Graduation Plan

Master of Science Architecture, Urbanism & Building Sciences

Graduation Plan: All tracks

Submit your Graduation Plan to the Board of Examiners (Examencommissie-BK@tudelft.nl), Mentors and Delegate of the Board of Examiners one week before P2 at the latest.

The graduation plan consists of at least the following data/segments:

Personal information	
Name	Jakub (Kuba) Wyszomirski
Student number	5781078

Studio		
Name / Theme	Building Technology	
Main mentor	Michela Turrin	Design Informatics
Second mentor	Charalampos Andriotis	Structural Design/ Artificial Intelligence
Argumentation of choice of the studio	The recent surge in machine learning has led to its application across various aspects of the construction industry. However, its potential in facilitating sequential decision-making within the built environment remains underexplored. Integrating reinforcement learning with building-integrated renewable energy sources presents an opportunity to bridge the gap between the current static approaches to photovoltaic panel deployment in residential settings and the application of artificial intelligence for sustainable energy production. What is more this topic enables the author to explore and develop solutions to a real problem with a substantial positive impact on society.	

Graduation project	
Title of the graduation project	ReinforceRay: Optimal Long-Term Planning of Photovoltaic System in Grid-Connected Residential Sector with Reinforcement Learning
Goal	
Location:	The electricity load data is taken from a typical terraced house constructed prior to 1945, located in Delft.
The posed problem,	Optimal planning for residential PV systems must navigate a complex landscape of often conflicting and mutually exclusive variables and objectives. To date, the primary focus in optimizing the economic feasibility of residential PV installations lacks integration of other variables unrelated to economic profitability, such as environmental impact considerations; the optimizations

	are carried out over a short periods of time; concentrate on specific, peculiar scenarios; make unrealistic assumptions about fluctuating time-dependent variables. The problem lies in effectively utilizing the multi-objective optimization and sequential decision-making capabilities of reinforcement learning to navigate the complex, multidimensional spaces involved in long-term planning for rooftop PV systems in grid connected, residential scenario, especially when considering factors of divergent and often mutually exclusive natures, along with their inherent uncertainties.
research questions and	Main question: How can reinforcement learning based recommendation workflow be used for long-term planning and design of residential grid-connected PV system under the uncertainty of future scenarios? Secondary Questions: How does the residential grid-tied photovoltaic system operate? How can we evaluate the economic profitability and environmental benefits of rooftop PV systems? Which variables to include in the optimization process? What constitutes the most appropriate model for forecasting the electricity yield of photovoltaic systems? How to generate future scenarios of the identified optimization variables for model training? Which reinforcement learning algorithm and in what configuration is most suitable for this problem? What kind of action, observation spaces and reward function to consider? How to deploy the trained model and how could it be used by the end user?

design assignment in which these result.	The purpose of this thesis is to develop, test and evaluate sequential decision-making workflow for the implementation and maintenance of a residential PV system using reinforcement learning (RL). The main deliverable is an optimally trained RL model with an applicable training environment with all relevant variables implemented and modelled. The model should be able to output the best planning strategy over the course of 25 years, with the timestep frequency (max. 1 year) according to its reward function. Upon successful completion, depending on time, further investigations may be undertaken looking at the boundary conditions, limitations, calibration testing and deployment including a mockup user interface to the trained model.

[This should be formulated in such a way that the graduation project can answer these questions.
The definition of the problem has to be significant to a clearly defined area of research and design.]

Process

Method description

1. Literature Review

The study will begin on examining residential grid-connected photovoltaic systems. Then, we will identify and elaborate on the various factors that influence decision-making processes at financial and environmental levels. Following this, it will focus on comprehending the objective functions as described in the literature and pinpointing the pertinent design constraints. Next, various methods of modelling photovoltaic panels in the context of long-term planning will be described and discussed. The focus will then shift to an exploration of reinforcement learning, including an overview of the RL landscape and more focused descriptions of algorithms. Subsequently, the literature for creating stochastic scenarios based on the identified independent variables for training the RL model will be explained. Finally reinforcement learning deployment considerations will be analyzed.

2. Toy Problem - minimal required to answer research question

This step acts as a controlled environment where the methodology can be evaluated. Here it is assumed that all relevant variables remain static throughout the optimization period. The primary goal of this step is to test and validate the developed approach regarding constructing the RL model environments, assess both of the selected algorithms, test and fine-tune the reward function and examine the

PV system modeling process. Once the algorithm converges well, we will move on to the next stage. The PV panels are modelled using a single-diode method from pvlib library. Three evaluation metrics are selected: cumulative reward, internal rate of return and global warming potential.

