

Student Declaration

Declaration on the Use of Generative AI Tools

I acknowledge the following uses of GenAI tools in this assessment:

- ☒ develop ideas.
- ☒ assist with research or gathering information.
- ☒ help me understand key theories and concepts.
- ☒ identify trends and themes as part of my data analysis.
- ☒ suggest a plan or structure for my assessment.
- ☒ give me feedback on a draft.
- ☒ generate images, figures or diagrams.
- ☒ proofread and correct grammar or spelling errors.
- ☒ generate citations or references.
- ☐ Other: [please specify]
- ☐ I have not used any GenAI tools in preparing this assessment.

I declare that I have referenced all use of GenAI outputs within my assessment in line with the University referencing guidelines. I certify that all material in this dissertation which is not my own has been identified.

Signature: **E.Kaygusuz**



Multi-Objective Optimisation of Swansea Bay Tidal Lagoon Operations Using NSGA-II

Submitted By:
Emre Kaygusuz

Student Number:
740062116

Supervisor:
Dr. Zeliang Wang

Module:
ECMM454 – MSc Computer Science Business Project Proposal

May 2, 2025

Abstract

This project investigates the optimisation of operational strategies for tidal range structures, concentrating on the Swansea Bay Tidal Lagoon as a case study. Using a multi-objective framework of the NSGA-II algorithm, the research aims to optimise energy generation and cost-effectiveness, enhancing economic viability. Optimisation targets two conflicting objectives: maximising total annual energy output and minimising unit cost per megawatt. A 0-dimensional model will simulate tidal operations efficiently, evaluating thousands of candidate strategies. Benchmarking against conventional methods, including Grid Search and Genetic Algorithms, will validate the proposed approach. The results aim to inform practical trade-offs, supporting the viability of tidal lagoon projects and contributing to the broader adoption of scalable, reliable renewable energy solutions in the United Kingdom and internationally.

Table of Contents

1	Introduction	3
2	Background	3
3	Problem Justification	4
4	Project Aim and Objectives	6
5	Project Deliverables	6
6	My Contribution	7
6.1	Development of the 0-D Modelling Framework	7
6.2	Implementation of the NSGA-II Optimisation Algorithm	7
6.3	Definition of Objective Functions	8
6.4	Validation and Benchmarking Strategy	8
7	Project Plan	9
8	Evaluation Criteria	10
9	Challenges and Limitations	10
10	Conclusion	10

1. Introduction

With the UK targeting 100% clean electricity generation by 2030 [1], the demand for innovative, scalable renewable energy solutions is more urgent than ever. Among emerging technologies, Tidal Range Structures (TRSs) - particularly tidal lagoons - represent a promising alternative to traditional renewables like wind and solar. They offer predictable and reliable energy generation alongside coastal resilience benefits, with minimal emissions and wildlife disruptions [2]. However, a critical challenge remains: optimising operational strategies to balance maximum energy output with minimum unit cost, given that tidal cycles restrict consistent generation throughout the day.

This project investigates whether improved operational strategies could significantly enhance the economic viability of tidal lagoons. Using the Swansea Bay Tidal Lagoon, a technically feasible yet ultimately cancelled prototype due to its high unit cost [3] as a case study, the research evaluates how optimisation can improve operational efficiency. Specifically, the study compares the performance of Non-Dominated Sorting Genetic Algorithm II (NSGA-II), a widely used multi-objective evolutionary meta-heuristic, with traditional Grid Search and Genetic Algorithm benchmarks. By incorporating realistic operational constraints and decision variables specific to tidal lagoon systems, this project aims to demonstrate how robust optimisation frameworks can unlock the potential of tidal lagoons as scalable, cost-effective contributors to the UK's clean energy transition, informing the design of scalable, cost-effective renewable energy projects worldwide.

Accordingly, this project seeks to answer the following research question:

How can multi-objective optimisation improve the energy output and economic feasibility of tidal lagoons such as Swansea Bay?

