ROBBINSDALE

Sustainability Committee Meeting
Wednesday, September 17, 2025
4100 Lakeview Avenue North
Robbinsdale, MN
6:00 PM

AGENDA

1. ROLL CALL: Greenberg, Hansen, Hanelitz, Hart, Heid, Lyng, Pendaz-Foster, Presler, Myers, Sande, Larson

2. CONSIDERATION OF MINUTES

   A. August 20, 2025 Meeting Minutes

3. NEW BUSINESS

4. OLD BUSINESS

   A. City Council Presentation Preparation

5. INFORMATION ONLY

   A. Birdtown Boo Bash - October 3, 2025

   B. Updates from Committee Members

6. ADJOURNMENT

MINUTES

ROLL CALL

Present: Hanelitz, Hansen, Hart, Heid, Larson, Myers, Myrfield, Pendaz-Foster
Absent: Greenberg, Lyng, Presler, Sande
Staff: Kayla Kirtz, Sustainability Coordinator

CONSIDERATION OF MINUTES

A. June 18, 2025 Meeting Minutes

Hanelitz motioned to approve the minutes of the June 18, 2025 Sustainability Committee meeting, and Heid seconded. The meeting minutes were unanimously approved.

NEW BUSINESS

A. Sub-Committee Updates

Each subcommittee provided an update from their meetings over the summer. Hanelitz presented slides from the Green Space and Land Use subcommittee. Heid, Hansen, and Pendaz-Foster shared a draft document from the Climate Action Planning subcommittee. Hart presented slides from the Community Engagement subcommittee. All documents shared from the subcommittees are included in the 08-20-2025 Sustainability Committee Meeting Agenda.

In preparation for the September meeting of the Sustainability Committee, Myrfield agreed to create a PowerPoint template for the subcommittees to use. Myrfield would share the template with Kirtz who will distribute it to the Committee. The Committee planned to spend the September Committee meeting refining the details of their presentation to the City Council. The Committee also agreed to schedule an additional meeting on Wednesday, October 1st at 6:00 p.m. at Robbinsdale City Hall to prepare their presentation.

B. Chamber of Commerce Meet & Greet Tabling

Kirtz asked if the Sustainability Committee would like to have their own table at the Chamber of Commerce Meet & Greet and the Committee said yes. Kirtz asked for volunteers and Hart, Myrfield, Heid, and Larson expressed interest. Kirtz said she would coordinate with Hart to make sure the Committee has the materials they need for tabling.

C. CERTs Seed Grants

Kirtz shared the Clean Energy Resource Teams (CERTs) Seed Grants with the group and noted that another round of funding is available for community clean energy projects. The grant application is due on October 1, 2025. Kirtz encouraged the Committee to read more about the grants and to brainstorm a few potential project ideas.

D. City Commission/Committee Code of Respect

Kirtz stated that City Manager Sandvik is asking for feedback on the draft City Commission/Committee Code of Respect. Kirtz requested that the Committee review the draft and provide any feedback to Kirtz by September 3rd.

OLD BUSINESS

None.

INFORMATION ONLY

The Committee agreed that it would be helpful for the City Manager to attend an upcoming Sustainability Committee meeting.

ADJOURNMENT

Kirtz adjourned the meeting at 8:22 p.m.

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Kayla Kirtz, Staff Liaision Date

ROBBINSDALE

TO:	Sustainability Committee
PREPARED BY:	Kayla Kirtz, Sustainability Coordinator
DATE:	September 17, 2025
RE:	Updates from Committee Members

Background:

Please see the attached documents:

1. "Model-based Climate Action Plans for ambitious local emissions reduction: A project-focused approach" shared by member Nick Heid.
2. Map of Robbinsdale public fruit trees shared by member Megan Hanelitz.
3. Email from Megan Hanelitz summarizing conversations with the City Forester about public fruit orchards.

Analysis:

Recommendation:

Attachments:

1. Article from Nick Heid
2. Robbinsdale Public Fruit Trees
3. Email from Megan Hanelitz

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Model-based Climate Action Plans for ambitious local emissions reduction: A project-focused approach

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ABSTRACT

Cities are increasingly developing Climate Action Plans to coordinate local emissions reduction; however, planners lack methodological guidance for consolidating many individual climate projects into a single plan. To close this gap, we frame the task of developing Climate Action Plans as a scheduling problem that determines optimal start times for emissions abatement projects given a specific budget. We characterize projects from empirical European data and find that considering uncertainty in cost and emissions abatement potential supports plans that are both ambitious and less prone to budget overruns than when neglecting uncertainty. We also identify difference between popular mitigation actions and those suggested under an optimal scheduling framework, which indicates potential for higher emission abatement ambition than observed in current Climate Action Plans. Our framework builds on cities' growing interest in computational models as decision-support tools while retaining the project-specific focus prominent in current stakeholder consultation practices.

1. Introduction

Cities coordinate their fights against climate change by creating "Climate Action Plans" or "Local Climate Plans" (Reckien et al., 2018). Climate Action Plans are local government roadmaps on how to mitigate and adapt to a changing climate (Reckien et al., 2018) and are potentially highly impactful environmental policies given that cities account for approximately three-quarters of global greenhouse gas emissions (Seto et al., 2014) and thousands of cities worldwide have already adopted some form of Climate Action Plan (C40 Cities, 2023; Lucchitta et al., 2024; REN21., 2021b; Woodruff and Stults, 2016).

City planners can turn to extensive guidance for identifying potential mitigation projects (C40 Cities, 2018; C40 Cities, 2020; GCoM, 2024c; ICLEI USA., 2019; Rocky Mountain Institute, 2017; UN Habitat and IIED, 2012; WRI, C40 Cities, and ICLEI, 2021) but face a dearth of support for uniting individual projects into a long-term plan. For example, the C40 "Climate Action Planning Framework" report states, "Cities should set out a methodology for prioritizing actions which will ensure that the highest-impact mitigation and adaptation actions are delivered first" but then fails to establish any methods for cities to follow (C40 Cities, 2020). Likewise, the Rocky Mountain Institute's "Carbon-Free City Handbook" does not list any decision-making strategies other than seeking input from stakeholders, regional actors, and peer networks (Rocky Mountain Institute, 2017). Meanwhile, work done by the Intergovernmental Panel on Climate Change (IPCC) lists several strategies for decision-making in a climate context but concedes that the

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methods have primarily only been tested in theoretical settings, and the utility of each is hence unknown (Jones Roger et al., 2014; New et al., 2022).

In the absence of alternative decision-making strategies, cities often frame the development of Climate Action Plans as a collaborative task in which residents, businesses, and municipal officials work together to define priority areas and projects (Fig. 1a; C40 Cities, 2020; Rocky Mountain Institute, 2017; UN Habitat and IIED, 2012). Engaging local stakeholders helps build social acceptance and achieve deeper emissions reductions (IPCC, 2022; Kaufmann et al., 2024; Rivas et al., 2022) and realize other co-benefits, like improved air quality, better street safety, and more walkable neighborhoods (Lwasa et al., 2023). These processes may be supported by tools such as marginal abatement cost curves (Kesicki and Ekins, 2012), public dashboards (Miles et al., 2023), network process modeling (Peris et al., 2013), and multicriteria decision-making processes (Cohen et al., 2019; Xue et al., 2022). However, there are signs that existing planning processes and tools are insufficient to deliver climate action. Systematic reviews have found that many Climate Action Plans strategies produce little benefit over "business-as-usual" emissions reductions (Baker et al., 2012; Deetjen et al., 2018; Lonergan and Sansavini, 2022; Woodruff and Stults, 2016) and struggle to realize the anticipated social co-benefits of coordinated climate action (Dodman et al., 2022). Challenges building ambitious Climate Action Plans are particularly acute in cities that are smaller, less wealthy, lack sufficient baseline emissions data, and host disputed climate change narratives (Reckien et al., 2015; Rivas et al., 2021; Tenali and McManus, 2022). However, even "frontrunner" cities like Copenhagen, Oslo, Kyoto, and Canberra struggle to achieve accelerated systemic decarbonization (Barrett et al., 2023). Identifying the most effective projects is marred by not understanding how cost and effectiveness vary from place to place. This challenge stems from a lack of baseline emissions data (Rivas et al., 2022), inherent project variability (e.g., technical parameters, design costs), and poorly understood local behavioral patterns (Lwasa et al., 2023). Problematically, there are cases where uncertainty about specific projects and policies impedes decision-making (City of Amsterdam, 2020; Mayor of London, 2018), delaying time-sensitive climate action.

Cities have recently begun turning to computational models for additional support in building their Climate Action Plans. In Europe, ClimateView software has been used to develop transition plans in Sweden (Malmö, Uppsala, Helsingborg), Germany (Karlsruhe, Dortmund, Mannheim), the Netherlands (Eindhoven, the Hague), and the United Kingdom (Newcastle, Nottingham, Bristol; ClimateView, 2023). The cities of Mumbai and Johannesburg both leveraged the C40 Pathways Model to develop three emissions reduction scenarios (C40 Cities Climate Leadership Group and C40 Knowledge Hub, 2022). In Canada, the city of Toronto

