Proceedings Paper:
Zakiah, A., Peng, C. and Wang, T. (2025) A framework for assessing the potential of community solar microgrids in urban areas using partially measured data. In: Journal of Physics: Conference Series. International Conference CISBAT 2025, 03-05 Sep 2025, Lausanne, Switzerland. IOP Publishing. ISSN: 1742-6588. EISSN: 1742-6596.

https://doi.org/10.1088/1742-6596/3140/3/032007

Journal of Physics:
Conference Series

PAPER • OPEN ACCESS

A framework for assessing the potential of community solar microgrids in urban areas using partially measured data

To cite this article: A Zakiah *et al* 2025 *J. Phys.: Conf. Ser.* **3140** 032007

View the article online for updates and enhancements.

A framework for assessing the potential of community solar microgrids in urban areas using partially measured data

A Zakiah[1,2*], C Peng[1] and T Wang[1]

[1] School of Architecture and Landscape, The University of Sheffield, Sheffield, UK
[2] Department of Architecture, Universitas Islam Indonesia, Yogyakarta, Indonesia

* azakiah2@sheffield.ac.uk, aisyah.zakiah@uii.ac.id

Abstract. A community solar microgrid presents a promising approach to increase clean energy utilisation in urban areas. While this system has been successfully established in off-grid rural areas, its adoption in urban areas remains limited. Nonetheless, it holds significant potential, particularly for countries that still depend on fossil fuels to produce electricity. One of the key challenges in accessing its feasibility is the lack of comprehensive measured data due to its limited establishment in urban areas. To address this, this paper presents a framework for evaluating the potential of community solar microgrids in urban settings using partially measured data. The analysis encompasses both technical and economic feasibility, employing a calibrated computational simulation to assess hourly load matching and battery sizing. The findings demonstrate the tested site's potential to meet its electricity demand with locally generated solar energy. Additionally, the study explores two different community solar microgrid scenarios—one focused on cost minimisation and the other on maximising clean energy use.

1. Introduction

Community solar microgrids offer a promising approach to increasing clean energy utilisation in urban areas. These systems enable clean energy sharing within a community while providing environmental and economic benefits. Although community solar microgrids have been successfully implemented in off-grid rural areas [1], their adoption in urban areas remains limited. Meanwhile, urban areas consume vast amounts of electricity for transport, industry, building operations and infrastructure [2]. The electricity consumption of buildings in urban areas also tends to be higher than in rural areas [3]. Given these factors, community solar microgrids hold great potential to be implemented in urban areas, particularly in countries that still rely on fossil fuels to generate electricity.

Community solar microgrids operate by generating solar energy locally, storing it within the community, and using blockchain-based management to enable energy sharing [4]. These systems can function independently or integrate with utility grids, with a local energy management system (EMS) overseeing electricity distribution and storage [5]. The EMS plays a critical role in optimising electricity allocation and managing storage capacity to ensure efficient energy use.

However, the feasibility of community solar microgrids in urban areas differs from rural settings due to variations in urban morphology. Factors such as shading and reflection effects due to urban form can significantly influence solar energy potential [6]. Additionally, urban areas accommodate more diverse building functions, such as office and commercial buildings, which differ from rural areas.

Journal of Physics: Conference Series **3140** (2025) 032007 doi:10.1088/1742-6596/3140/3/032007

As urban community solar microgrids are not yet widely established, collecting real-world measured data for potential analysis remains a challenge. This study addresses this by combining validated software to model and analyse energy performance and use measured data for calibration. The objectives are to (1) develop a framework to evaluate the technical and economic viability of solar microgrid adoption in urban communities and (2) test it for a real office complex in Jakarta, Indonesia.

2. Workflow

The framework proposed in this paper provides a data analysis process that evaluates both technical and economic feasibility. It follows three main steps: (1) calibration of computational simulation results with measured data, (2) hourly load-matching analysis at the community scale, and (3) battery sizing and financial assessment for different scenarios. The overall workflow is illustrated in **Figure 1**.

2.1. Computational Simulation Calibration with Measured Data

The calibration process covers both energy use and radiation simulations. Measured data was recommended to calibrate simulation results to reach acceptable tolerances [7]. Measured data collected from a sample building or energy use intensity (EUI) data of a specific building type can be used for this calibration [8].