2. Background

Tidal range structures (TRSs), such as barrages and lagoons, generate electricity by exploiting the predictable head differences between the sea and an enclosed basin, using the resulting water flows to drive turbines [4]. A tidal lagoon is an artificial reservoir formed by constructing breakwaters along the coastline to maintain a controlled tidal head [5]. As tides rise and fall, sluice gates regulate seawater exchange, while turbines convert the resulting kinetic energy into electricity. As illustrated in Figure 1, tidal lagoons, compared to barrages, offer reduced environmental impact, improved integration with coastal infrastructure, and the ability to operate bidirectionally, generating power during both flood and ebb tides.¹ These advantages, combined with the high predictability of tidal cycles, make lagoons a compelling option for reliable renewable energy generation.

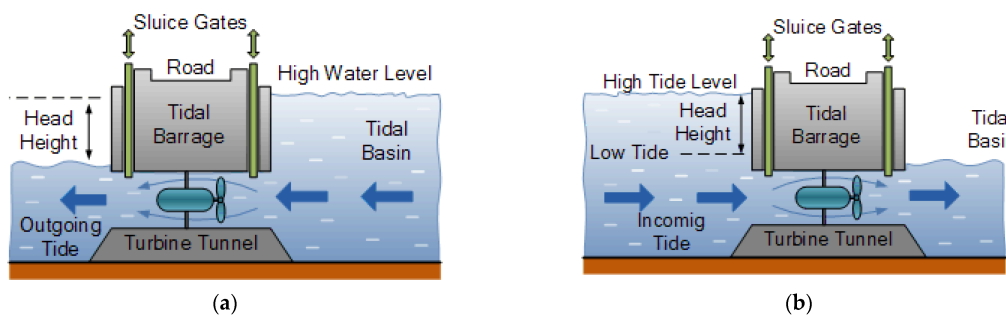


Figure 1: Tidal lagoon operation during (a) ebb tide and (b) flood tide (Adapted from [6]).

The Swansea Bay Tidal Lagoon, developed by Tidal Lagoon Power (TLP), was proposed as the world's first full-scale, energy-generating tidal lagoon and is one of the most extensively studied tidal power projects, designed to generate 320 MW, approximately 50% more than France's Rance Barrage, with an expected annual

¹Note: While Figure 1 illustrates basic tidal power principles using a barrage structure, tidal lagoons typically enclose coastal areas rather than spanning estuaries. The operational concepts of head height management and bidirectional generation remain similar.

output of 400 GWh, enough to supply up to 155,000 homes [7]. The project involved constructing a 9.5–10.5 km seawall near the Rivers Neath and Tawe, enclosing approximately 11–11.5 km² of water. Power generation would rely on low-head bulb turbines operating during flood and ebb tides [7].



Figure 2: The location of the proposed Swansea Bay Tidal Lagoon in Wales, UK. The lagoon enclosure, turbine housing, and sluice gate structures are shown relative to the surrounding coastline.

Beyond renewable energy production, the Swansea Bay lagoon promised substantial additional benefits: it aimed to reduce annual carbon emissions by approximately 236,000 tonnes, support the local economy through job creation, and provide coastal protection against erosion and flooding [7]. As a prototype, Swansea Bay was intended to demonstrate the technical and environmental feasibility of tidal lagoon technology and act as a model for future large-scale deployments.

3. Problem Justification

Despite achieving its technical objectives, the Swansea Bay Tidal Lagoon project was ultimately rejected due to its high unit cost relative to alternative renewable and nuclear energy options, as shown in Table 1. The table compares the output capacities, total costs, and unit costs of selected tidal and nuclear energy projects. The Swansea Bay Tidal Lagoon exhibits a significantly higher unit cost of £4.0 million per MW compared to other tidal structures, such as the Cardiff-Weston Barrage (£1.75 million/MW) and the Cardiff Tidal Lagoon (£2.7 million/MW) [8]. This substantial cost difference ultimately led to the project's rejection, despite its technical feasibility [3].

Project	Output (MW)	Cost (£bn)	Unit Cost (£m/MW)
Cardiff-Weston Barrage	8,640	15.0	1.75
Shoots Barrage	1,050	2.3	2.1
Cardiff Tidal Lagoon	3,000	8.0	2.7
Swansea Tidal Lagoon	320	1.3	4.0
Hinkley Point 3 Nuclear	3,200	22.9	7.6

Table 1: Comparison of costs and unit costs for selected tidal and nuclear energy projects (Adapted from [8]).