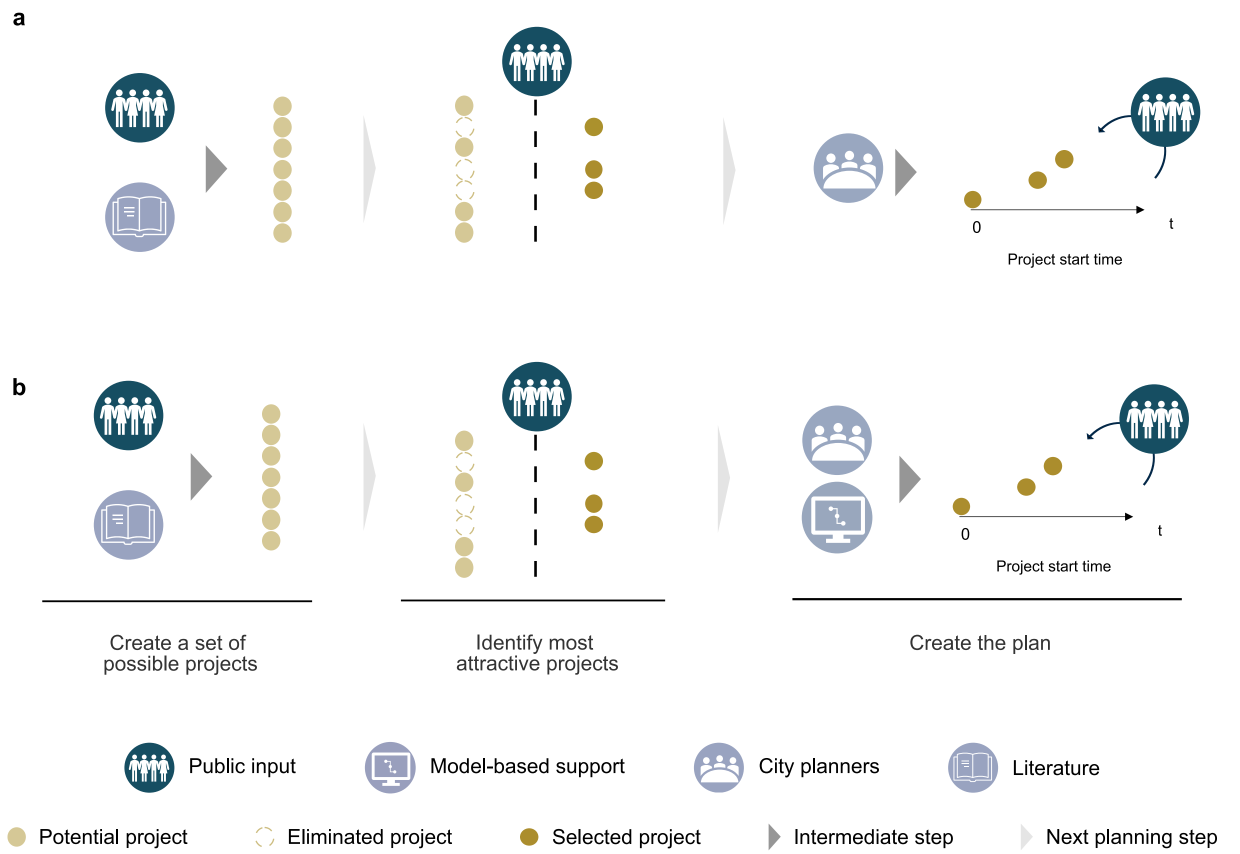

Fig. 1. Overview of local Climate Action Planning processes, summarized in the three steps: creating a set of possible projects; identifying the most attractive options; and creating a Climate Action Plan. Opportunities for public consultation are highlighted. (a) A typical planning process. (b) A model-supported planning process that retains the same focus on individual projects and the same opportunities for public engagement as in existing planning processes.

used the CityInSight model to identify net-zero transition pathways, stimulate community dialogue, and investigate the equity impacts of different decarbonization strategies (City of Toronto, 2021; Rossini and Baxter, 2017). The bourgeoning interest in applying model-based analysis to the task of guiding local climate action highlights the willingness of city planners to incorporate a wider set of decision-making tools into the local climate planning process.

The increasing use of models for guiding local climate plans is encouraging, but several obstacles must still be overcome. First, there is a lack of transparency surrounding existing modeling tools, impeding external assessment. In addition, a limited number of cities have access to existing tools because the most prominent models are held by organizations. This limitation particularly affects planning processes in smaller and less wealthy cities since nongovernmental organizations would prioritize larger, more highly emitting cities and private organizations would likely target cities that are better able to pay consulting fees. Second, it is unclear how compatible continuous trajectory-focused modeling is with the discrete, project-focused planning paradigm currently dominant in Climate Action Plans. The trajectory-focused approach is beneficial in the sense that it can better capture path dependencies than a project-focused approach; the empirical focus on transition modeling is also consistent with wider urban decarbonization optimization literature. However, it can be more difficult to elicit meaningful community feedback on a continuous, abstract transition pathways model than on specific, tangible projects. Difficulty understanding how to interpret and apply model-based planning recommendations have been identified as a barrier to transferring quantitative results to local climate and energy action (Cheng et al., 2022; City of Hamburg, 2011; McGookin et al., 2021; Ratheiser et al., 2019), which underlines the value of methods that can be integrated into existing planning practices.

In sum, local climate planning still lacks decision-making support tools that provide tangible outputs in uncertain environments. To close this gap, we propose applying mathematical optimization to the task of identifying optimal Climate Action Plans for emissions reduction. Specifically, we frame the development of Climate Action Plans as a scheduling task, which we explore using empirical data in a case study of a representative European city. Developing Climate Action Plans is similar to solving a generic scheduling problem in the sense that planners must determine how to schedule specific actions in a constrained environment; here, we consider the task of identifying the start times for individual projects in a budget and staff-constrained environment, which both limit the number of possible climate projects (UN Habitat, 2014). In addition, the uncertainties faced by climate planners are similar to uncertainties faced in other scheduling problems; for example, in terms of project impact and cost (Fang and Sansavini, 2019; Nesbitt et al., 2021).

We contribute to climate action planning methodology by demonstrating a systematic, transparent approach for developing municipal Climate Action Plans under uncertainty. Our modeling approach retains a direct connection to existing project- and stakeholder-focused practices (Fig. 1), while presenting the benefits of modeling approach in navigating planning complexities. The proposed model supplements current approaches and reflects local, contextual priorities, thereby supporting both distributional and procedural justice. Finally, we extend the existing climate-focused optimization literature by applying an existing decision support tool to a novel application.

The remainder of this paper is structured as follows. Section 2 introduces the methodology. Results are presented in Section 3. Section 4 discusses the significance of the results and Section 5 concludes.

2. Methodology

We develop a Climate Action Plan for a representative European city to demonstrate the potential of stochastic optimization towards developing Climate Action Plans. To do so, we first construct a representative project portfolio based on European data. Next, we schedule the projects to identify climate-optimal and budget-compliant Climate Action Plans for our case study city. Finally, we test the plan's performance in a simulation experiment to highlight the benefits of considering uncertainty within the decision-making process.

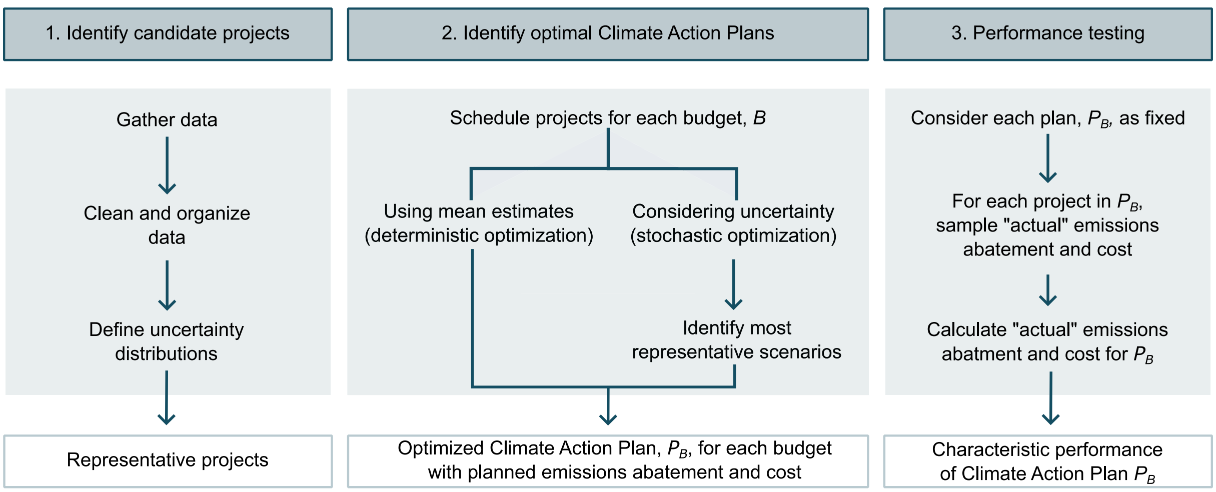

Fig. 2. Overview of the research methodology.

Fig. 2 provides an overview of the entire methodology.

2.1. Building a representative project portfolio

We construct a representative project portfolio based on actual carbon abatement projects planned by European cities. We source our data from the Carbon Disclosure Project "2021 Cities Emissions Reduction Actions" database (CDP, 2022), which lists carbon abatement projects voluntarily listed by cities. Each database entry includes a short project description and quantitative descriptions about the project and links to additional project webpages. Relevant to this study are project cost, lifetime, and anticipated greenhouse gas emissions reduction potential, measured in metric tons of carbon dioxide equivalents (tCO_2e). Although the global database contains approximately 17,000 global project entries, fewer than 1000 have complete information in terms of project description, cost, lifetime, and anticipated greenhouse gas emissions. While the Carbon Disclosure Project database is a comparatively exemplary resource, gaps in self-reported data also exemplify the general challenge of sourcing city-level climate data (also see Section 4.2).

We identify classes of carbon abatement projects implemented by cities based on the self-reported information provided in the Carbon Disclosure Project database. This step allows us to identify classes of project and typical cost, time, and abatement potentials, as well as uncertainty range. DeepL Translate (DeepL Translate, 2022) was used to translate the project descriptions for project descriptions in languages other than the authors' own languages. Generally, projects were classified according to sector, the actor responsible for achieving the emissions abatement, and the nature of the project or action. The list of typical projects was iteratively developed: a newly identified action was added to the list while existing categories were refined as subcategories emerged. For example, an initial project category was "Waste", but that category was later refined into multiple more specific projects.

While the database includes data from all over the world, we only consider the European data in our case study. We utilize European data to consider as much empirical data as possible while respecting that carbon and cost estimates are somewhat linked to geography. European markets are highly interconnected (European Commission, 2012; European Union, 2019), which makes our approach reasonable for a first investigation. Of course, a more precise approach would consider data from only the most similar cases, but this refinement is outside the scope of the present work (also see Section 4.3).

