYM24], including to help visualise multi-criteria decision making for decarbonisation prioritisation [LSJ24]. Our work builds directly on this tradition. While some studies have used glyphs to represent energy data (e.g., [XLL*22], used a rose bar glyph for geothermal energy benefits), our use of a mirrored streamgraph glyph to specifically compare cost versus carbon savings over a simulated timeline, promoting at-a-glance understanding of the complex, timeseries decarbonisation plans.

Finally, our use of squarified grids draws from research on value-by-area cartograms [NAK16, Sli18, BDHL21b], where geography is intentionally abstracted to enhance comparison and ensure that small but significant geographic areas are not visually overlooked. While we do not resize areas based on a variable, we adopt the principle of abstracting geography into a regular grid. This approach, which turns the map into a functional canvas for comparison, has been shown to improve the readability of complex spatial data by giving each spatial unit equal visual prominence, a known challenge in traditional cartography [KCR20, CBC*15].

## 3. System Design and Methodology

The system's design was directly shaped by a requirements analysis conducted through a close, ongoing collaboration with an industry partner and engagement with domain specialists in the energy sector. A key insight from this process was that planners are often overwhelmed by the complexity of balancing competing technical, social, and economic priorities, which can lead to overly simplistic, monolithic strategies. This core challenge directly informed our design imperative: to create a system that shifts from rigid, monolithic plans to flexible, modular, and interpretable 'plan components'. The system was therefore explicitly designed to support four core planning tasks that emerged from this analysis:

*T1: Identify and Characterise Target Cohorts*. Exploring the building stock to identify specific groups of buildings for intervention.

*T2: Author Scenarios via Modular Composition.* Authoring a strategy by composing it from smaller, focused parts.

*T3: Compare Spatio-Temporal Outcomes to Evaluate Trade-offs.* Comparing projected outcomes across geography and objectives.

*T4: Explore Design Alternatives through Iteration*. Iteratively proposing, testing, and refining strategies to discover a more effective and equitable plan.

To support these tasks, we developed a system comprising a visual analytics interface tightly coupled with a backend decarbonisation model.

### 3.1. The Visual Analytics Interface

The interface (Figure 1) consists of four linked components designed to facilitate a seamless planning workflow.

The **Table View** (Figure 1B) provides a familiar spreadsheet-like interface for sorting, selecting, and viewing raw building data. It is tightly linked with the **Map View** to support consecutive filtering, allowing users to move between spatial and statistical selections to identify and narrow down cohorts (T1).

The **Timeline View** (Figure 1C) serves as the main planning canvas. It is linked to the **New Intervention panel** (Figure 1A), where planners configure and specify 'plan components'. By layering these components on the timeline, users can author a complex scenario (T2) from modular parts. The timeline also act as an interface to the underlying model: changing the timeline (e.g., dragging the intervention block or changing the order) trigger model recalculation, updating the output directly on the map.

The **Map View** (Figure 1D) serves a dual function as both a control for spatial filtering (supporting T1) and a canvas for visualizing outcomes (supporting T3). To visualize outcomes, the Map View uses multivariate glyphs instead of traditional GIS layers. In "Decarbonisation Potential", each glyph is a compact information graphic where visual channels (e.g., length or colour of spokes) are mapped to key performance indicators like technology adoption, carbon savings, or cost. This allows for the at-a-glance comparison of multiple metrics within a single spatial unit. The same map view visualises time-series data (i.e., a mirrored streamgraph of cost versus carbon savings) in "Decarbonisation Timeline", allowing a planner to see the projected trajectory of an area over several years based on the model output. To enhance legibility at higher aggregation levels, the system can render geographies as squarified grids (cartograms, Figure 2 bottom), intentionally sacrificing spatial fidelity for analytical clarity. Ultimately, the tight integration of the **Table View**, **Timeline**, and **Map View** creates the seamless, human-in-the-loop workflow that is essential for exploring design alternatives through rapid iteration (T4).

