Energy Community PV Facility Location Optimisation

Dena Tayebi*
Paula Carroll
Debajyoti Biswas
paula.carroll@ucd.ie
debajyoti.biswas@ucd.ie
University College Dublin
Dublin, Ireland
Orcid: 0000-0003-1029-1668

Abstract

Energy Communities (ECs) in urban areas often focus on Photovoltaic (PV) panels for renewable electricity generation as space or planning permission for wind farms are usually not available. ECs need to decide the best location for PV panels to serve the EC electricity needs. We propose a Mixed-Integer Linear Programming (MILP) model for the PV facility location problem. Using a real-world University campus as a test instance modelling exercise, we jointly optimise PV siting, capacity selection, and electricity sharing, recommending PV installation in strategic hubs to service electricity demand for campus buildings. A structured sensitivity analysis highlights how variation in budget and demand impacts the number and type of PV systems deployed, and demand coverage across the campus, providing decision support for urban EC planning.

Keywords

Energy Communities, Photovoltaic (PV), Renewable Energy, Facility location, Mixed Integer Linear Programme

1 Introduction

ECs are increasingly recognised as a key instrument for renewable energy initiatives and enabling active citizen participation in the clean energy transition. In dense urban environments, PV systems are often the most viable technology, as space, planning constraints, and performance may limit alternatives such as wind generation. Consequently, ECs must decide how to allocate limited space and investment budgets to best meet their collective electricity demand while navigating policy frameworks designed to support community-led renewable energy projects.

European policy initiatives explicitly support small-scale and community-led renewable generation. In Ireland, the Small-Scale Renewable Electricity Support Scheme (SRESS) is a tariff support mechanism for Renewable Energy Communities (RECs), small and medium-sized enterprises, and other local actors, supporting solar PV projects between 50 kW and 1 MW, and a separate tariff category for installations up to 6 MW [7]. By targeting projects below utility scale, SRESS lowers barriers to market entry and encourages coordinated investment in distributed PV systems. However, the scheme does not specify how PV capacity should be optimally distributed across multiple buildings within an EC, leaving this as a complex decision problem for planners involving trade-offs between spatial constraints, economic efficiency, and demand coverage objectives.

Existing studies tend to address PV deployment and energy sharing in isolation. There is limited work on optimisation models that explicitly support community-level planning consistent with the objectives of small-scale renewable support schemes, particularly those that integrate spatial, economic, and policy constraints within a single analytical framework. From an OR perspective, this highlights the need for decision-support models to support ECs [1], and to guide PV siting and sizing decisions under budget, capacity, and demand coverage constraints.

In this paper, we propose a MILP model for the PV facility location problem in an urban EC. The model determines the location and capacity of PV installations across a set of buildings while accounting for roof space availability, investment costs, and demand coverage targets. We use the MILP model as a modelling exercise for a hypothetical EC in a real-world university campus, illustrating how the model can support strategic planning decisions for community-oriented renewable energy initiatives.

Related Work and Research Gap PV systems in urban environments have been studied through multiple lenses: renewable and distributed generation, and decentralised energy systems. Early works rely on GIS-based and multi-criteria decision analyses to identify suitable locations based on geographical, environmental, and socio-economic indicators [5, 12]. While effective for feasibility assessment, these approaches do not explicitly optimise investment decisions across multiple demand nodes.

Optimisation approaches address PV deployment as a facility location or capacity expansion problem. MILP formulations are used to determine placement and sizing of PV installations under budget, capacity, and demand constraints [10, 11]. These models provide rigorous decision-support frameworks but typically assume either a single aggregated load or independent installations, limiting their applicability to ECs where electricity sharing among geographically dispersed members is a key design feature.

Policy support for ECs and active citizen participation in energy markets, particularly within the EU, motivates research on collective renewable investment. Several studies demonstrate that coordinated PV deployment can increase self-consumption and reduce system-wide costs compared to decentralised systems [2, 3, 9]. Ownership structures, tariff mechanisms, and benefit allocation within ECs reflecting contemporary support schemes for small-scale renewables are explored in [8]. However, these contributions often rely on heuristic allocation rules, without explicitly optimising investment choices against demand coverage requirements.