Beyond high upfront costs, government analysis also revealed that supporting a series of tidal lagoons would increase the average UK consumer's energy bills by £700 more by 2050 compared to a mix of offshore wind and nuclear energy [9]. These findings reinforce the need to optimise operational strategies to improve economic viability and make tidal lagoons more competitive in the broader renewable energy market. As such, enhancing operations through optimisation methods has become a key focus of recent research.

To simulate tidal lagoon operations, this project adopts a 0-Dimensional (0-D) model, a simplified and computationally efficient approach that estimates water levels and energy generation over time [10]. The 0-D model is

much faster than complex hydrodynamic 2-D models, providing sufficient predictive accuracy for operational optimisation. The difference in predicted energy output between 0-D and 2-D models is relatively small, with only a 4.6% decrease observed across tested cases [11]. This trade-off makes the 0-D model ideal for supporting computationally intensive optimisation algorithms, enabling effective strategy development without prohibitive simulation times.

Previous research into optimising TRSs has focused on traditional methods such as Grid Search and nature-inspired Genetic Algorithms (GAs). These methods have demonstrated moderate gains in operational efficiency, especially in 0-D and 2-D models [11]. However, even enhanced strategies such as Enhanced Half-Tide Grid Search (EHN) and Deep Reinforcement Learning (DRL) have yielded only marginal improvements under more realistic hydrodynamic conditions [12]. These findings suggest that while early optimisation approaches improved performance relative to fixed strategies, they remain limited in addressing the full multi-objective nature of tidal lagoon operations.

In response to these limitations, this project adopts NSGA-II, a proven multi-objective evolutionary algorithm. Unlike GA, Particle Swarm Optimisation (PSO), or Simulated Annealing (SA), NSGA-II explicitly manages trade-offs between conflicting objectives, approximates Pareto-optimal fronts efficiently, and maintains diversity among solutions [13]. These characteristics make NSGA-II particularly suitable for optimising tidal lagoon operations where balancing energy output maximisation and cost minimisation is critical. Despite the promising potential of NSGA-II, its application to tidal range structure optimisation and specifically to the Swansea Bay Tidal Lagoon remains unexplored in existing literature, thus highlighting the novelty and contribution of this study.

This broader gap highlights a clear opportunity to apply and benchmark advanced multi-objective optimisation techniques, such as NSGA-II, to improve tidal lagoon operational strategies.

While Genetic Algorithms (GAs) outperform Fixed Grid Search methods in both 0-D and 2-D simulations, improvements over Enhanced Half-Tide methods (EHN) remain marginal, particularly under more realistic hydrodynamic conditions [11].

Optimisation Methodology	Energy (GWh)		Change in Energy (0-D vs 2-D)	Difference (0-D vs 2-D)
	0-D model	2-D model		
Grid Search (Fixed)	21.3	19.7	–	-7.5%
GA	24.0	23.0	+16.0%	-4.6%
Grid Search (EHN)	24.0	22.9	+16.0%	-4.6%

Table 2: Comparison of energy generation performance using different optimisation methodologies in 0-D and 2-D models (Adapted from [11]).

This suggests that while GA offers some advantages, it still faces limitations under more realistic hydrodynamic conditions.

Optimising tidal lagoon operations requires balancing conflicting objectives, namely maximising energy output while minimising unit cost. To address this multi-objective formulation, this project adopts NSGA-II, widely recognised for its ability to efficiently approximate Pareto-optimal fronts while maintaining a balance between convergence and diversity through mechanisms such as crowding distance [13].

While NSGA-III offers improvements for problems involving more than three objectives [14], NSGA-II remains the preferred standard for two- or three-objective optimisation tasks. Compared to other nature-inspired metaheuristics such as Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO), and Simulated Annealing (SA), NSGA-II offers more structured diversity maintenance and superior trade-off management between conflicting objectives [15]. PSO and SA are often faster for single-objective problems but lack mechanisms for Pareto-based search, while ACO is better suited to discrete combinatorial problems than continuous

energy strategy optimisation.