3. Full – Scale Development - medium goal

After completing and assessing the toy problem, the experimental process progresses to the Full-Scale Development stage. Here, the complexity of the variables increases gradually. Those include: electricity tariff, CAPEX, new PV performance improvement, grid emission factor, net metering and gradual PV efficiency loss. Each variable is modelled and introduced individually, followed by an evaluation of the algorithm's performance and output. This step-by-step approach continues until all the specified variables are incorporated into the training process. In this stage the reward function is going to be further evaluated. If the model converges well we can increase the timestep density from one year to 6 months and further to one quarter. On this stage alternatives to a simple neural network as the policy or value functions such recurrent neural network (RNN) and Long-Short Term Memory (LSTM) are going to be tested.

4. Model Deployment - optimal goal

The final phase of the proposed workflow involves developing a front-end recommendation system for the model. This system will serve as a demonstrative interface, which could be potentially integrated into an actual PV monitoring system. The implementation of this interface will either be actualized by creating a genuine interactive interface, or more realistically within the thesis time frame, through a mock UI designed in a 2D graphic software, illustrating the essential functionalities.

In general the following tools will be used (subject to change):
Python – Open AI Gymnasium, PyTorch, Stable Baselines 3, Gradio, pvlib, plotly and other common libraries (numpy, matplotlib, pandas, etc.)

Literature and general practical references

The following are the primary sources encompassing literature reviews, comparative studies and literature most relevant to the topic of this thesis. However a more extensive list is given in the report.

Grid Connected PV System Planning:

Abo-Khalil, A.G., Sayed, K., Radwan, A. and El-Sharkawy, I.I.A. (2023). Analysis of the PV System Sizing and Economic Feasibility Study in a grid-connected PV System. *Case Studies in Thermal Engineering*, 45. doi:https://doi.org/10.1016/j.csite.2023.102903.

Al Garni, H.Z., Awasthi, A. and Ramli, M.A.M. (2018). Optimal design and analysis of grid-connected photovoltaic under different tracking systems using HOMER. *Energy Conversion and Management*, 155, pp.42–57. doi:https://doi.org/10.1016/j.enconman.2017.10.090.

Fan, Y. and Xia, X. (2017). A multi-objective optimization model for energy-efficiency building envelope retrofitting plan with rooftop PV system installation and maintenance. *Applied Energy*, 189, pp.327–335. doi:https://doi.org/10.1016/j.apenergy.2016.12.077.

Khezri, R., Mahmoudi, A. and Aki, H. (2022). Optimal Planning of Solar Photovoltaic and Battery Storage Systems for grid-connected Residential sector: Review, Challenges and New Perspectives. *Renewable and Sustainable Energy Reviews*, 153, p.111763. doi:https://doi.org/10.1016/j.rser.2021.111763.

Kouro, S., Leon, J.I., Vinnikov, D. and Franquelo, L.G. (2015). Grid-Connected Photovoltaic Systems: An Overview of Recent Research and Emerging PV Converter Technology. *IEEE Industrial Electronics Magazine*, 9(1), pp.47–61. doi:https://doi.org/10.1109/mie.2014.2376976.

Morey, M., Gupta, N. and kumar, A. (2023). A comprehensive review of grid-connected solar photovoltaic system: Architecture, control, and ancillary services. *Renewable Energy Focus*, 45, pp.307–330. doi:https://doi.org/10.1016/j.ref.2023.04.009.

Vartiainen, E., Masson, G., Breyer, C., Moser, D. and Román Medina, E. (2019). Impact of Weighted Average Cost of capital, Capital expenditure, and Other Parameters on Future Utility-scale PV Levelised Cost of Electricity. *Progress in Photovoltaics: Research and Applications*, 28(6). doi:https://doi.org/10.1002/pip.3189.

PV Modelling:

Shiva Gorjian and Ashish Shukla (2020b). *Photovoltaic Solar Energy Conversion: Technologies Applications and Environmental Impacts*. London: Academic Press, pp.313–346.

Holmgren, W.F. *et al.* (2015) ‘PVLIB Python 2015’, *2015 IEEE 42nd Photovoltaic Specialist Conference (PVSC)* [Preprint]. doi:10.1109/pvsc.2015.7356005.

Kuitche, J. M. (2010). 'Statistical Lifetime Prediction for Photovoltaic Modules' [PowerPoint presentation]. *Arizona State University & TUV Rheinland PTL.* Available at: https://www.energy.gov/eere/office-energy-efficiency-renewable-energy (Accessed: 20 January 2024).