Network-aware models incorporating power flow constraints, voltage limits, and grid reinforcement costs have also been proposed to analyse the integration of PV into electrical distribution networks [6]. While offering detailed operational insights, their computational complexity and data requirements can limit use in early-stage planning or community-led decision processes.

---

*All authors contributed equally to this research.

INOC '26, Liège (Belgium)

10.48786/inoc.2026.10

Policy frameworks targeting small-scale and community-based generation emphasise accessibility, simplicity, and transparency, suggesting a need for tractable optimisation models that capture key economic and spatial constraints without excessive network detail.

Despite this growing body of work, limited research provides optimisation-based decision support for urban ECs that jointly addresses PV facility location, technology selection, and electricity sharing under explicit demand coverage targets. Furthermore, the cost implications of progressively higher coverage targets remain largely unexplored when these decisions are made jointly under practical planning constraints. This paper addresses these gaps by developing and applying a MILP formulation tailored to urban-type ECs enabling modelling exercises and systematic analysis of cost–coverage trade-offs within policy-relevant constraints.

Contribution Our contributions to the literature are as follows:

- We develop a MILP model that integrates PV facility location, capacity selection, and electricity sharing for urban ECs under budget, space, and demand coverage constraints;
- We demonstrate the model using a real-world case study at University College Dublin (UCD), with a minimum spanning tree grid representation for spatial building coordinates, and a focus on rooftop PV;
- We provide quantitative decision-support insights into the impact of budget and electricity demand on the extent of demand coverage using PV systems, and associated costs through a structured sensitivity analysis;
- We offer policy and implementation recommendations for schemes like SRESS, including optimal phasing strategies and infrastructure considerations.

2 Methodology

We propose a methodological framework to support PV planning in urban ECs. We first introduce the real-world case study that motivates the modelling assumptions and provides the empirical input data. We then present the MILP formulation followed by implementation details.

2.1 Case Study Context: University College Dublin (UCD) Campus

We use a UCD campus as a real-world testbed for modelling exercises representing a typical urban EC with multiple buildings, heterogeneous demand profiles, and constrained rooftop space. UCD is a public university with a large campus spanning 133-hectares in south Dublin located at 53° north. We extract electricity demand data for each building from the campus Building Energy Management System (BEMS). We also extract PV production for the small number of existing PV installations. Analysis of the campus demand and supply potential show that demand far exceeds potential PV supply, hence battery storage need not be considered [4].

The campus comprises 82 buildings with diverse functions (academic, administrative, student residences), providing a realistic setting for EC PV allocation challenges. We obtain building footprints and roof areas from campus GIS resources and OpenStreetMap, processed to extract building identifiers, coordinates, and available roof capacities. We convert building locations from geographic coordinates (latitude and longitude) into a three-dimensional Cartesian coordinate system to compute inter-building distances in meters. For a building with coordinates (ϕ, λ), where $R = 6{,}371{,}000$ m is the Earth's radius and ϕ, λ are in radians, the corresponding Cartesian coordinates (x, y, z) are defined as:

$$x = R \cdot \cos(\phi) \cdot \cos(\lambda), \tag{1}$$

$$y = R \cdot \cos(\phi) \cdot \sin(\lambda), \tag{2}$$

$$z = R \cdot \sin(\phi), \tag{3}$$

The Euclidean distance between buildings i and j is:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}. \tag{4}$$

These pairwise distances represent spatial relationships between all buildings. We construct an undirected weighted graph where nodes correspond to buildings and edges are weighted by Euclidean distance. We create a Minimum Spanning Tree (MST) to represent the electrical network that connects all buildings with minimal total edge weight. The MST represents a cost-efficient framework for potential electricity sharing in modelling exercises, providing a simplified yet meaningful approximation of the campus electrical infrastructure suitable for planning-level analysis. Figure 1 illustrates the campus MST distribution network, which serves as the grid infrastructure for evaluating PV facility location, capacity selection, and electricity sharing decisions within the campus EC.

2.2 Optimisation Model Formulation

We formulate the PV facility location problem for ECs as a MILP that determines optimal placement and sizing of PV systems across multiple buildings subject to budget, spatial, and policy constraints. A MILP model is suitable for this problem as it captures binary installation decisions (whether to install PV in a location or not) and continuous power flows, while maintaining computational tractability for realistic problem sizes. Our MILP notation follows.