As a final step, we remove outlier data points from the data set. Removing outliers necessarily narrows the uncertainty distributions associated with each project but is a necessary precautionary measure to control for:

(a) Potential human errors in how the data was reported to the Carbon Disclosure Project, an issue also affecting other datasets (Lucchitta et al., 2024);
(b) Market-specific conditions that skew carbon, cost, and time estimates beyond the normal range; and
(c) Possible misinterpretations of the original project descriptions.

We identify outliers based on absolute and relative thresholds for cost per capita and emissions reduction per capita. We remove data points with zero cost or zero emissions reduction, the presence of which we attribute to human errors during data reporting. We eliminate data points with stated emissions reduction potential above $1 kgCO_2e$/capita or costing more than 500 €/capita. We also omit data points with cost per capita or emissions reduction per capita beyond the 80th percentile of the overall ranges observed within each project class. Alternative outlier detection methods based on clustering (Dalgaard, 2008) were also tested but failed to yield convincing results due to the high dispersion of values within each project class. The outliers do not exhibit any systematic relationships with project class, countries, or cities (including population); however, these relationships should be revisited in future work (see Section 4.3).

Projects with fewer than three remaining data points were excluded from the final case study to define uncertainty distributions to project cost and emissions. Representative projects were then defined using the cleaned data. Specifically, uncertainty distributions for project emissions abatement potential and cost were defined using Program and Evaluation Research Task (PERT) distributions, which are typically applied when considering sparse, expert-elicited data (Malcolm et al., 1959; U.S. Nuclear Regulatory Commission, 2017; Xing and Morrow, 2016). Averages were used to calculate the project duration. As a final step, the population-normalized cost and emissions estimates were used to calculate the total cost for a representative population set equal to the median number of inhabitants for each record in the cleaned data set, which is 800,215. Scaling the emissions and cost for a population of 800,215 provides a modeling basis consistent with the input data for this representative case study; the specific results and budget scenarios therefore align with the Climate Action Plan of a large city. If more data were available, it would become advantageous to filter data to consider the experience of similarly sized cities to account for possible scale effects (see Section 4.3).

Importantly, the data collected by the Carbon Disclosure Project lists only implementation costs and not overall lifetime cost-benefit (CDP, 2024). As such, costs in this work strictly refer to implementation costs and do not consider the fact that some projects may present costs savings, e.g., energy efficiency measures (Babiker et al., 2022).

2.2. Scheduling algorithms

Once a set of representative projects is characterized, it can be passed to a scheduling algorithm to determine which projects to run and when to run them. We identify Climate Action Plans by scheduling representative projects with mathematical optimization. Optimization methods find the optimal solution to a problem given the problem is formulated in terms of decision variables (possible actions), objectives, and constraints. Here, the objective is to identify project start times to find the maximum emissions abatement given a set of budget and staffing constraints (Fig. 3). Specifically, we generate Climate Action Plans for a set of budgets ranging from

50 million € to 400 million €, while limiting the number of projects that can be executed simultaneously to five and setting a maximum planning horizon of 20 years.

In our case study, we consider two scheduling algorithms: deterministic and stochastic optimization. Both algorithms are based upon the "Resource Constrained Project Scheduling Problem" presented by Nesbitt et al. (2021). While other scheduling algorithms exist (e.g., Fang and Sansavini, 2019; Kall and Mayer, 2011; Lamas et al., 2023; Pianykh et al., 2024), the Nesbitt et al. formulation is advantageous since it allows us to account for uncertainty in project time and cost while considering precedence constraints (i.e., cases where Project A must occur before Project B), accounting for conditional non-anticipativity (i.e., uncertainty about specific projects is not resolved until the project occurs), and can be solved using a heuristic method to address very large problems (thousands of tasks). Since our case study only considers 19 projects, we do not apply the heuristic method and calculate the exact solution. The model description is located in Appendix A but the reader is deferred to the original publication for a more extended overview (Nesbitt et al., 2021).

The first algorithm we consider is a deterministic optimization, which finds the optimal solution considering only a single value for each parameter. We find the deterministic solution for the expected emissions reduction and expected cost. These solutions essentially correspond to the best possible schedules if uncertainty is not considered.

The second algorithm we apply is stochastic optimization, which finds the best possible solutions under uncertainty. The uncertainty is integrated mathematically by having the optimization algorithm find a solution considering a range of possible scenarios, each with an associated likelihood of occurrence (Kall and Mayer, 2011). Here, we determine a representative set of scenarios using a two-step computational approach. In the first step, many possible actual scenarios are generated using Latin Hypercube Sampling (LHS), while the second step identifies a set of computationally tractable representative scenarios to be considered within the optimization.

The LHS generates potential scenarios by sampling parameter distributions, which in our case are derived from empirical data (see Section 3.1). LHS proceeds by sampling from an evenly divided cumulative distribution function, which helps ensure that the samples drawn reflect the entire distribution. LHS assumes that the parameters are independent (Santner et al., 2018). For our case study, LHS is an appropriately simple approach because we do not consider probability distributions with heavy tails and the uncertain parameters do not feature a clear dependency structure, i.e., we fail to detect a relationship between higher project cost and emissions reduction. Alternative sampling methods would be required if either of these cases were considered. For example, importance sampling helps create representative samples in the case of heavy-tailed distributions (Zio, 2013), while defining the joint probability distribution between variables is appropriate when the realizations of uncertain variables are correlated (Sun et al., 2020).

LHS establishes a range of possible scenarios but optimizing over the entire set is computationally infeasible. We, therefore, identify a smaller and representative set of scenarios from all those generated with LHS using a scenario reduction process (Conejo et al., 2010). The scenario reduction process aims to find the subset of scenarios that best retain the stochastic information contained within the larger, original set and yield an optimal solution close in value to the solution that would be obtained by optimizing over all scenarios (Conejo et al., 2010). Here, we apply the Fast Forward Selection (FFS) method, which uses the probability distance to find the optimal subset of scenarios generated by the LHS. The FFS algorithm begins by identifying the scenario that best represents the entire set of possibilities and adds it to the set of representative scenarios (Conejo et al., 2010). The algorithm then finds the scenario that best represents the remaining scenarios in the original set and proceeds until the desired number of scenarios is attained. The likelihood of occurrence for each of the scenarios in the representative set is determined by associating the probability of each non-selected scenario with the nearest selected scenario (Conejo et al., 2010). FFS is computationally efficient, although other scenario reduction techniques are also possible (Heitsch and Römisch, 2003). Critically, the value of the reduced scenarios is in their collective representation and coverage of project emissions and costs combinations rather than in the information contained within any individual scenario. In that sense, our probabilistic scenarios differ from narrative scenarios often featured in climate literature, e.g., the Shared Socioeconomic Pathways (IPCC, 2019), which entail specific world views and assumptions.

We generate our results using 7 representative scenarios derived from 50,000 possible scenarios, the former of which is commensurate with both the number of scenarios conceivable to experts and the number often considered in scheduling literature (Fang and Sansavini, 2019; Nesbitt et al., 2021). We use 50,000 samples because the results are stable at this level, i.e., additional

Optimization term	Problem -specific attributes	Intuition
Decision variables	Project start times	A plan is built by deciding when to execute specific projects (if at all)
Objective	Maximize emissions reduction over a 20-year planning period	Mimic the mitigation aspect of Climate Action Plans
Constraints	Such that: • The budget is respected • No more than five projects occur simultaneously	• Replicate budget constraints • Replicate staffing limitations

Fig. 3. Mapping the climate action planning process to mathematical optimization.

sampling does not result in changes to the proposed schedules.

2.3. Simulations

The scheduling algorithms produce Climate Action Plans that maximize expected emissions reduction given cost and staffing constraints, but actual outcomes vary depending on how the plans are implemented. To better understand the performance variability of the proposed Climate Action Plans, we calculate the resulting emissions reductions and costs associated with implementing each plan. Specifically, we:

1. Take the algorithm-proposed schedule as a fixed plan
2. For each of the planned projects, sample emissions reduction and cost from the uncertainty distribution typical of that project (see 3.1)
3. Calculate the plan's total "actual" emissions reduction and cost

We run the simulation 1000 times to determine the range of possible outcomes from a given plan. These results can be used to help policymakers go beyond the uncertainties associated with single projects and understand the uncertainties associated with the entire Climate Action Plan.

2.4. Implementation

Data was collected and processed using Microsoft Excel and Python (Microsoft Corporation, 2018; Python Software Foundation, 2021). All scheduling algorithms were implemented using MATLAB 2021 with Yalmip and Gurobi (Gurobi Optimization, LLC, 2022; Löfberg, 2004; MathWorks, 2024). The results were generated using an Intel® Xeon® W-1290P processor.