### 3.2. The Decarbonisation Simulation Model

The analytical core of our system is a backend simulation model that projects the year-on-year impact of intervention plans. The model takes as input a dataset of individual buildings and a set of user-defined plan components from the interface. It respects annual budget constraints (with optional rollover) and allocates interventions based on one of two user-selected optimisation strategies:

- **Carbon-first**: This strategy prioritises interventions based on carbon efficiency. For all possible technologies, the model calculates the cost-per-tonne of carbon saved for each building. It then creates a priority queue of all potential interventions across the entire cohort, ordered from most to least carbon-efficient. The yearly budget is spent dequeuing and applying the most efficient interventions first.
- **Tech-first**: This strategy focuses on deploying a single specified technology. The model sorts all suitable buildings based on a base ranking and adjusts this with any custom priority rules (e.g., targeting buildings in fuel poverty). It then applies the intervention sequentially to the ranked buildings until the allocated yearly budget is exhausted.

For each scenario authored by the user, the model outputs a detailed time-series dataset quantifying changes in building stock properties, intervention costs, and carbon savings. This output serves as the primary data source for the visualisations in the Map View.

### 3.3. Implementation and Data Processing

To ensure interactivity and a responsive user experience, the visual analytics dashboard was developed using Observable Framework,


Proceedings published by Eurographics - The European Association for Computer Graphics.

**Figure 2:** *Above: Multivariate and multiscale geographic data shown at different levels of aggregation (Building level → Gridded → LSOA level → LA level). Below: 'Squarifying' administrative boundaries into a cartogram to reduce visual clutter.*

which provides built-in reactivity to the JavaScript components. The interface components (Figure 1), including the Table View, Timeline, and Map View glyphs, were implemented as tailor-made JavaScript components, allowing for tight integration and communication between the different views.

The backend simulation model, which handles the intervention scenarios, is also built within this framework. Data processing is handled client-side to facilitate real-time feedback. The initial building stock data, including geospatial information and performance indicators, is loaded as a static dataset. When a user authors a scenario, the model scripts process this data in-memory, calculating the year-on-year impacts based on the selected optimisation strategy (**'Carbon-first'** or **'Tech-first'**) and budget constraints. The resulting time-series output is then passed directly to the frontend components for immediate visualisation on the Map View. The source code for the app is available at `https://github.com/danylaksono/decarbonisation-glyphmap-planner/`.

## 4. Discussion

Our work contributes a visual analytics methodology designed to re-frame the complex process of local decarbonisation planning. By breaking down the workflow into distinct tasks (T1-T4) and supporting them with an integrated system, we can analyse the merits and limitations of our approach, focusing on how the interface and model empower planners.

### 4.1. Enabling Modular and Interpretable Planning (T1, T2)

A primary merit of our approach is how the visual interface facilitates the authoring of interpretable, modular planning paradigm, which re-frames how complex strategies are constructed. Current decision-support systems often rely on monolithic optimisation, where a single model processes all possible technologies and constraints to produce a single 'optimal' plan. While powerful, this can be a 'black box' for planners. By 'modular', we mean that planners can author a strategy from discrete, layered, and independently defined 'plan components'.

To provide a concrete example of the workflow, a planner might first use the linked **Table View** (Figure 1B) and **Map View** (Figure 1D) to identify a cohort (T1), such as 'all residential buildings with an EPC rating of D or lower within a specific neighbourhood designated as a high priority for fuel poverty alleviation'. They could then use the **New Intervention** panel (Figure 1A) to author a component (T2) for this cohort, such as a PV Solar Panel with a budget of £10 million allocated over five years, which then appears on the Timeline View (Figure 1C). This process makes the strategy transparent, as each component's intent is explicit, mirroring the reality of public policy where multiple initiatives overlap. A limitation, however, is that this modularity is dependent on the planner's ability to resolve complexity.