Therefore, NSGA-II offers the best compromise between solution quality, computational efficiency, and multi-objective handling required for optimising tidal lagoon operations.

4. Project Aim and Objectives

This project aims to develop and apply an optimisation framework to enhance the operational performance of tidal range structures (TRSs), focusing specifically on the Swansea Bay Tidal Lagoon. The framework will incorporate realistic operational constraints and explore multi-objective optimisation strategies that balance energy output maximisation with unit cost minimisation. In addition to technical optimisation, the project will assess the wider business and economic impacts of the Swansea Bay Tidal Lagoon, including its potential contributions to local job creation, infrastructure development, tourism growth, and community engagement initiatives, thereby evaluating the broader socio-economic viability of tidal lagoon projects. Furthermore, the project will evaluate how operational improvements and enhanced economic feasibility at Swansea Bay could influence the development of future tidal lagoon projects across the United Kingdom and internationally, positioning Swansea Bay as a scalable prototype for broader tidal energy deployment.

To achieve these aims, the project will pursue the following objectives:

- Critically review existing modelling approaches and optimisation techniques to identify gaps and justify the use of NSGA-II.
- Develop a computational 0-Dimensional modelling framework for Swansea Bay operations.
- Implement a multi-objective optimisation framework using the NSGA-II.
- Benchmark NSGA-II against traditional methods, including Grid Search and single-objective Genetic Algorithms, using total energy generation and unit cost as performance indicators.
- Analyse trade-offs between energy output and operational costs across optimised strategies.
- Evaluate the scalability, economic viability, and generalisability of the developed optimisation framework for future tidal lagoon deployments.

5. Project Deliverables

The project will deliver the following key outputs:

- Development of a 0-Dimensional (0-D) tidal lagoon model simulating Swansea Bay operations (Phase 2).
- Implementation of a multi-objective optimisation framework based on NSGA-II, balancing energy output and unit cost (Phase 3).
- Development of benchmarking scripts and comparative analysis tools to evaluate NSGA-II against Grid Search and Genetic Algorithm baselines (Phase 4).
- Execution of parameter tuning and sensitivity analysis experiments to optimise algorithmic performance and assess robustness (Phase 4).
- Generation of visual outputs including Pareto fronts and comparative performance charts to support interpretation of optimisation results and trade-offs (Phase 4).
- Compilation of a comprehensive final MSc project report documenting methodologies, validations, results, and critical evaluations (Phase 5).
- Maintenance of a structured project logbook capturing key activities, technical decisions, and reflections (Phase 5).
- Submission of a reproducible zipped codebase and dataset package, including all simulation scripts, NSGA-II implementation, benchmarking tools, and a README for setup and usage (Phase 5).

- Delivery of a pre-recorded 10-minute project presentation with an accompanying professionally designed slide deck (Phase 5).

6. My Contribution

Certain phrasing and structural refinements in the methodology and background sections were supported using ChatGPT, in accordance with university guidance on responsible use of generative AI tools [16].

6.1 Development of the 0-D Modelling Framework

This project adopts a 0-Dimensional (0-D) modelling approach to simulate the operational performance of the Swansea Bay Tidal Lagoon [7]. The model captures the mass balance between the impounded basin and the open sea using time-stepped calculations, estimating water levels and energy generation through a backward-difference method.

The model parameters, including turbine specifications, sluice gate areas, and project cost estimates, are adapted from publicly available sources on the Swansea Bay Tidal Lagoon project [17]. Tidal cycle data for simulation is sourced from the UK Tide Gauge Network, hosted by the British Oceanographic Data Centre [18], enabling realistic simulation of the impounded basin and open sea levels during operational cycles.

The 0-D model balances sufficient predictive accuracy with rapid computational speed, enabling the efficient evaluation of thousands of candidate operational strategies during the multi-objective optimisation process. Previous studies [11] indicate that the difference in predicted energy output between 0-D and 2-D models is relatively small, with only a 4.6% decrease observed, justifying the use of the simplified model for optimisation tasks. While suitable for this study, the 0-D model does not capture detailed spatial hydrodynamics, which could become significant for larger lagoons or more complex basin geometries.