Ozcan, H.G., Gunerhan, H., Yildirim, N. and Hepbasli, A. (2019). A comprehensive evaluation of PV electricity production methods and life cycle energy-cost assessment of a particular system. *Journal of Cleaner Production*, 238, p.117883. doi:https://doi.org/10.1016/j.jclepro.2019.117883.

Perez, R., Ineichen, P., Seals, R., Michalsky, J. and Stewart, R. (1990). Modeling daylight availability and irradiance components from direct and global irradiance. *Solar Energy*, 44(5), pp.271–289. doi:https://doi.org/10.1016/0038-092x(90)90055-h.

Stochastic Modelling of Variables

Ibe, O.C. (2013). *Markov Processes for Stochastic Modeling*. San Diego, CA: Elsevier Science, pp.329–347.

Merton, R.C. (1976). Option Pricing When Underlying Stock Returns Are Discountinous. *Journal of Financial Economics*, 3, pp.125–144.

Moon, Y. and Baran, M. (2018). Economic analysis of a residential PV system from the timing perspective: A real option model. *Renewable Energy*, 125, pp.783–795. doi:https://doi.org/10.1016/j.renene.2018.02.138.

Penizzotto, F., Pringles, R. and Olsina, F. (2019). Real Options Valuation of Photovoltaic Power Investments in Existing Buildings. *Renewable and Sustainable Energy Reviews*, 114(109308). doi:https://doi.org/10.1016/j.rser.2019.109308.

Weron, R. (2014). Electricity Price forecasting: a Review of the state-of-the-art with a Look into the Future. *International Journal of Forecasting*, [online] 30(4), pp.1030–1081. doi:https://doi.org/10.1016/j.ijforecast.2014.08.008.

Reinforcement Learning:

Sutton, R.S. and Barto, A. (2018). *Reinforcement Learning : an Introduction*. Cambridge, Ma ; Lodon: The Mit Press.

Brunton, S.L. and Jose Nathan Kutz (2022). *Data-driven Science and Engineering: Machine learning, Dynamical systems, and Control*. Cambridge, United Kingdom, New York, Ny: Cambridge University Press.

Fu, Q., Han, Z., Chen, J., Lu, Y., Wu, H. and Wang, Y. (2022). Applications of Reinforcement Learning for Building Energy Efficiency control: a Review. *Journal of Building Engineering*, 50, p.104165. doi:https://doi.org/10.1016/j.jobe.2022.104165.

Jung, S., Jeoung, J., Kang, H. and Hong, T. (2021). Optimal Planning of a Rooftop PV System Using GIS-based Reinforcement Learning. *Applied Energy*, 298(117239). doi:https://doi.org/10.1016/j.apenergy.2021.117239.

Liu, C., Jing Yang, R., Yu, X., Sun, C., Rosengarten, G., Liebman, A., Wakefield, R., Wong, P.S. and Wang, K. (2023). Supporting Virtual Power Plants decision-making in Complex Urban Environments Using Reinforcement Learning. *Sustainable Cities and Society*, 99, pp.104915–104915. doi:https://doi.org/10.1016/j.scs.2023.104915.

Model Deployment:

Google PAIR. (2019). *People + AI Guidebook*. 2nd ed. People + AI Research.

Chen, Z., Xiao, F., Guo, F. and Yan, J. (2023). Interpretable Machine Learning for Building Energy management: a state-of-the-art Review. *Advances in Applied Energy*, [online] 9, p.100123. doi:https://doi.org/10.1016/j.adapen.2023.100123.

Reflection

1. What is the relation between your graduation (project) topic, the studio topic (if applicable), your master track (A,U,BT,LA,MBE), and your master programme (MSc AUBS)?

The MSc AUBS programme, among others, focuses on innovation within the field of architectural engineering. It has a multi-disciplinary emphasis that encourages students to explore topics that connect different fields.

The project at hand has an obvious, deep connection to the building technology master track as it focuses on building integrated renewable energy sources and multi-objective decision making with the use of advanced computational tools. It exceeds the boundaries of BT however integrating elements of planning and management in the built environment, as well as computer sciences.

2. What is the relevance of your graduation work in the larger social, professional and scientific framework.

This thesis contributes to the practical understanding of applying RL for the optimization of residential PV systems and related decision-making. Scientifically, the research enriches the field of applied energy informatics by providing a concrete example of how advanced computational techniques can address real-world problems in energy management. It ventures into dynamic optimization that accounts for variability and uncertainty in long-term planning.

On the societal front, the research directly addresses the need for more efficient and environmentally friendly energy solutions at the household level. The development of a robust RL-based framework provides homeowners with a clear strategy to optimize their energy costs and reduce their carbon footprint. The outcomes of this research could potentially lower the barriers to the adoption of PV systems by demystifying the economic and ecological trade-offs involved.