### 4.2. Visualising Complex Trade-offs with Glyphs (T3)

Once a scenario is authored, the system must support the critical task of comparing spatio-temporal outcomes (T3). The design of the Map View's glyphs directly addresses this. In *"Decarbonisation Potential"* option, the key merit is in providing an integrated view of multiple performance indicators, which overcomes the analytical fragmentation of toggling map layers. The *"Decarbonisation Timeline"* option presents timeseries data, directly contrasts projected carbon saved and budgets spent for each year (Figure 3). This direct encoding of decarbonisation timeline reduces cognitive burden of having to go through layers of choropleth maps with slider in conventional GIS tool, allowing planners to see where and when the budget is being spent and how effective it is. Any changes to the model parameter in **Timeline View** (e.g., changing project duration) directly affects these glyphs, enabling experimentation with different intervention configurations. Another key aspect is the multi-scale ability to see the data and the model output at different level of geographic aggregation, specifically from individual buildings to local area (LSOA) and local authority (LA) levels as shown in Figure 2 (above). The platform use consistent glyph designs to represent multivariate data uniformly across these scales (Figure 3), providing the planners with a consistent understanding of the trade-offs across multiple level of hierarchies.

The limitation of this information-dense approach is the potential for visual clutter in geographically compact areas. While the use of cartograms reduces this limitation and enhances analytical clarity for comparison, the animated morphing might adds temporal complexity: the planners must track motion over time, which can increase cognitive burden (Figure 2, below). Another limitation to the aggregated view is a problem known as *"Modifiable Areal Unit Problem (MAUP)"*, which might lead to misleading interpretations of spatial patterns, as statistical results can vary significantly depending on how spatial units are defined or aggregated. Currently, each mode only shows a single type of glyph: radial glyph for showing decarbonisation potential, and stream-graph glyph for projected decarbonisation timeseries. Future improvements should allow some degree of liberty for the planners to choose the best representation of the data (e.g., [LSJ24]).

### 4.3. Fostering Iteration with a Human-in-the-Loop Model (T4)

The cornerstone of our methodology is its support for the meta-task of exploring alternatives through iteration (T4). This is enabled by the tight coupling of the visual interface with the responsive simulation model. The merit of this human-in-the-loop workflow is that it transforms planning into a dynamic dialogue. The continuous, rapid cycle of authoring a component (T2), simulating its impact with the model, and observing the outcome (T3) allows planners to test hypotheses and learn from feedback. While the simulation model might be able to yield 'optimal' result (e.g., "carbon-first" option targeted for all buildings), the actual policy-making might involves dynamic considerations (e.g., 'better to prioritise buildings with high rate of fuel poverty, or targeting wealthy neighbourhood for rapid adoption of green technology?'). Leveraging human-in-the-loop allows decision to be made based on these dynamic, multivariate parameters.

The primary limitation is that the workflow's effectiveness is constrained by the simulation model's speed. Any significant lag in generating results would break the feeling of interactivity and hinder the iterative dialogue. Currently, the dashboard also does not allow planners to store their intervention configurations as historical settings. This would allow further comparison tasks between different stack of configuration. At the moment there are no mechanism for collaborative discussion between planners, where different judgements can be compared to each other, facilitating discussion and promoting transparency.

### 4.4. Limitations and Future Work

While this work establishes a robust methodology, its most significant limitation is the absence of a formal user evaluation with local authority planners. The collaboration with industry partners ensured our design choices were rooted in real-world needs, providing essential foundational validation for the system's features and workflow. This iterative, collaborative process served as a continuous, informal formative evaluation, ensuring the tool remained aligned with user requirements throughout its development. However, a rigorous user study is the clear next step to empirically assess the system's effectiveness and usability. A secondary limitation lies in the simplification of the underlying simulation model, which provides strategic projections rather than definitive predictions.

Future work will focus on both enhancing the simulation model's fidelity and, most importantly, conducting contextual studies with local authority planners. These studies will be designed to rigorously assess how this system empowers them to tackle key planning tasks, from identifying cohorts (T1) to iterating on design alternatives (T4), and whether it ultimately leads to more effective and equitable decarbonisation strategies.