The model parameters for the Swansea Bay Lagoon simulation are summarised in Table 3.

Parameter	Value
Number of Turbines	16
Number of G_P	95
Grid Frequency (Hz)	50
Turbine Diameter (m)	7.35
Turbine Capacity (MW)	20
Turbine Orientation	Ebb
Turbine Discharge Coefficient (dimensionless)	1.36
Sluice Area (m ²)	800
Sluice Discharge Coefficient (dimensionless)	1.00

Table 3: Swansea Bay Tidal Lagoon 0-D model parameters. (Adapted from [17])

The 0-D model simulations and NSGA-II optimisation framework will be implemented in Java, chosen for its object-oriented structure, strong support for modular design, ease of debugging, and wide compatibility across platforms, which aids reproducibility and scalability.

6.2 Implementation of the NSGA-II Optimisation Algorithm

Following the justification presented in the Background and Justification section, NSGA-II was selected for this project. NSGA-II is a well-established evolutionary algorithm known for approximating Pareto-optimal solution fronts while preserving solution diversity via crowding distance mechanisms [13].

Compared to alternative nature-inspired metaheuristics such as Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO), and Simulated Annealing (SA), NSGA-II offers more structured diversity maintenance

and superior management of conflicting objectives. Algorithms like PSO and SA are often faster for single-objective problems but lack explicit mechanisms for exploring Pareto fronts, while ACO is primarily suited to discrete combinatorial problems rather than continuous optimisation of energy generation strategies.

Given that this project optimises only two objectives—maximising total energy output and minimising unit cost—NSGA-II is preferable, avoiding the added complexity introduced by many-objective frameworks such as NSGA-III. Maintaining solution diversity through crowding distance is critical to ensure a wide range of viable operational strategies that offer different trade-offs between cost and energy output, enabling flexible decision-making based on project priorities.

NSGA-II's strengths in convergence, diversity preservation, and trade-off management make it the most appropriate optimisation approach for enhancing the operational strategies of the Swansea Bay Tidal Lagoon²

6.3 Definition of Objective Functions

The optimisation framework developed in this project addresses two conflicting objectives:

1. **Maximise total annual energy output (E_{annual})** The first objective aims to maximise the total energy generated over a full tidal cycle across one year, measured in gigawatt-hours (GWh).
2. **Minimise unit cost of energy generation (C_{unit})** The second objective seeks to minimise the unit cost, defined as the ratio of total capital cost to installed capacity, measured in pounds per megawatt (£/MW).

The optimisation problem can thus be mathematically formulated as:

$$\text{Maximise } E_{\text{annual}} \quad (\text{GWh}) \quad (1)$$

$$\text{Minimise } C_{\text{unit}} = \frac{C_{\text{total}}}{P_{\text{installed}}} \quad (\text{£/MW}) \quad (2)$$

where:

- E_{annual} is the total annual energy output,
- C_{total} is the total estimated project cost (£),
- $P_{\text{installed}}$ is the total installed capacity (MW).

These objectives inherently conflict, with output-maximising strategies potentially increasing operational costs, and cost-minimising strategies risking reduced energy generation efficiency. For instance, strategies optimised for minimum unit cost may achieve lower installed capacity and total output, whereas strategies maximising energy yield may entail higher capital investments and operational complexity. Initially, the objective functions will be treated without explicit normalisation, as both are expressed in different but compatible units. However, if preliminary tuning reveals strong dominance of one objective over the other, appropriate scaling will be applied to ensure balanced optimisation performance. The multi-objective optimisation framework (NSGA-II) will then be employed to identify a Pareto-optimal set of operational strategies representing different trade-offs between these two objectives.

6.4 Validation and Benchmarking Strategy

The validation process will assess both the predictive accuracy of the 0-D model and the quality of the optimisation results. Model validation will involve comparing simulated annual energy outputs against published estimates for the Swansea Bay Tidal Lagoon, with deviations within $\pm 5\%$ considered acceptable. Optimisation results will be evaluated based on the characteristics of the generated Pareto fronts, focusing on convergence, solution diversity, and qualitative shape inspection, with quantitative metrics such as hypervolume or generational distance considered where feasible. Benchmarking against Grid Search and Genetic Algorithm baselines will verify the performance improvements achieved by NSGA-II, while sensitivity analyses using different random seeds will assess the robustness and repeatability of optimisation outcomes.