The initial parameters for energy simulation were set, including building construction set, window-to-wall ratio (WWR), cooling heating system, and programs. The simulation results are compared with measured data for calibration. The iterative process may involve adjusting simulation parameters to achieve a better fit with the measured data. Once satisfactory simulation settings are established and meet the calibration criteria, they are used to simulate a community block.

The simulation model, including a single building for validation and a community block for community solar microgrid testing, was modelled in Rhinoceros as a simplified 3D model. Simulation settings include historical weather data in EPW format for energy and radiation simulations. These simulations utilise validated software Ladybug Tools, including Ladybug for radiation simulation, Honeybee for building energy simulation and Dragonfly for urban energy simulation in combination with the EnergyPlus engine [9], [10].

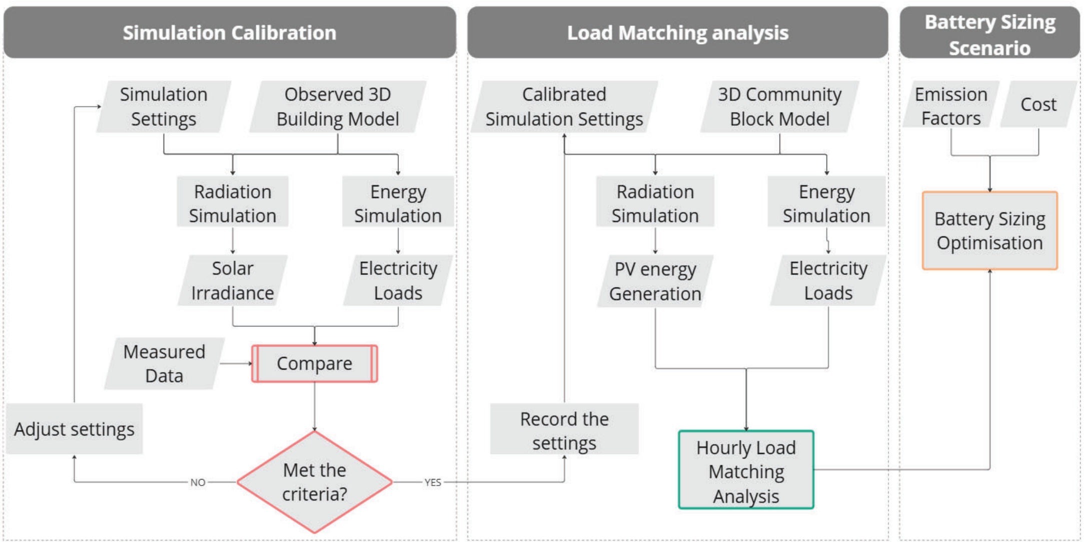


Figure 1. Framework for Assessing Urban Community Solar Microgrid Potential using Partially Measured Data

Calibration is assessed using standard statistical methods to verify the accuracy, including the Mean Bias Error (MBE) and Coefficient of Variation of Root Mean Square Error (CV(RMSE)) [10].

According to previous studies and ASHRAE (Guideline 14-2014, 2014), the acceptance criteria for calibration are MBE **5**% and CV(RMSE) **15%** for monthly data; MBE **10%** and CV(RMSE) **30%** for Hourly data. These calculations are defined in equations (1-2).

$$MBE\,(\%) = \frac{\sum_{i=1}^{N_p}(m_i - s_i)}{\sum_{i=1}^{N_p}(m_i)} \times 100 \tag{1}$$

$$CVRMSE\,(\%) = \frac{\sqrt{\frac{\sum_{i=1}^{N_p}(m_i - s_i)^2}{N_p}}}{\overline{m}} \times 100 \tag{2}$$

where S_i represents simulated data, m_i represents measured data, and N_p is the total amount of data.

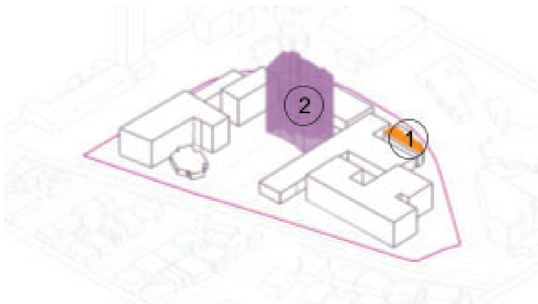
2.2. Hourly Load Matching Analysis
The community-scale computational energy simulation employs the same tools as the calibration process. A combination of Dragonfly and URBANopt allows for multi-building energy simulations within a community block [11]. The simulation outputs provide hourly increments of solar radiation and energy demand data. These data are essential for conducting a detailed load-matching analysis of community solar microgrids.