Sets and Indices.

- B: Set of buildings, indexed by b
- S: Set of available PV system types/sizes, indexed by s
- E: Set of network connections (edges) between buildings

Parameters.

- k_s [kW]: Nominal capacity of PV system type s
- c_s [€/kW]: Unit installation cost of PV system type s
- $\bar{K}_b$ [kW]: Maximum PV capacity available at building b
- D_b [kWh]: Electricity demand of building b
- $\mathcal{B}$ [€]: Total budget available for PV installations
- α [-]: Minimum fraction of total community demand to be covered by local PV generation
- β [h]: Ratio of hourly PV electricity production (kWh) to PV capacity (kW).
- P [€/kWh]: Penalty cost for unmet demand

Decision Variables.

- $x_{b,s} \in \{0, 1\}$: Binary variable indicating whether PV system type s is installed on building b
- $g_b \geq 0$ [kW]: PV capacity installed on building b
- $f_{i,j} \geq 0$ [kWh]: Energy flow from building i to building j
- $u_b \geq 0$ [kWh]: Unmet electricity demand at building b

Model temporal aggregation. We formulate the MILP for a single planning period, for the modelling exercises we use a horizon of 1 hour. We run the model for hourly energy management based on PV production βg_b and electricity demand D_b for each campus building b. Note that βg_b gives the effective electricity generation in kWh. Based on historical campus data from the BEMS $\beta = 0.1$. We apply this conversion factor to the installed PV capacity g_b (kW). The energy flow variables $f_{i,j}$ represent the hourly average electricity levels (kWh) and are included to identify the electricity flow patterns between buildings to indicate where infrastructure investment may be required. Unmet demand u_b is the amount of demand of building b not serviced by total PV production. The MILP models is as follows:

Objective Function.

$$\min \sum_{b \in B} \sum_{s \in S} x_{b,s}\, c_s\, k_s + P \sum_{b \in B} u_b \tag{5}$$

Constraints.

$$\sum_{s \in S} x_{b,s} \le 1 \qquad \forall b \in B, \tag{6}$$

$$g_b = \sum_{s \in S} k_s x_{b,s} \qquad \forall b \in B, \tag{7}$$

$$g_b \le \bar{K}_b \qquad \forall b \in B, \tag{8}$$

$$\sum_{b \in B} \sum_{s \in S} c_s k_s x_{b,s} \le \mathcal{B}, \tag{9}$$

$$\beta g_b + \sum_{i:(i,b) \in E} f_{i,b} + u_b = D_b + \sum_{j:(b,j) \in E} f_{b,j} \qquad \forall b \in B, \tag{10}$$

$$\beta \sum_{b \in B} g_b \ge \alpha \sum_{b \in B} D_b, \tag{11}$$

$$x_{b,s} \in \{0,1\} \qquad \forall b \in B,\ s \in S, \tag{12}$$

$$g_b \ge 0 \qquad \forall b \in B, \tag{13}$$

$$f_{i,j} \ge 0 \qquad \forall (i,j) \in E, \tag{14}$$

$$u_b \ge 0 \qquad \forall b \in B. \tag{15}$$

The objective minimises total system cost, comprising PV installation costs and penalty costs for unmet demand (which is satisfied by purchasing from the grid). Constraints (6) ensure at most one PV system is installed per building. Constraints (7) define PV generation at each building based on installed capacity. Constraints (8) enforce rooftop capacity limits for PV installation. Constraints (9) respect the total investment budget. Constraints (10) maintain energy balance at each node, accounting for local generation, electricity flow between neighbours, and unmet demand. As noted, the demand in our campus EC exceeds PV supply, hence no storage is considered, and the EC may buy from the grid as needed. The flow variables enable us to consider how energy exchanges could be facilitated and what network expansion would be required to facilitate such flows. Constraints (11) ensure the policy-driven minimum demand coverage target is met. We assume that the budget is sufficiently big to avoid infeasibility. The constraints (13) to (15) are domain constraints.