## 5. Conclusion

This paper presented a visual analytics system designed to address the profound challenges UK local authorities face in developing effective and equitable decarbonisation plans. We introduced a dual-pronged contribution: a component-based planning paradigm that makes the creation of complex, multi-objective strategies cognitively manageable, and a multi-scale glyph visualisation that offers clear spatio-temporal insights into plan impacts. Our approach, which tightly integrates data exploration, modular planning, and an embedded simulation within a human-in-the-loop workflow, successfully bridges the gap between high-level policy goals and building-level data.

The primary advantage of our system is its ability to make the planning process more transparent, flexible, and iterative. However, we acknowledge its limitations, including the inherent simplifications of the underlying model and the potential for visual clutter in dense geographic areas. Future work will focus on enhancing the simulation's fidelity, conducting formal contextual studies with planning professionals, and developing dedicated features for comparing competing plan scenarios. Ultimately, this work provides a robust framework and a practical tool to support the critical, data-driven decisions necessary to accelerate the path to net zero.

## Acknowledgement

We thank Advanced Infrastructure Ltd. (AITL) for the data and for co-funding this work along with City St. George's, University of London.

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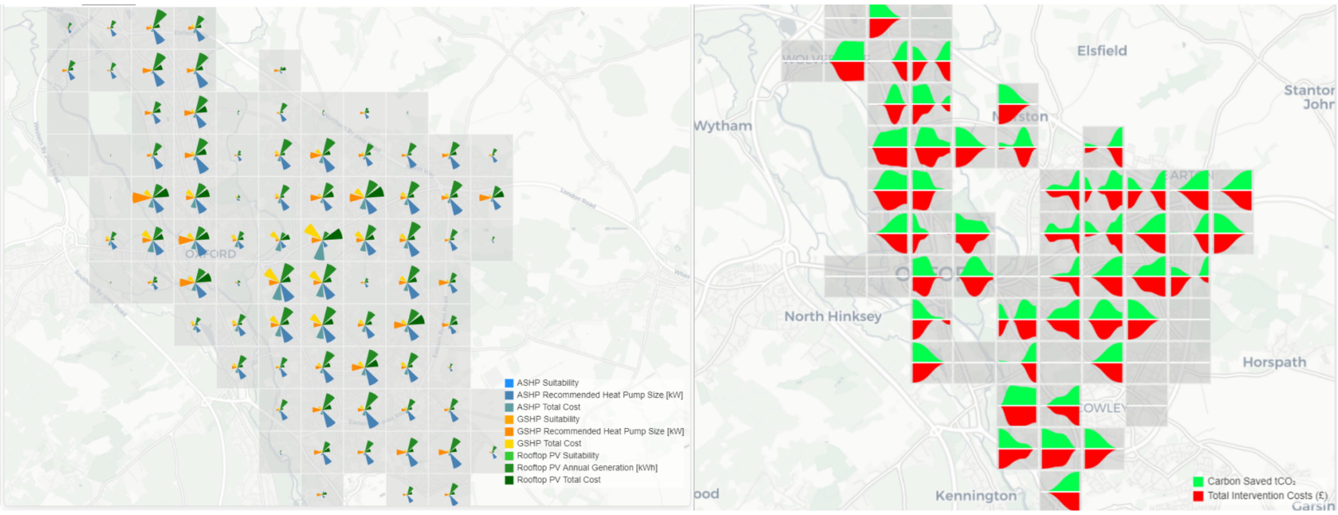


**Figure 3:** *Map view showing aggregated buildings. Left: Decarbonisation Potential from building stock data. Right: Model output showing Decarbonisation Timeline for each planned year. Each glyph shows the timeline progresses from left to right: the leftmost point represents the most recent year, and each subsequent point to the right represents a later planned year in the timeline.*


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