2.3. Battery Sizing Scenario
Following the load-matching analysis, battery sizing is performed under two main scenarios: (1) Cost-Minimisation Strategy - This scenario optimises financial efficiency by minimising electricity costs, and (2) Resilience Strategy - This scenario maximises the utilisation of clean energy within the community. Additionally, the economic viability of battery storage solutions is assessed by calculating the capital cost and Net Present Value (NPV) [12].

3. Result and Discussion

3.1. Case Study
An office complex in Jakarta, Indonesia, serves as the case study for testing the modelling framework. **Figure 2a** shows the selected office complex where community solar microgrid testing will be performed. **Figure 2b** shows the buildings from the area where the partial data were collected. Building 1 has a PV-integrated roof system where the solar energy generation was collected, and building 2 is an office building where the energy demand data was collected. The measured data collected from the case study area were monthly energy use and daily PV energy generation.


a. Satellite View

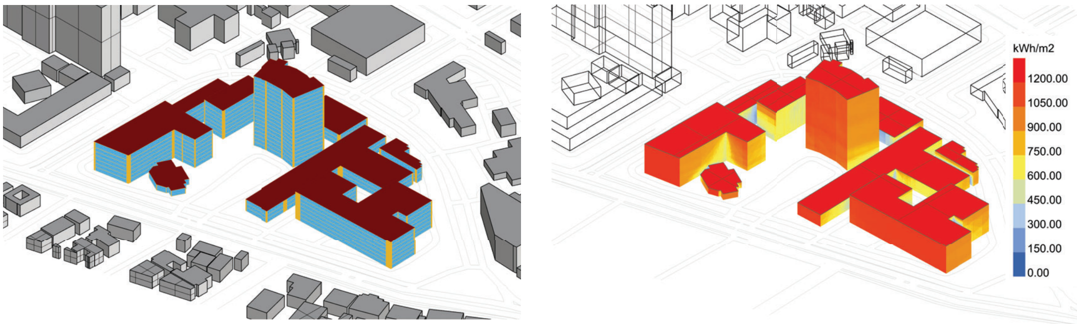


b. Modelled in Rhinoceros 3D

Figure 2. Case Study Area

The community scale simulation applied to the whole office complex with the assumption that all buildings have the same building construction and program. The building energy simulation model was configured using Dragonfly features to set construction, program, thermal zones (see **Figure 3a**) while the solar radiation simulation was applied to both the roof and wall surfaces (see **Figure 3b**).

The calibration process for energy use simulation is only done once in this case study since this community consists of only office buildings. Applying this framework for more diverse areas, with more than one building function, should incorporate energy use calibration to each building function type. This differentiation on the simulation setting does not apply to the radiation simulation.



a. Building Energy Simulation **b.** Solar Radiation Simulation

Figure 3. Community Scale Simulation Model

3.2. Simulation Calibration Using Partially Measured Data

Energy simulation calibration incorporates several iterations of the simulation settings. Three iterations were tested in this case study and compared them to measured data as presented in **Figure 4**. Adjusting the occupancy pattern and set point temperature is recommended by previous studies for iterative refinements [13]. The iteration tested includes:

- Option 1: standard cooling setpoint (24^0C),
- Option 2: standard infiltration rate, lower cooling setpoint (0.0001 m^3/s per m^2 facade) (18^0C),
- Option 3: higher infiltration rate, lower cooling setpoint (0.0004 m^3/s per m^2 facade) (18^0C).

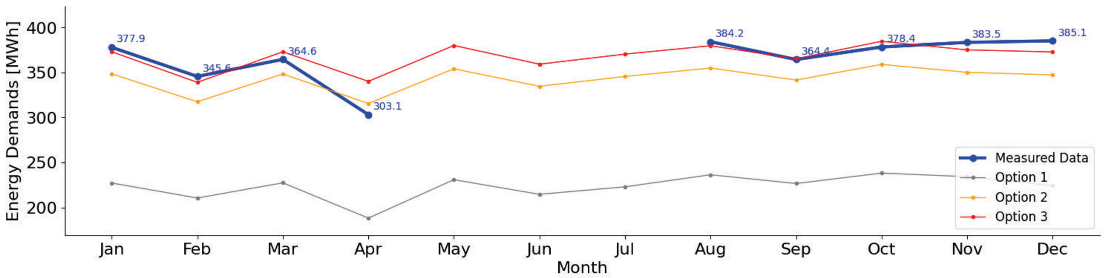


Figure 4. Energy Simulation Results Compared To Measured Data

The total result is reliable, even the simulation parameters tested are assumptions, since it matches with measured data and EUI data. The annual energy use result for Option 3 is 3,302.82 MWh. With a 25,100 m^2 building floor area, the EUI calculated is 131.59 kWh/m2/year. This result matches the data from B2TKE-BPPT where, based on a survey in 2020, the EUI of large office buildings in Jakarta is in a range between 118.22 - 192.53 kWh/m2/year [14].