2.3 Implementation and Data Sources

We implement the MILP in Python 3.9.13 using Gurobi 11.0.3. We derive key parameter values from the following sources:

- **PV costs:** Commercial reference installation costs [1] expressed for community-scale PV installations in the SRESS-eligible capacity range (50 kW–1 MW)
- **Budget:** Typical campus sustainability fund allocations (€400,000)
- **Demand data:** Historical campus building energy consumption from the BEMS for 2024
- **PV production:** Historical campus building PV production from the BEMS for 2024
- **Roof capacities:** GIS analysis of building footprints with 40% usable area assumption

For visualisation we use Folium for interactive mapping and NetworkX for graph operations. Solution times average 3–15 seconds on a standard laptop (Intel i5, 16GB RAM), demonstrating practical applicability for EC planning scenarios and iterative analysis.

3 Results and Analysis

We apply the MILP model to the UCD campus EC, first describing the network structure and baseline demand to contextualise the optimisation results. We then analyse optimal PV siting and sizing, electricity sharing patterns, cost allocation, and the effects of varying budget and demand. The results highlight trade-offs between investment, spatial constraints, and policy-driven coverage targets in community-scale PV planning.

3.1 Campus Network Representation and Baseline Characteristics

We model the electrical network of the UCD campus as a MST connecting 82 buildings. Figure 1 shows the MST network, which represents the infrastructure backbone for sharing electricity between buildings. The average hourly total electricity demand aggregated across the UCD Belfield campus 82 buildings in 2024 from the BEMS is 4147.13 kWh, the equivalent of a small city. Individual building average hourly demands range from 0.6 kWh to 244 kWh. The available rooftop PV capacities per building range between 7.7 kW to 271.9 kW, reflecting heterogeneous building sizes and orientations.

3.2 Optimal PV Installation Configuration

Under the baseline scenario, with a minimum of 1.3% demand coverage using PV ($\alpha = 0.013$) and a €400,000 budget, the optimisation model allocates installation of PV systems on ten buildings: 2, 8, 16, 49A, 51, 60, 70, 76, 77, 78. We summarise the selected system types and actual installed capacities in Table 1, while in Figure 1 shows the PV locations, building IDs, Energy flows are indicated by the edge width. The selected PV installations reflect roof availability, budget constraints, and network position within the SRESS-eligible capacity range. Rather than distributing generation uniformly across the campus, the optimal solution concentrates PV capacity on a strategically located subset of buildings, relying on electricity sharing to meet demand at non-generating sites. This shows the importance of jointly optimising PV placement and sharing decisions in EC planning.

Based on the optimal solution, we observe that 95% of the budget of €400,000 is utilised for installation of PV equipment across the different buildings, with 50 kW PV systems installed on 7 buildings and 60 kW PV systems on 3 buildings, leading to 1.31% coverage of the overall campus average hourly demand of 4147.13 kWh.