3. Results

3.1. Carbon abatement projects in European cities

We identify 47 types of unique projects implemented by European cities, the top five most common projects being street lighting

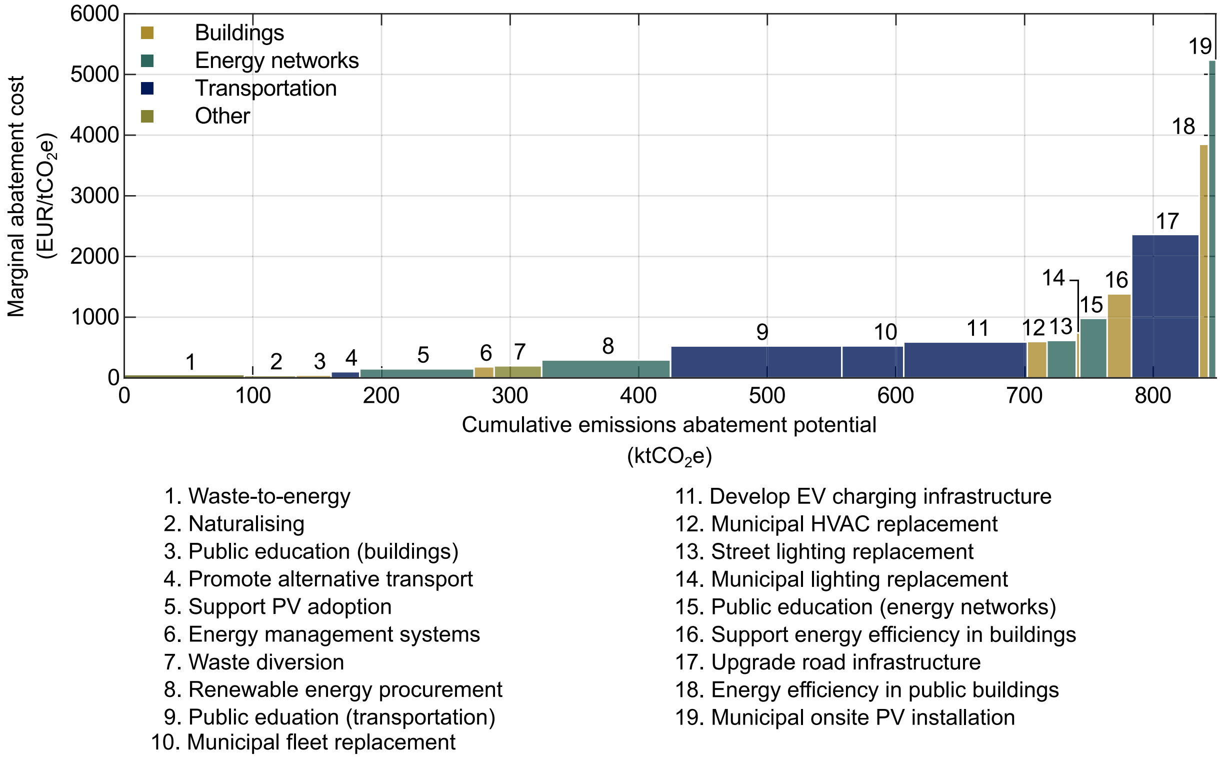

Fig. 4. Marginal abatement cost curve of all projects considered. The emissions abatement potential is specific to the case study. Abbreviations: eff.: efficiency; EV: electric vehicle; HVAC: heating, ventilation, air conditioning; infr.: infrastructure; PV: photovoltaic; transp.: transportation. Marginal abatement costs are provided in Appendix B.

replacement, public education campaigns in the building sector, installing solar photovoltaic (PV) at municipal facilities, upgrading municipal vehicle fleets to upgrading local road infrastructure (Appendix B). The 47 projects highlight the wide variety of options available to cities in their pursuit of lowering local emissions: projects targeted at increasing renewable energy (Athens, Ljubljana, Sunderland) and increasing energy efficiency (Helsingør, Prato) aim to directly reduce emissions, while other measures target behavioral changes, like encouraging more sustainable transportation by implementing projects to upgrade road infrastructure (Leeds, Podgorica, Tampere, Torino, Trondheim) and increase the competitiveness of public transportation (Podgorica, Porto, Valencia). Cities' administrative capacity is also evident in the ability to develop energy efficiency requirements (Richmond, Gaziantep) and transportation regulations (Braga, Valencia). Cities also engage in innovative projects like developing local green financing systems (Reading, Westminster) and testing remote work (Rome) as a means to support climate action. Some cities (Assisi, Trondheim, Valencia) list feasibility studies as part of their climate mitigation actions, highlighting their need for further assessment to be confident in their planning processes. Our results agree with previous research suggesting that cities distribute emissions mitigation efforts across a range of sectors (Aboagye and Sharifi, 2023).

We identify 19 unique types of projects that, after outlier removal, provide sufficient data to characterize project emissions and cost (see Methods 3.1 and Appendix B). The 19 representative projects we consider account for experience from 142 unique projects from 44 cities in 13 European countries. Fig. 4 shows that expected marginal abatement costs associated with different projects range from around 30 €/tCO_2e (waste-to-energy and public education in the buildings sector) to nearly 5000 €/tCO_2e (energy efficiency repairs

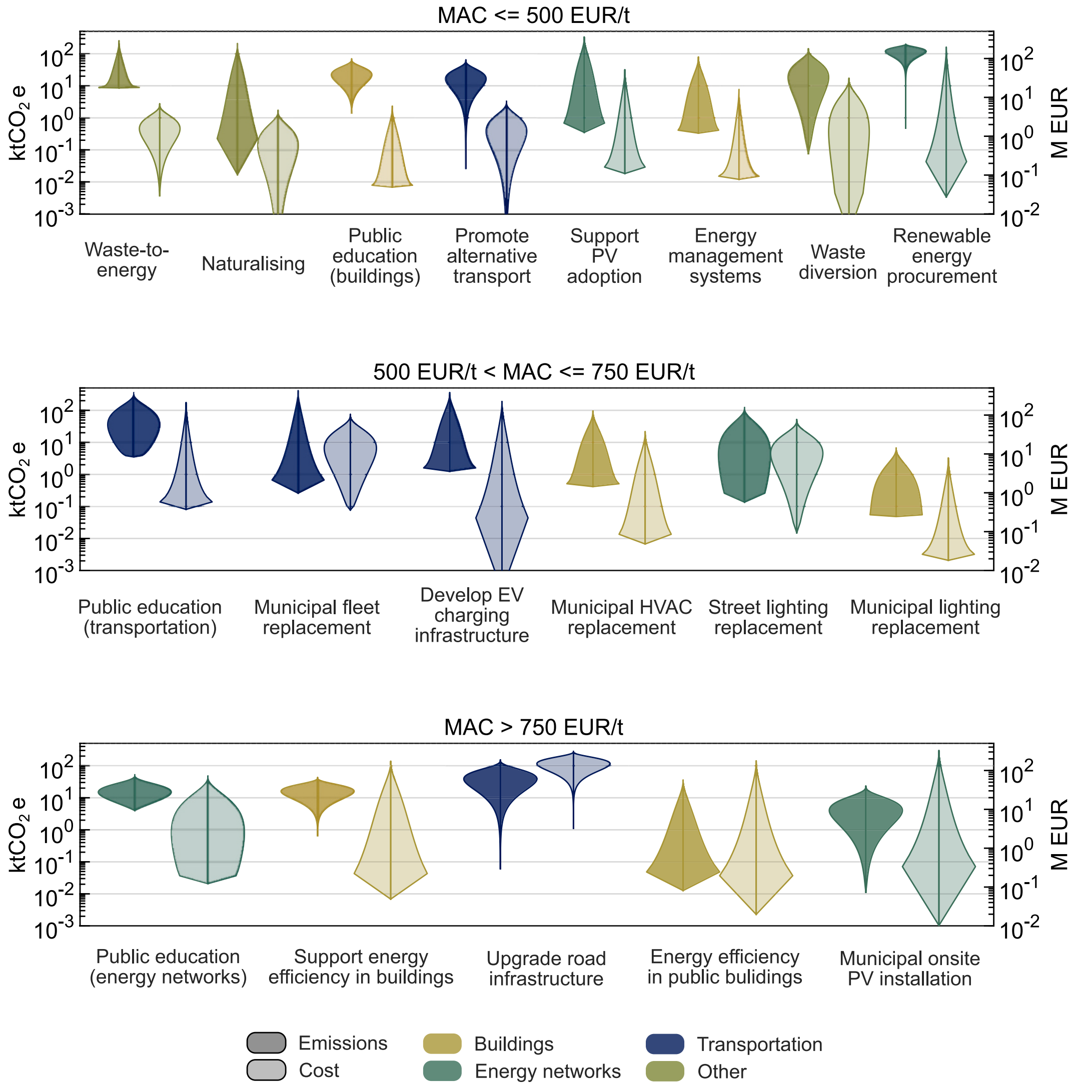

Fig. 5. Uncertainty in emissions abatement potential and cost for representative city (population of 800 thousand). MAC: Marginal abatement cost. The distributions shown are PERT distributions based on the collected data (see Section 2.1). Results for emissions and cost are shown in darker- and lighter-colored distributions, respectively. Projects are listed in order of lowest-to-highest marginal abatement cost (left-to-right, top-to-bottom panels) and colored by sector.

and renovations). Most marginal abatement costs (13/19) exceed 105 €/tCO_2e, the all-time high for the European Emissions Trading System at the time of writing.

The apparent difference between project costs and those on the public Emissions Trading System may be due to a combination of factors. First, cities' apparent cost-effectiveness would increase by accounting for the lifetime cost-benefit in the marginal abatement cost calculation, as is typical for marginal abatement cost calculations, and not only the cost (Section 2.1 and Section 4.3; Kesicki and Ekins, 2012). Second, it is possible that cities have difficulty accessing the least-cost emissions options. For example, municipalities may not be allowed to invest in projects outside municipal boundaries (Climate Policy Initiative, 2021). Finally, the prevalence of the more costly projects reflects some of the responsibilities of municipal governments: for example, cities must periodically upgrade road infrastructure (1850 €/tCO_2e) and vehicle fleet (750 €/tCO_2e) irrespective of climate goals.

Considering only expected marginal abatement costs overlooks the range of potential project outcomes (Fig. 5). The shape of uncertainty distributions varies between projects, with some projects demonstrating relatively uniform distributions across a range of outcomes (e.g., cost of renewable energy procurement and waste-to-energy plants; cost and emissions abatement for public education schemes for transportation) and others showing long-tailed distributions even after the outlier removal procedure (Methods 3.1). Additional data would help smooth these curves. Most projects show wider variation in expected emissions abatement than for expected costs, except those with the highest marginal abatement costs. In addition, project cost and expected emissions abatement potential vary independently of their marginal abatement costs; none of the variation is captured in a marginal abatement cost curve (Fig. 4), highlighting a limit of using marginal abatement cost curves as a decision-making tool (Kesicki and Ekins, 2012).

3.2. Optimal Climate Action Plans

Optimal Climate Action Plans show the potential to abate between roughly 250–700 ktCO_2e, depending on the budget available (Fig. 6a) for our representative case study. All schedules achieve their planned emissions reduction before the end of the maximum planning horizon (years 14–16 versus a planning horizon of 20 years), indicating that budget is the limiting factor for the current case study (Fig. 6b).