The statistical result for option 3 shows MBE is 0.48% and CV(RMSE) is 3.86%. This calibration mainly focuses exclusively on the predicted simulation result and does not consider uncertainties or inaccuracies in input parameters or the precision of the simulated environment.

The PV energy generation potential is calculated based on the solar irradiation result from the simulation combined with PV module specification data and system losses. The simulation result compared to measured data shows statistical results of MBE is 1.56% and CV(RMSE) is 10.90%.

3.3. *Hourly Load Matching*

Load-matching analysis assesses the alignment between locally generated solar energy and community energy demand. The hourly electricity load reveals how energy demand fluctuates across different days and times. In office buildings, demand typically peaks during working hours. Similarly, hourly PV energy generation indicates the potential of various building surfaces to produce solar energy. Urban morphology factors, such as building proximities and average building height within a community block may affect PV energy generation [6]. This study highlights that while energy demand is primarily influenced by building function, solar energy generation is more affected by urban form. A load-matching assessment is essential to evaluate the balance between these two factors.

The simulation results for a community-scale office complex indicate that energy demand exceeds its solar energy potential, as shown in **Figure 5**. However, some excess PV energy is generated during the day on weekends. This surplus could be stored in a battery system and discharged when demand is higher. However, determining the appropriate battery capacity requires careful economic assessment.

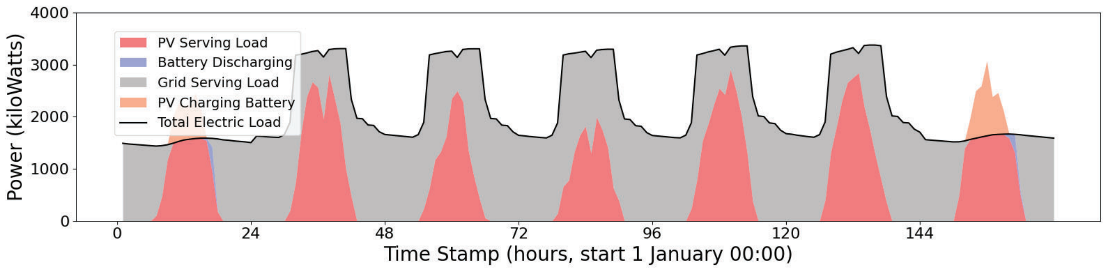


Figure 5. Hourly Load Matching of Case Study Area - Office Complex

This framework can also perform individual building checks on annual energy consumption and PV energy potential, showing each building's capability to provide solar energy to meet its energy needs.

3.4. *Battery Sizing Scenarios for Urban Community Solar Microgrids*

Battery sizing analysis and NPV can show the economic feasibility for different types of strategy. For tested case study, no battery storage is recommended in the minimising-cost strategy. Which potentially caused by cheap electricity prices in Indonesia, thus having a battery storage categorised as not cost effective. Additionally in the resilience strategy with 6 hours power outage annually, the NPV seems not feasible which shows negative value after 25 years (see **Table 1**).

Table 1. Battery Sizing Scenario

Focus Strategy	PV Sizing (kW)	Optimal Battery Power (kW)	Optimal Battery Capacity (kWh)	NPV ($)
Cost	2,240	0	0	304,891
Resilience	2,240	1,534	7,014	-$3,415,390

4. Conclusion

This paper presents a framework to assess the potential of community solar microgrids in urban settings using partially measured data. This framework may benefit the community solar microgrid potential analysis in areas where complete measured data is challenging to obtain. The testing data uses many assumptions since there is no observation on scheduling and occupant behaviour, which may lead to less accuracy on hourly load-matching data. Future research that compares the simulation with more detailed period-measured data, hourly or 15-minute intervals data may result in better accuracy.