---

[1] For example: https://wizerenergy.ie/commercial-pv-systems/

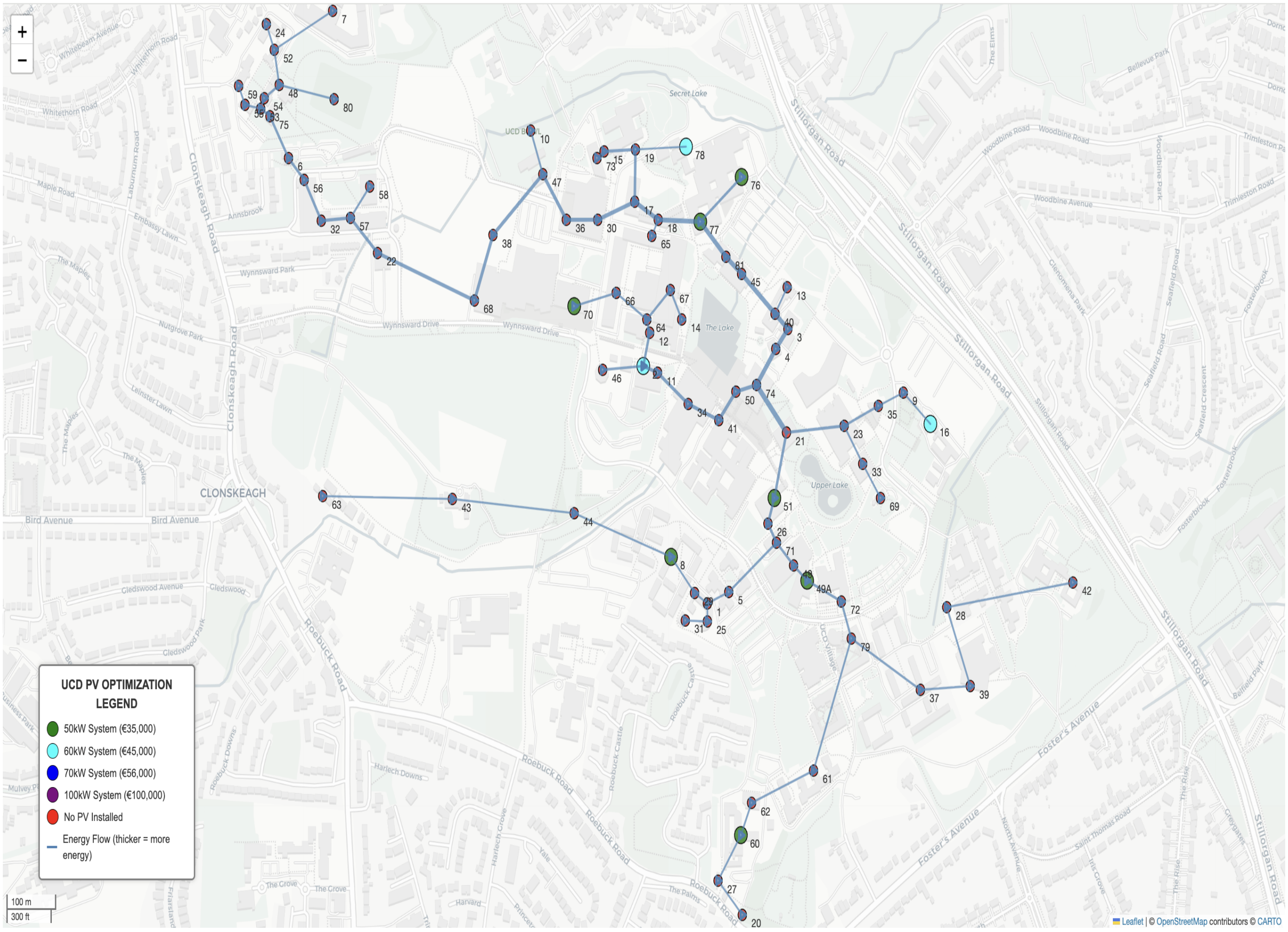

Figure 1: MST connecting UCD campus buildings on the map of Dublin, overlaid with optimal PV installations and energy flows. Nodes correspond to buildings and indicate installed PV capacity (size/color), edges represent feasible electrical connections weighted by Euclidean distance, and edge thickness indicates electricity flow magnitude; building IDs are annotated for reference.

Table 1: Optimal PV Installation Configuration for the Baseline Scenario

Building	PV Installed (kW)	Demand (kWh)	Cost (€)
2	60.0	121.76	45,000
8	50.0	8.56	35,000
16	60.0	2.01	45,000
49A	50.0	10.97	35,000
51	50.0	49.88	35,000
60	50.0	10.58	35,000
70	50.0	47.61	35,000
76	50.0	213.15	35,000
77	50.0	213.15	35,000
78	60.0	5.98	45,000
Total	**530.0**	**683.64**	**380,000**

3.3 Sensitivity Analysis

In this section we discuss the impact of variation in key parameters like budget and demand on the output of the model.

3.3.1 *Variation in Budget:*

In order to assess the impact of financial budget on demand coverage using PV, and associated installation costs, we solve the optimisation model for different budget levels and demand coverage requirements. In Table 2 we summarise the results while in Figure 2, we illustrate the demand coverage and budget relationship. We observe that the demand coverage increases linearly with budget. Interestingly, besides the number of PV installations, the distribution of installations across different configurations also changes. As budget increases, there is an increase in the deployment of higher capacity PV (70 kW or 100 kW), resulting in a linear increase in the overall PV installation costs and the marginal costs (€/kW). This indicates that an increase in budget leads to prioritisation of installation of higher capacity PV systems to meet demand.