Neglecting the variability in project outcome leads to plans that have higher planned emissions than when considering uncertainty;

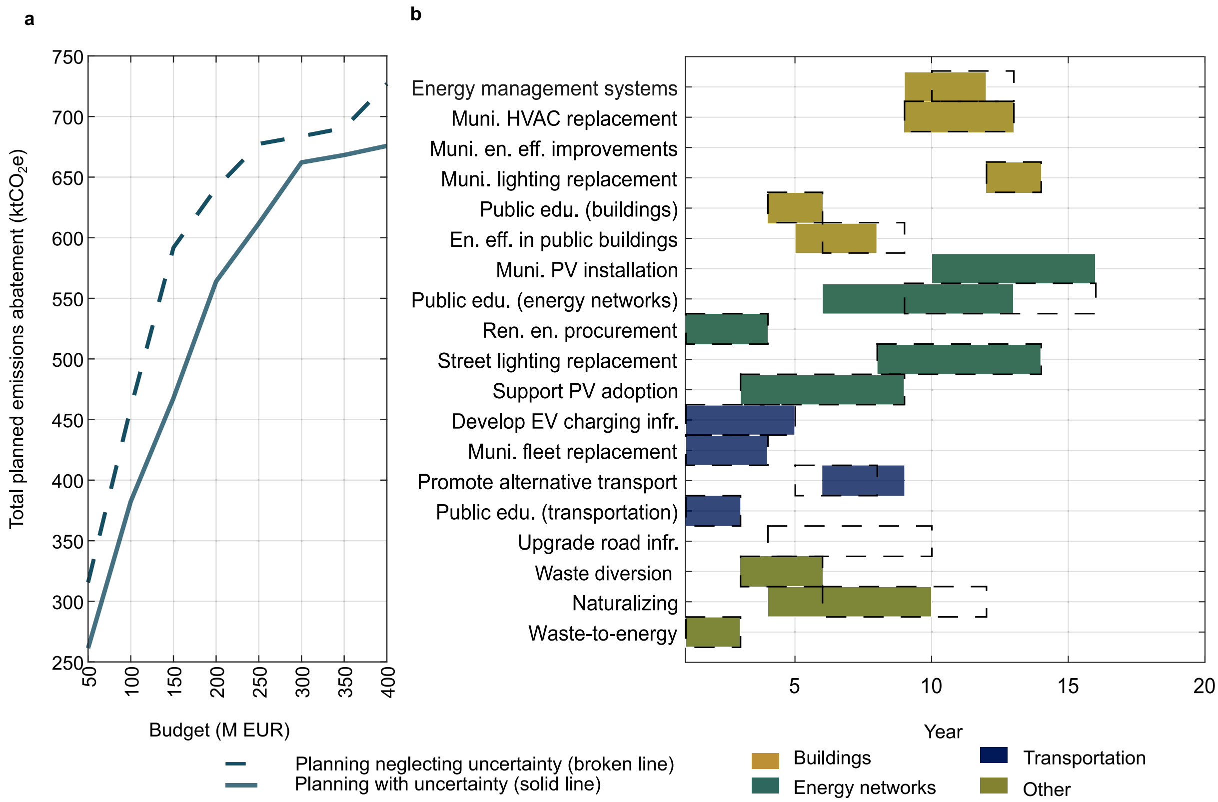

Fig. 6. Overview of optimal Climate Action Plans. (a) Target emissions reduction per available budget. (b) Projects scheduled for maximum budget (400 million €). The solid line shows (a) the total planned emissions abatement and (b) the project scheduling when considering project uncertainty (results of the stochastic optimization). The dashed line shows the corresponding (a) abatement and (b) project scheduling when neglecting uncertainty (results of the deterministic optimization). Edu: education. En: energy. Eff: efficiency. Infr.: infrastructure. Muni: municipal. Ren.: renewable. Syst.: systems.

however, these differences can be attributed to relatively minor changes in project schedules: the decision to implement a project or not was consistent for at least 75 % of projects in each budget tested, while the mean average deviation in start time for projects jointly selected was always less than one year, the shortest time unit considered. For example, in the maximum budget case (400 million €), the only difference between the two schedules is whether to run a project to improve energy efficiency for public buildings or to run a public education campaign on energy efficiency and provide support (information and financial) for the public to implement energy efficiency projects on their own.

The minor deviations in project selection and start time lead to meaningful differences in terms of the financial reliability of the Climate Action Plan (Fig. 7). Overall, considering uncertainty within the planning process reduces the likelihood of being over budget by 10 %. Even in simulations when the budget is exceeded, considering uncertainty within the planning process reduces budget exceedance by 5 % on average, with budget overages in the single-digit range. The worst-case costs were also reduced by 18 % on average.

Considering uncertainty within the planning process also improves the likelihood that Climate Action Plans will be able to meet or exceed their emissions targets rather than fall short. Considering uncertainty leads to better planned-versus-realized emissions abatement, increasing the performance by 3 %, 2 %, and 5 % for the median, lower-, and upper quartile levels, respectively, across all simulations. These differences are even more pronounced in situations (simulations) where budget constraints are met (+5 % for the median, 4 % for the lower quartile, and 8 % for the upper quartile). These results highlight that considering uncertainty creates plans that tend to overperform rather than underperform. This finding is politically relevant since voters expect accountability from their

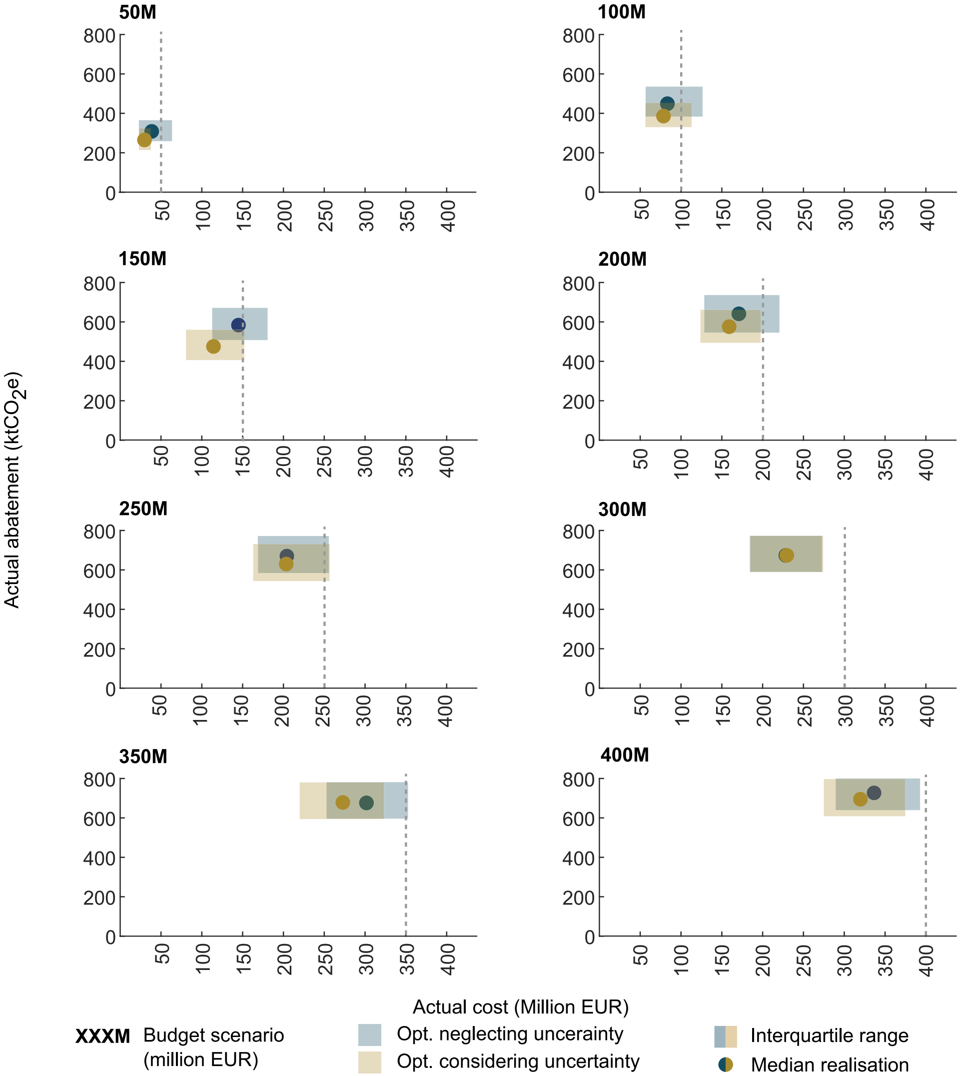

Fig. 7. Realized cost and abatement of Climate Action Plans designed with and without consideration of uncertainty. Each panel shows the results for different budget scenarios (budget indicated by the bold number at the upper left of each panel). Shaded areas show the interquartile range, while solid dots show the median result.

elected officials. Mean absolute average deviations in realized abatement were negligibly different (<1 % increase) for plans built considering uncertainty than those without; however, this minor trade-off in prediction precision is negligible given the aforementioned improvement in financial and abatement reliability.

Notwithstanding the benefits of considering variability in projects' cost and emissions abatement potential within the planning process, the final cost and emissions abatement of any given Climate Action Plan are highly uncertain. Fig. 7 shows cost variations spanning tens of millions of dollars and abatement variations in the range of up to nearly 200 ktCO_2e. The plans feature such great variance due to the variation observed in the project dataset: reported data for some projects, like developing electric vehicle charging infrastructure, feature nearly order-of-magnitude differences between estimates. Relying on a more refined data set, e.g., derived for a specific country rather than for Europe as a whole, would likely reduce the variability of the proposed plans. Even the "perfect" data set would retain some uncertainty, e.g., due to the natural fluctuations in material prices and human inconsistencies in reporting. To eliminate the risk of exceeding the budget or guaranteeing a minimum level of emissions abatement, a robust optimization approach is required instead of the current stochastic optimization approach.