Acknowledgements
This research was supported by the Indonesia Endowment Fund for Education (LPDP) Scholarship, Republic of Indonesia. The author would also like to thank the Ministry of Public Works and Housing of the Republic of Indonesia (Kementerian PUPR) for permitting the data collection for this study.

References
[1] C. Zürpel, 'Solar Microgrids: How to Successfully Tackle the Electrification Challenge in the Rural Global South', 2024, *SSRN*. doi: 10.2139/ssrn.4900805.
[2] Y. He, J. Jiao, Q. Chen, S. Ge, Y. Chang, and Y. Xu, 'Urban long term electricity demand forecast method based on system dynamics of the new economic normal: The case of Tianjin', *Energy*, vol. 133, pp. 9–22, Aug. 2017, doi: 10.1016/j.energy.2017.05.107.
[3] H. A. Bekhet and N. S. B. Othman, 'Assessing the Elasticities of Electricity Consumption for Rural and Urban Areas in Malaysia: A Non-linear Approach', *Int. J. Econ. Finance*, vol. 3, no. 1, p. p208, Jan. 2011, doi: 10.5539/ijef.v3n1p208.
[4] K. C. Seto *et al.*, 'From Low- to Net-Zero Carbon Cities: The Next Global Agenda', *Annu. Rev. Environ. Resour.*, vol. 46, no. 1, pp. 377–415, Oct. 2021, doi: 10.1146/annurev-environ-050120-113117.
[5] J. D. Mina-Casaran, D. F. Echeverry, C. A. Lozano, and A. Navarro-Espinosa, 'On the Value of Community Association for Microgrid Development: Learnings from Multiple Deterministic and Stochastic Planning Designs', *Appl. Sci.*, vol. 11, no. 14, p. 6257, Jul. 2021, doi: 10.3390/app11146257.
[6] M. C. Brito, P. Redweik, C. Catita, S. Freitas, and M. Santos, '3D solar potential in the urban environment: A case study in lisbon', *Energies*, vol. 12, no. 18, 2019, doi: 10.3390/en12183457.
[7] F. Karlsson, P. Rohdin, and M.-L. Persson, 'Measured and predicted energy demand of a low energy building: important aspects when using Building Energy Simulation', *Build. Serv. Eng. Res. Technol.*, vol. 28, no. 3, pp. 223–235, Aug. 2007, doi: 10.1177/0143624407077393.
[8] Y. Q. Ang, Z. M. Berzolla, and C. F. Reinhart, 'From concept to application: A review of use cases in urban building energy modeling', *Appl. Energy*, vol. 279, p. 115738, Dec. 2020, doi: 10.1016/j.apenergy.2020.115738.
[9] F. Kharvari, 'An empirical validation of daylighting tools: Assessing radiance parameters and simulation settings in Ladybug and Honeybee against field measurements', *Sol. Energy*, vol. 207, pp. 1021–1036, Sep. 2020, doi: 10.1016/j.solener.2020.07.054.
[10] M. Možina, L. Pajek, P. D. Nadarajah, M. K. Singh, and M. Košir, 'Defining the calibration process for building thermal performance simulation during the warm season: a case study of a single-family log house', *Adv. Build. Energy Res.*, vol. 18, no. 2, pp. 180–215, Mar. 2024, doi: 10.1080/17512549.2024.2350944.
[11] T. Charan *et al.*, 'Integration of Open-Source URBANopt and Dragonfly Energy Modeling Capabilities into Practitioner Workflows for District-Scale Planning and Design', *Energies*, vol. 14, no. 18, p. 5931, Sep. 2021, doi: 10.3390/en14185931.
[12] R. Kandari, N. Neeraj, and A. Micallef, 'Review on Recent Strategies for Integrating Energy Storage Systems in Microgrids', *Energies*, vol. 16, no. 1, p. 317, Dec. 2022, doi: 10.3390/en16010317.
[13] V. F. Mendes, A. S. Cruz, A. P. Gomes, and J. C. Mendes, 'A systematic review of methods for evaluating the thermal performance of buildings through energy simulations', *Renew. Sustain. Energy Rev.*, vol. 189, p. 113875, Jan. 2024, doi: 10.1016/j.rser.2023.113875.
[14] B2TKE– BPPT, 'BENCHMARKING SPECIFIC ENERGY CONSUMPTION DI BANGUNAN KOMERSIAL', 2020. [Online]. Available: https://simebtke.esdm.go.id/sinergi/assets/content/20210527150029_Laporan_Akhir_SEC-130120.pdf