3.3.2 *Variation in Demand:*

In the baseline scenario, we consider the average hourly demand for 2024 for all buildings in the campus. We further test the model for the maximum hourly demand, the median hourly demand, and the average hourly demand for the noon hour (12:00-13:00) where sunshine and PV production is expected to be at its peak, and present our results in Table 3. We adjust the α parameter for the fixed budget of €400,000 in

Table 2: Impact of Budget on Demand Coverage and PV Cost

Budget (€)	α	PV (kW)	Coverage	PV Cost (€)	50 kW	60 kW	70 KW	100 kW	Total Installations	Marginal cost (€/kW)
400,000	0.013	530	1.31%	380,000	7	3	0	0	10	716.98
500,000	0.0175	710	1.75%	500,000	13	1	0	0	14	704.23
600,000	0.021	850	2.1%	595,000	17	0	0	0	17	700
700,000	0.024	980	2.42%	695,000	16	3	0	0	19	709.18
800,000	0.027	1100	2.72%	770,000	22	0	0	0	22	700
900,000	0.03	1220	3.02%	860,000	22	2	0	0	24	704.92
1,000,000	0.033	1340	3.31%	965,000	16	9	0	0	25	720.15
1,100,000	0.036	1460	3.61%	1,085,000	4	21	0	0	25	743.15
1,200,000	0.038	1540	3.81%	1,173,000	4	13	8	0	25	761.69
1,300,000	0.04	1620	4.0%	1,272,000	4	8	12	1	25	785.19
1,400,000	0.042	1700	4.2%	1,382,000	4	6	12	3	25	812.94
1,500,000	0.043	1740	4.3%	1,448,000	4	8	8	5	25	832.18

order to ensure feasibility of the model. We observe some variation in the proportion of demand coverage by PV in the different scenarios, ranging between 0.51% to 1.31%. When we consider maximum PV production based on historical data ($\beta = 0.88$), the demand coverage for the maximum demand scenario (11016.71 kWh) goes up to 4.47%. Thus, from a campus energy management perspective, it is important to account for a range of supply and demand scenarios for contingency planning, because in reality, both PV production and electricity demand can vary significantly based on time of the day and weather.

Table 3: Demand coverage for different demand scenarios

Demand metric	Hourly Demand (kWh)	α	Coverage
Average (Overall)	4147.13	0.013	1.31%
Average (Noon)	5765.28	0.009	0.9%
Median	3169.6	0.018	1.81%
Max	11016.71	0.005	0.51%

4 Discussion

We interpret the optimisation results in the context of campus-scale EC planning and small-scale renewable support schemes. Rather than focusing on numerical outcomes, our discussion highlights the broader insights that emerge from the modelling exercise, including the role of spatial concentration, network structure, and demand coverage targets in shaping optimal investment decisions. The findings are discussed from both a planning and policy perspective, with emphasis on their relevance to real-world ECs operating under budgetary and infrastructural constraints.

4.1 Implications for Campus Energy Planning

Our analysis reveals several critical insights for UCD's sustainability strategy and similar campus or EC energy initiatives:

Strategic Hub Locations: Buildings 2, 8, 16, 49A, 51, 60, 70, 76, 77, 78 emerge as optimal initial installation sites due to their central network positions and rooftop potential. This suggests a phased implementation strategy: prioritise these hub buildings in initial phases, then expand to neighboring buildings as budget allows.

Budget allocation: A higher budget evidently allows for an increase in the installed PV capacity. In addition, it facilitates the installation of PV systems with higher capacity, boosting electricity demand coverage across the campus.