3.3. Sectoral importance

An effective carbon abatement plan requires involvement from all sectors, a finding that is consistent across both scheduling strategies and all tested budgets (Fig. 8a). This result supports the multi-sectoral approach currently taken by real cities (3.1).

Fig. 8a highlights that the number of projects selected does not necessarily translate to the share of planned emissions abatement. For instance, projects in the buildings sector always occupy a higher share of projects than anticipated emissions abatement; conversely, projects in the transportation and energy sectors account for a higher share of emissions reduction than number of projects. The difference in emissions versus project "intensity" is linked to the nature of the projects themselves: the selected transportation and energy sector projects have higher shares of emissions reductions per project because single projects can influence the entire city, such as through contracts for renewable energy supply or implementing high-efficiency lightbulbs on local streets.

The planned share and number of projects also have implications for the composition of the project management team itself. In the optimal planning case with the lowest budget, transportation accounts for the smallest share of projects and emissions abatement: project coordinators could see if an existing team member could take on additional responsibilities rather than hiring a new team member. Alternatively, higher-budget planning contexts with greater dependence on transportation projects might benefit from a transportation specialist or sub-team.

The shares of sectoral abatement in the optimal planning case do not generally align with the sectoral share of global emissions (Fig. 8b): the buildings, energy, and transportation sectors tend to account for a larger share of planned emissions abatement than a global emissions inventory would suggest. This discrepancy has two main implications for urban planners. First, locally effective Climate Action Plans might have significantly different emissions reduction strategies than suitable for a general case. For example,

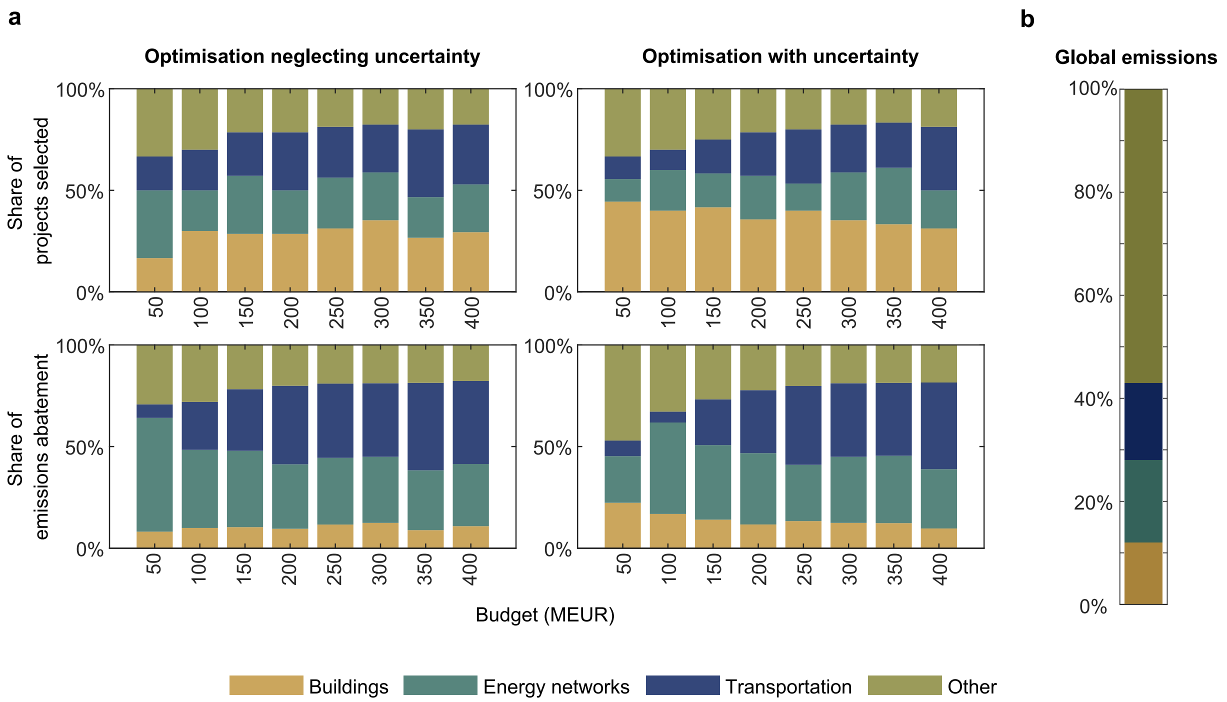

Fig. 8. Sectoral projects according to the share of projects selected and share of emissions in the Climate Action Plan according to scheduling method and budget. Global sectoral emissions shown in (b) for reference (IPCC, 2022).

transportation represents a far larger share of potential emissions reduction in our case study than global emissions profiles would suggest. In other words, planners should be sure to develop climate action considering local costs and emissions abatement potentials (Rivas et al., 2021). Second, the role of cities in reducing local emissions can extend beyond direct action. Namely, cities can enable decarbonization by taking on coordinating roles, incentivizing decarbonization, and developing clear, proactive regulations to enable decarbonization. This additional responsibility would be particularly valuable for addressing Scope 3 and industrial emissions, which account for 57 % of global emissions (shown under "Other" in Fig. 8b; IPCC, 2022)). Possible actions for the city outside the scope of direct emissions reduction projects include developing supply chain labeling schemes (City of Vancouver, 2020) and coordinating industrial partnerships for joint emissions reduction projects, e.g., waste heat (European Commission, 2018), eco-industrial parks (Perrucci et al., 2022; UN Industrial Development Organization, World Bank Group, and Deutsche Gesellschaft für Internationale Zusammenarbeit, 2017).

Another insight from Fig. 8 is the relative importance of "other" projects (naturalization, waste diversion, and waste-to-energy plants) to lower-budget scenarios. This finding is encouraging as existing municipal departments (e.g., waste management and parks) could implement these projects. Moreover, the "other" type of projects most consistently selected across all budgets for both scheduling methods (Fig. 9):

- Naturalizing ("other")
- Waste diversion ("other")
- Waste-to-energy plants ("other" sector)
- Increasing public education in building management
- Promoting alternative modes of transport
- Supporting public photovoltaic (PV) adoption
- Installing energy management systems in municipal buildings

Implementing these projects are comparatively method- and budget-robust choices, which could help planners justify their inclusion in Climate Action Plans.

Interestingly, solar PV installation at municipal facilities is one of the least frequently selected carbon abatement projects (Fig. 9) despite being the second most popular project implemented by real cities. This discrepancy could be due to two factors. First, local governments might seek to install PV in city facilities to provide visible, public evidence of their climate awareness. Second, actual

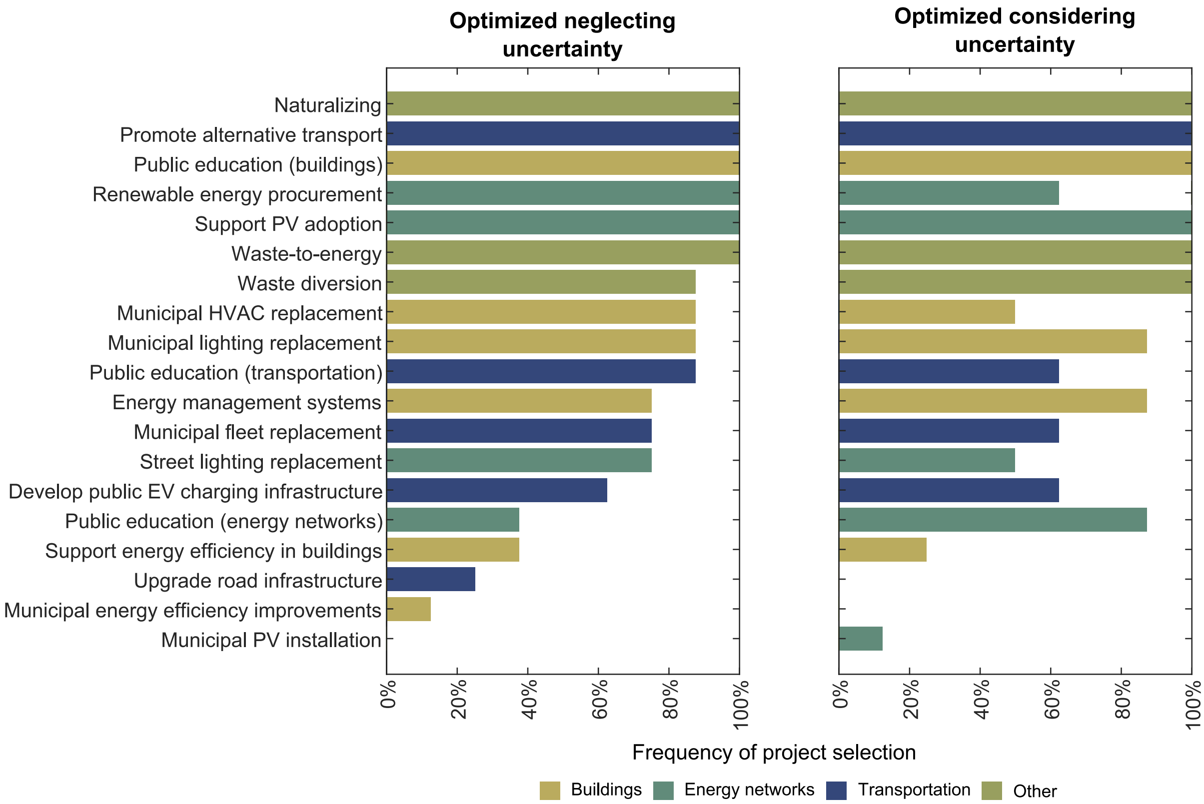

Fig. 9. Frequency of project selection across all budgets and planning methods. Projects are listed in order of most-to-least frequent selection across all scheduling methods and budgets.

Climate Action Plans might have budgets below our tested minimum threshold of 50 million €, making installing solar PV on government buildings one of the only options available. The former possibility highlights that climate action can serve multiple and non-climate purposes, including political appearance. The latter possibility illustrates the value of collective action in achieving more ambitious climate action: pooling resources between several local governments could help achieve more ambitious climate action by gathering the financial resources to implement projects with higher capital costs (Armstrong, 2023).