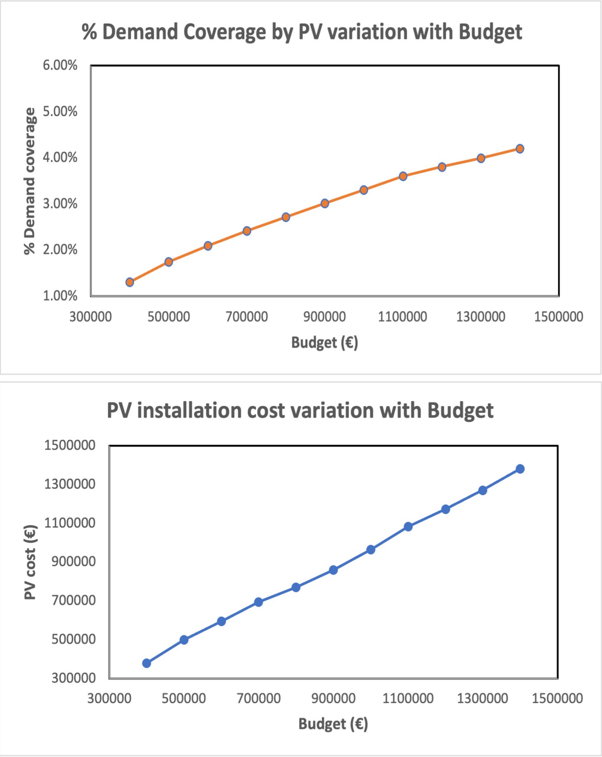

Figure 2: Impact of budget ($\mathcal{B}$) on (a) % demand coverage & (b) PV installation costs.

Roof area constraints: Urban ECs may not have ground space, but in a campus setting, there could be possibilities to explore ground mounted PV installation to circumvent the spatial limitations on buildings rooftops. This can enhance electricity demand coverage.

4.2 Policy Recommendations for Supports

The results of the optimisation model suggest several potential adjustments to enhance the effectiveness of SRESS-like policies.

Flexible Deployment Within Capacity Bands: While SRESS defines eligibility through capacity ranges rather than fixed system sizes, in practice community projects often gravitate toward standardised installations. Our results suggest that encouraging finer-grained capacity choices within the SRESS bands (e.g., uneven or asymmetric allocation across buildings) could improve spatial efficiency and reduce connection costs.

Phased Implementation Support: Policies could explicitly support phased approaches by offering multiple application windows, allowing communities to implement optimal hub-first strategies identified through modelling exercises like ours.

Coverage Target Flexibility: Rather than rigid percentage targets, policies could adopt tiered incentives that reflect diminishing returns at high coverage levels, encouraging cost-effective rather than exhaustive PV deployment.

4.3 Limitations and Future Research Directions

While our model provides valuable planning insights, we acknowledge some limitations and suggest future research directions. The MST is a simplified representation, while suitable for planning-level analysis, neglects actual grid constraints like voltage limits, line capacities, and three-phase imbalances. Future work could incorporate more detailed power flow models or validate MST approximations against actual campus grid data. Additionally, our single-period model uses point estimates for supply and demand; incorporating time series (hourly/daily profiles) and seasonal variations would better capture mismatch between PV generation and demand patterns, potentially suggesting complementary technologies like storage. The model currently considers only PV rooftop systems, but extending it to include other renewables (e.g., heat), storage systems, or demand response would provide more comprehensive planning support. Deterministic parameters (demand, costs, generation) could be extended to factor in uncertainty to account for prediction errors, weather variability etc. Finally, while demonstrated on a campus, the model could be tested on diverse community types (residential, mixed-use, industrial) to assess generalisability and identify context-specific adaptations.

5 Conclusion

In this paper, we present a MILP model for optimising PV facility location in urban ECs, addressing the gap between policy objectives for community-led renewable generation and practical planning tools. Applied to a real-world university campus case study, the model demonstrates how strategic PV placement combined with electricity sharing can meet demand coverage requirements within budget constraints; it also highlights how only a small amount of demand coverage (1.31% in baseline) can be achieved owing to roof area constraints and low PV capacity utilisation, despite high budgets. Large university campuses like that of UCD resemble small cities in terms of electricity needs and therefore need significant investment in PV systems to reduce reliance on the grid.

Our key findings include: (1) optimal solutions concentrate PV capacity on strategically located hub buildings rather than uniform distribution; (2) a higher budget allocation improves demand coverage and facilitates deployment of higher capacity PV systems; (3) demand coverage requirements need to be adjusted for different electricity consumption scenarios for efficient planning, and (4) network topology significantly influences optimal PV siting decisions. The model provides actionable insights for campus sustainability planning and policy design. For UCD, it identifies Buildings 2, 8, 16, 49A, 51, 60, 70, 76, 77, 78 as priority installation sites and suggests targeting 1.3-4.3% coverage for cost-effectiveness. For policymakers, it recommends flexible system sizes, connection subsidies, and phased implementation support within schemes like SRESS.

By bridging technical optimisation with practical planning constraints, this work contributes to the development of more efficient and effective energy communities, supporting the transition to decentralised, participatory energy systems. Future research will address model limitations through temporal expansion, uncertainty incorporation, and application to diverse community contexts.

Acknowledgments

This research was supported by an ERA-NET Cofund grant under the CHIST-ERA IV Joint Call on Novel Computational Approaches for Environmental Sustainability (CES) project *"Supporting Energy Communities—Operational Research and Energy Analytics" (SEC-OREA)*. Dena Tayebi was part-funded by the Irish Research Council.

References

[1] Cristian Aguayo, Paula Carroll, and Evita Kairiša. 2023. Data, Analytics and Algorithms to support Local Energy Communities. In *2023 IEEE 64th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON)*. IEEE, Riga, Latvia, 1–5. doi:10.1109/RTUCON60080.2023.10412878

[2] Shoaib Ahmed, Amjad Ali, and Antonio D'angola. 2024. A review of renewable energy communities: concepts, scope, progress, challenges, and recommendations. *Sustainability* 16, 5 (2024), 1749.

[3] Edoardo Barabino, Davide Fioriti, Emanuele Guerrazzi, Ivan Mariuzzo, Davide Poli, Marco Raugi, Ehsan Razaei, Eva Schito, and Dimitri Thomopulos. 2023. Energy Communities: A review on trends, energy system modelling, business models, and optimisation objectives. *Sustainable Energy, Grids and Networks* 36 (2023), 101187.

[4] Paula Carroll, Manya Singh, and Debajyoti Biswas. 2026. Reference Load Profiles for University Campuses. In *International Workshop on Big Optimization 2025*, Christian Blum, Claudia Cavallaro, Carolina Crespi, and El-Ghazali Talbi (Eds.). Springer Nature Switzerland, Cham, 162–172. doi:10.1007/978-3-032-15455-2_12

[5] Yassine Charabi and Adel Gastli. 2011. PV site suitability analysis using GIS-based spatial fuzzy multi-criteria evaluation. *Renewable Energy* 36, 9 (2011), 2554–2561.

[6] Chao Chen, Weifeng Peng, Cheng Xie, Shufeng Dong, and Yibo Hua. 2025. Photovoltaic Hosting Capacity Assessment of Distribution Networks Considering Source–Load Uncertainty. *Energies* 18, 8 (2025), 2134.

[7] Government of Ireland. 2025. Small-Scale Renewable Electricity Support Scheme Tariff Rates, Volumes and Key Design Features Decision Paper. https://assets.gov.ie/static/documents/sress-key-decisions-public-document.pdf. Accessed January 2026.

[8] Jens Lowitzsch, Christina E Hoicka, and Felicia J van Tulder. 2020. Renewable energy communities under the 2019 European Clean Energy Package–Governance model for the energy clusters of the future? *Renewable and Sustainable Energy Reviews* 122 (2020), 109489.

[9] Anna Mutule, Olegs Borscevskis, Victor Astapov, Irina Antoskova, Paula Carroll, and Evita Kairisa. 2025. PV Energy Communities in Residential Apartments: Technical Capacities and Economic Viability. *Sustainability* 17, 7 (2025). doi:10.3390/su17072901

[10] Luis A Gallego Pareja, Oscar Gomez Carmona, and Jesãšs M López-Lezama. 2025. A MILP Model for Simultaneous Optimal Placement, Sizing, and Operation of PV Distributed Generation and D-STATCOMs in Distribution Systems. *IEEE Access* (2025).

[11] David Pozo and Javier Contreras. 2012. A chance-constrained unit commitment with an nK security criterion and significant wind generation. *IEEE Transactions on Power systems* 28, 3 (2012), 2842–2851.

[12] Juan M Sánchez-Lozano, Carlos Henggeler Antunes, M Socorro García-Cascales, and Luis C Dias. 2014. GIS-based photovoltaic solar farms site selection using ELECTRE-TRI: Evaluating the case for Torre Pacheco, Murcia, Southeast of Spain. *Renewable Energy* 66 (2014), 478–494.