4. Discussion

4.1. Practical implications

Our results underscore the value of quantitative models in navigating complexities faced by urban climate planners in developing Climate Action Plans. Although current guidance for urban climate planning is focused on a narrow set of projects and neglects discussions of uncertainty, we show that cities are already implementing a highly diverse set of climate actions that each have variable cost and emissions abatement outcomes. Considering these uncertainties within the decision-making process is valuable since it identifies the small changes to Climate Action Plans needed to make plans that are more robust against the worst outcomes. In addition, applying a scheduling framework helps identify projects that are robust choices across a range of budgets, bringing certainty to the decision-making process; conversely, it also helps identify projects that only make sense in the most budget-constrained scenarios.

Our results also provide empirical confirmation that cities have meaningful roles to play as both emissions abaters and coordinators. As abaters, cities can leverage existing departments to lead emissions reductions through naturalization and waste management projects. As coordinators, cities can support emissions reductions of their citizens by creating enabling conditions, such as financial incentives and appropriate infrastructure. This latter role may be especially important, as municipality operations typically contribute only a minority of emissions relative to the overall city emissions (Lucchitta et al., 2024). Our results show that larger budgets facilitate higher emissions reduction; however, cities may lack the funds for achieving ambitious climate action (Climate Policy Initiative, 2021; REN21., 2021a). Aligning climate plans with higher levels of government and leveraging the interests of large local emitters can help realize local change (City of Melbourne, 2023; Rivas et al., 2021). Cities may also coordinate with one another to pool resources required to sponsor a joint project, like expanding regional transit.

Incorporating quantitative methods into Climate Action Planning should be seen as a tool to support meaningful stakeholder interaction and not as an obstacle. Retaining the connection to project planning – i.e., discussion of specific initiatives – within the optimization-based scheduling framework presented here (Fig. 1b) enables the same community engagement processes as available in current consultation-informed planning processes without precluding consideration to any of the specific contextual elements (geographic, socioeconomic) often reflected in Climate Action Plans. For example, locals can suggest emissions abatement projects for consideration, advocate for most pertinent co-targets for climate action (e.g., job creation), prioritize action areas (e.g., which parts of the city should benefit from naturalization projects first), suggest contract requirements (e.g., share of local hires or local content), inform project communications strategies (e.g., regarding frequency and format), and recognize challenges in the plan as a whole, e.g., infeasibility or undesirability of two specific projects occurring simultaneously (Fig. 10). Taking these steps to build community acceptance is key to successful plan deployment (Aboagye and Sharifi, 2023) and achieving more profound sustainability transition in

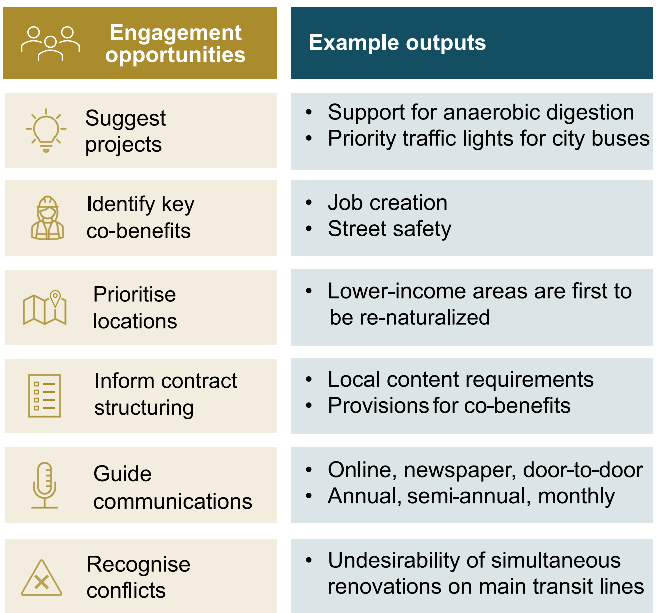

Fig. 10. Opportunities for public consultation while developing scheduling-based Climate Action Plans.

the long-term (Kaufmann et al., 2024).

Modeling results are particularly useful in stakeholder engagement processes when quantitative results are combined with visual storytelling. Visual presentation can act as information conduits, supporting more constructive discussions, creative inclusive risk governance strategies, and helping stakeholders differentiate between perceived and calculated risks (Jones Roger et al., 2014; Miles et al., 2023; Schweizer et al., 2022). For example, presenting the planned schedule (Fig. 6b) and provides a more tangible basis for feedback than could an emissions trajectory alone (Fig. 6a). Similarly, presenting project uncertainties visually (Fig. 5) facilitates participation from a wider range of stakeholders than would be possible if the uncertainty was only discussed in mathematical terms (e.g., in terms of coefficients for the uncertainty distribution).

4.2. Practical applications and future work

Our scheduling approach must still overcome several hurdles to support real-life planning efforts. First, continued work collecting, standardizing, and sharing data is therefore critical to the success of all model-based planning approaches (Bloomberg Cities, 2024; GCoM, 2024a; GCoM and Google, 2024; ISO, 2018; Kona et al., 2020). Our approach would specifically benefit from additional data on sector- and city-specific emissions, as available data is often incomplete (CDP, 2022; Kona et al., 2021; Lucchitta et al., 2024). Closing the data gap would facilitate data-based planning in a wider range of world regions and enable more accurate project characterization. For example, characterizing project emissions and costs by region (e.g., across Nordic countries) or municipality size (e.g., village, town, city) would allow planners to base their decisions upon the experience most relevant to their planning context.

Second, cities may struggle to implement our model – and other model-based planning approaches – without external technical support. Ideally, this support would be provided via a free online platform where cities could run a scheduling model based on their local data. In the meantime, non-governmental organizations, universities, or specialized consulting firms could provide support. Sharing experience city-to-city would also support institutional learning and capacity building, which are key enables for deeper local climate action (Kreibiehl et al., 2022; Lucchitta et al., 2024). Finally, cities must take measures to secure the funding, staff, and social license needed to implement their desired Climate Action Plan. The former is a consistent global challenge (Climate Policy Initiative, 2021; Kreibiehl et al., 2022), while the latter two require location-specific solution strategies.

In this work, we find the optimal project schedule to maximize emissions reduction for a pre-determined budget. However, we note that our project-based methodology has at least two other applications. First, our approach could be used to select local climate targets. Typically, cities commit to climate targets before identifying the specific pathways for achieving those targets (Lwasa et al., 2023; Rivas et al., 2021). Establishing local emissions reduction potential and budget constraints could help cities make more realistic climate targets and, by doing so, engender greater accountability for the promises made by local government. Second, finding the maximally abating Climate Action Plans would also provide a reference for evaluating the effectiveness of Climate Action Plans produced under any other decision-making mechanism. This comparison would provide greater transparency of cities' planned emissions abatement and complement existing methodological approaches for evaluating Climate Action Plans (Baker et al., 2012; Reckien et al., 2018).

One organization that would be well placed to support cities overcome these hurdles is the Global Covenant of Mayors for Climate & Energy (GCoM; GCoM, 2024b). The GCoM aims to support cities and local governments in contributing to climate action. The organization hosts a wide range of planning tools and resources, including algorithmic and decision-making support (GCoM, 2024c). The GCoM hosts a global alliance of over 13,000 cities, providing a key networking service and an efficient means to communicate and enable new ideas in local climate action planning.

We note that implementing a model-based Climate Action Plan will face many of the same challenges as plans created using other approaches, for example as presented by personnel changes, budget limits, restrictions on financial and jurisdictional powers (OECD, 2022; REN21., 2021a), and evolving political priorities. Nonetheless, we argue that a model-based planning approach, particularly one integrated into a wider participatory planning process (McGookin et al., 2024), can support data-based policy choices that foster greater public buy-in and, as such, may be more resistant to evolving political conditions at other jurisdictional levels.

4.3. Methodological limitations and future work

While our methodological approach extends the methodology of model-based local climate planning by integrating a project-based focus, the approach does feature some simplifications compared to real-world planning processes. First, we frame climate planning as a single-objective problem of reducing emissions; however, city planners often strive to achieve other goals in parallel with their climate action, e.g., resilience-building, improved air quality, and reduced noise pollution (Lwasa et al. 2023). Although our approach can account for these parallel and possibly competing objectives outside the scheduling process itself (see Fig. 1 and Fig. 10), future work could extend the single-objective modeling framework to a multi-objective modeling framework to consider non-climate benefits directly within the project selection and scheduling process. Future work could also conduct stepwise scheduling to account for evolving local priorities.

Second, our results are based on limited data. Our data is limited in that it only considers project costs and not lifetime cost-benefit (Section 2.1). Our data does not account for purchasing power standards across nations and markets, and it only considers a subset of existing climate action projects. These limitations affect the apparent cost-competitiveness of specific projects (Appendix B) and neglect the potential of novel emissions reduction options. In addition to increasing the amount of available data (see Section 4.2), future work could also estimate the emissions reduction potential of specific projects by leveraging statistics and machine learning. The process of generating synthetic data could be particularly valuable in contexts where limited or no comparable regional data exists and for cities with a very small number of comparable data points, e.g., megapolitan cities, island communities, and remote northern communities.

Third, we consider only a representative case study location, which prevents us from a deeper, more tailored analysis of local response to specific projects. Picking a more specific location would allow us to understand how the sequencing of individual projects affect each plans' aggregate emissions-reduction potential and would enable the use of complementary modeling approaches that better capture the decision-making processes of individual economic agents (Barbrook-Johnson et al. 2024).

Finally, our model does not consider variability in the organizational factors necessary to convert an ambitious plan into practical action. Namely, we assume that policy goals remain constant for the planning horizon and that funding and staff can be secured to implement each plan successfully. Future work could relax these assumptions by optimizing over a rolling horizon, considering the deployment challenges of individual projects (Cabeza et al. 2023; Lucchitta et al. 2024), or framing the planning task as the optimal selection of real options (Nembhard and Aktan 2009).

In addition to overcoming these methodological limits, future work should also seek to compare modeling approaches based on projects versus those based on trajectories. Conducting a rigorous comparison of the approaches in terms of public engagement opportunities, recommended strategies, data requirements, public trust, and institutional capacity requirements would benefit local planners and modelers to understand which approach is most appropriate in specific contexts.

5. Conclusion

City governments are well-positioned to drive climate action by directly reducing emissions, enabling others to do the same, and developing context-appropriate solutions. However, municipal climate action planners face a dearth of support in terms of how to assemble individual climate projects into a coordinated Climate Action Plan. As a result, climate planning decisions are often made without the full support of existing methodological tools.

We work to close this gap by framing the development of Climate Action Plans as a scheduling task, which we solve with mathematical optimization. Overall, our approach is beneficial in that it is transparent, integrates current modeling and stakeholder practices, and supports decision-making under uncertainty. In our case study of a representative European city, we find that optimal climate plans for every budget include projects from all sectors, thereby providing empirical evidence to support cities' tendency to engage in a diverse set of projects. The consistent multi-sectoral appeal is underlined by a set of six key projects (naturalizing, waste diversion, waste-to-energy plants, promotion of alternative transport, support for public photovoltaic installation, installing energy management systems in municipal buildings, and offering public education in the buildings sector) who are selected in all tested budget scenarios. Considering uncertainty within the scheduling leads to small changes in Climate Action Plans that lead to plans that are less ambitious but are more financially reliable than when neglecting uncertainty; considering uncertainty within the decision-making process can therefore support greater accountability in city-led climate action.

Providing a larger set of decision-support tools to local climate planners supports more ambitious and reliable Climate Action Plans. While it is unlikely that scheduling or other purely techno-economic analyses will ever be the sole mechanism with which cities plan their emissions reduction, scheduling methods can complement existing stakeholder consultation processes by providing systematic, evidence-based decision-making support. Being intentional in what models are used and how they support climate planning helps to ensure that specific contextual elements (e.g., geographical, socio-economic) usually reflected in Climate Action Plans are also maintained in model-supported processes. Besides providing support in terms of scheduling individual projects, identifying optimized climate plans would also be useful in assessing the cost- and abatement effectiveness of plans created via alternative planning schemes. This type of analysis would complement existing methodologies for assessing climate plans, including those based on plan typology, policy specificity, and *ex-post* assessments (Baker et al., 2012; Reckien et al., 2018).

Nonetheless, the ultimate benefit of model-based planning methods is limited by the availability of financing, data, and organizational capacity. Access to finance is a challenge for successfully deploying all local climate action plans (OECD, 2022; REN21., 2021a), but successful model-based planning activities face additional challenges with respect to data and organizational capacities because models inherently require more data and experience to develop, interpret, and trust. One way of overcoming these hurdles is to leverage capacities in universities and global organizations, like the Global Covenant of Mayors, to provide centralized data and modeling hubs. Universities and global organizations could also help increase local institutional capacity and build trust in model-based planning within local planning offices by sharing experts with local offices to act as consultants and by running workshops, teaching sessions, and specialized courses. Such initiatives are underway within the energy sector and offer lessons could be transferred to the climate planning space (McGookin et al., 2024). In the end, future work must not only seek to improve modeling methodologies but also look to ensure that the essential components for implementation are in place.

CRediT authorship contribution statement

Katherine Emma Lonergan: Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Josef Felix Köll:** Investigation, Data curation. **Giovanni Sansavini:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization.

Declaration of competing interest

The authors declare no competing interests.

Data availability

All data used in this study is publicly available under the linked references. Code will be shared under reasonable request to the corresponding author, G.S.

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Appendix A. Optimization model

The optimization model used is based on the formulation presented by Nesbitt et al. (2021) and is presented in Eqs. A1-A9 using parameters described in Table A.

The objective function is described by Eq. A1 and corresponds to maximizing the total emissions, E, considering each scenario, ω, likelihood of occurrence, p_ω, and project, n, over the entire planning horizon, T. Project start times are specified by binary matrix X_{nt}^{ω}, with a value 1 indicating project start time. Emissions reductions are achieved at the end of the project duration, $d_{n\omega}$. The discount rate γ promotes earlier rather than later emissions reduction and is set to 0.97, which corresponds to the changing rate for the social cost of carbon of 3 % (Nordhaus 2017; Pindyck 2019). Eq. A2 specifies that each project may only start once, while Eq. A3 requires any project that starts to terminate within the scheduling horizon, T. Eqs. A4 and A5 set maximum limits for resource consumption over the entire scheduling horizon and over each time step, respectively. These limits are chosen by the modeler and, in our case study, refer to the maximum total budget that can be spent (50–400 million €) and the maximum number of projects per period (five). Eqs. A6 and A7 specify that the start time for each project in each scenario must be within δ periods of the start time specified in the baseline scenario, Y. We allow a maximum deviation of project start time to be two years between each scenario. Finally, Eqs. A8 and A9 are the conditional non-anticipativity constraints, which requires that schedules for scenarios ω and ω' must coincide up to time t when the scenarios can be distinguished (e.g., by activity value; see Nesbitt et al., 2021). Note that the problem formulation is designed for a stochastic optimization but that the deterministic problem, i.e., omitting uncertainty, is solved considering the same problem structure but only one scenario with a probability of occurrence of 1. The interested reader is referred to Nesbitt et al. (2021) for a more thorough explanation.

Table A
Variables.

Indices	
δ	Maximum difference between activity start times in different scenarios
n	Project number
t	Time
r	Resource
ω	Scenario
Parameters	
$d_{n\omega}$	Duration of project n in scenario ω
$r_{n\omega}$	Resource utilization of project n in scenario ω
$E_{n\omega}$	Emissions abatement of project n in scenario ω
$c_{n\omega}$	Cost of project n in scenario ω
L_r	Maximum limit for resource r
l_r	Maximum resource limit per period for resource r
Q_{nr}	Total demand of activity n for resource r
q_{nr}	Per period demand of activity n for resource r
p_ω	Probability of scenario ω
Sets	
$D^{\omega\omega'}$	The set of differentiating activities between scenario ω and ω'
N	Number of projects
$\mathrm{P_N}$	Projects that must be completed prior to project N
T	Maximum horizon
R	Resources
Ω	Set of all scenarios
Decision variables	
X_{nt}^{ω}	1 if project n begins at time t, 0 otherwise
$\widehat{X}_{nt}^{\omega}$	1 if project n begins within $t - d_{n\,\omega} : t$
Y_{nt}	1 if the baseline start time of project n is t, 0 otherwise
$Z_{nt}^{\omega\omega'}$	0 if $X_{nt}^{\omega} = X_{nt}^{\omega'}$

The motivation behind using the Nesbitt et al. formulation is to facilitate future, more complex case studies; however, other problem formulations (Fang and Sansavini, 2019; Kall and Mayer, 2011; Lamas et al., 2023; Pianykh et al., 2024) could also be applied. We consider a slightly simplified solution strategy as compared to Nesbitt et al. since the scope of our problem is much smaller than that considered in the original work. Specifically, we do not consider uncertainty in project duration and consider far fewer tasks to be scheduled (19 versus over 15,000). Consequently, we solve the problem only the monolith structure rather than relaxing the problem and applying heuristic scheduling methods, as done in the original paper. We also modify the resource constraints such that resources are consumed evenly over the project duration rather than entirely during the first project period.

$$max_{X_{nt}^{\omega} Y_{nt}^{\omega} Z_t^{\omega\omega'}} \sum_{\omega\in\Omega}\sum_{t\in T}\sum_{n\in N} p_\omega \bullet \gamma^{t+d_n^{\omega}-1} \bullet E_n^{\omega} \bullet X_{nt}^{\omega} \tag{A1}$$

Such that

$$\sum_{t'=1}^{t} X_{nt}^{\omega} \leq 1 \quad n \in N;\ \omega \in \Omega \tag{A2}$$

$$\sum_{t'=1}^{t} X_{nt}^{\omega} \leq 1, n \in N; \omega \in \Omega, \sum_{t'=1}^{t} X_{nt'}^{\omega} \leq \sum_{t'=1}^{t-d_{n'}^{\omega}} X_{n't'}^{\omega} \quad n \in N;\ n \in P_N;\ t \in T;\ \omega \in \Omega \tag{A3}$$

$$\sum_{t\in T}\sum_{n\in N} Q_{nr} \bullet X_{nt}^{\omega} \leq L_r \quad r \in R;\ \omega \in \Omega \tag{A4}$$

$$\sum_{n\in N} q_{nr} \bullet \widehat{X}_{nt}^{\omega} \leq l_r \quad r \in R;\ t \in T;\ \omega \in \Omega \tag{A5}$$

$$\sum_{t'=1}^{t} Y_{nt'} \leq \sum_{t'=1}^{min\{Tt+\delta\}} X_{nt'}^{\omega} \quad n \in N;\ t \in T;\ \omega \in \Omega \tag{A6}$$

$$\sum_{t'=1}^{t} X_{nt'}^{\omega} \leq \sum_{t'=1}^{min\{Tt+\delta\}} Y_{nt'} \quad n \in N;\ t \in T;\ \omega \in \Omega \tag{A7}$$

$$Z_t^{\omega\omega'} \leq \sum_{n\in D^{\omega\omega'}} \left(\sum_{t'=1}^{t-d_n^{\omega}} X_{nt'}^{\omega} + \sum_{t'=1}^{t-d_n^{\omega'}} X_{nt'}^{\omega'} \right) \quad t \in T;\ \omega \in \Omega;\ \omega' \in \Omega;\ \omega \neq \omega' \tag{A8}$$

$$X_{nt}^{\omega'} - Z_t^{\omega\omega'} \leq X_{nt}^{\omega} \leq X_{nt}^{\omega'} + Z_t^{\omega\omega'} \quad n \in N;\ t \in T;\ \omega \in \Omega;\ \omega' \in \Omega;\ \omega \neq \omega' \tag{A9}$$

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.uclim.2025.102452.

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