²Assistance with phrasing, clarification of optimisation concepts, and structuring of this section was provided using ChatGPT, an AI language model [16].

7. Project Plan

The project will be structured into five main phases, each addressing a critical stage of the research and development process. Required sources and datasets will be utilised at appropriate stages, and potential risks will be mitigated through contingency planning.

Phase 1: Literature Review and Problem Refinement (April – May 2025)

- Conduct a focused literature review on the application of NSGA-II in multi-objective optimisation problems, with an emphasis on renewable energy systems and operational optimisation strategies.
- Review existing Swansea Bay Lagoon studies to extract relevant technical specifications, cost estimations, and operational challenges.
- Refine the project scope and finalise the model parameterisation and optimisation strategy based on detailed insights from NSGA-II methodologies and Swansea Bay case studies.
- **Risk:** Limited existing NSGA-II applications specific to tidal lagoon optimisation. **Mitigation:** Broaden the review to include related applications in hydropower and estuarine energy systems if needed.

Phase 2: Model Development and Data Collection (May – June 2025)

- Implement the 0-D model of the Swansea Bay Tidal Lagoon in Java.
- Collect and pre-process tidal cycle data from the UK Tide Gauge Network (BODC, 2025).
- Validate initial model outputs against published energy estimates, targeting deviations within $\pm 5\%$ as acceptable.
- **Risk:** Tidal data gaps or processing errors. **Mitigation:** Use interpolation techniques or fallback to synthetic tidal datasets based on literature.

Phase 3: Optimisation Framework Development (May – June 2025)

- Implement the NSGA-II multi-objective optimisation framework.
- Set up baseline Grid Search and single-objective Genetic Algorithm for benchmarking.
- Conduct preliminary parameter tuning (e.g., population size, mutation rate).
- **Risk:** Implementation complexity or convergence issues. **Mitigation:** Begin with smaller population sizes and gradually scale up after verifying correctness.

Phase 4: Experiments and Analysis (July – August 2025)

- Run full-scale optimisation experiments across operational strategies.
- Benchmark NSGA-II against Grid Search and GA using performance indicators such as energy output, unit cost, and Pareto front spread.
- Conduct sensitivity analyses to assess the robustness of results.
- **Risk:** Excessive computational time for large experiments. **Mitigation:** Prioritise experiments based on expected information gain and parallelise where possible.

Phase 5: Reporting and Dissemination (July – August 2025)

- Draft and revise the final MSc project report, documenting methodologies, validations, and results.
- Prepare visualisations, including Pareto fronts and comparative performance charts.
- Complete a structured project logbook and submit a zipped codebase for reproducibility.
- Record a 10-minute project presentation with an accompanying slide deck.
- **Risk:** Time management challenges during report writing. **Mitigation:** Complete the first draft by mid-August to allow ample time for revision.

8. Evaluation Criteria

The success of the project will be evaluated based on the following criteria:

- **Model Accuracy:** Validation of the 0-D model by comparing predicted annual energy outputs against published Swansea Bay estimates, with deviations within $\pm 5\%$ considered acceptable.
- **Optimisation Performance:** Quality of Pareto fronts generated by NSGA-II, evaluated based on convergence, solution diversity, and qualitative shape analysis. Quantitative metrics such as hypervolume and generational spread will be considered where appropriate.
- **Benchmarking Results:** Demonstrated improvement of NSGA-II compared to baseline methods (Grid Search and Genetic Algorithms) in terms of energy output, unit cost, and Pareto front diversity.
- **Sensitivity and Robustness:** Stability of optimisation results across multiple runs using different random seeds, confirming consistency and minimising stochastic variability.
- **Computational Efficiency:** Completion of full optimisation experiments within practical computational constraints, with targeted run times under 12 hours per full experiment.
- **Reporting and Reproducibility:** Comprehensive reporting of methodologies, validations, results, and critical analysis, alongside submission of a fully reproducible zipped codebase and dataset.

9. Challenges and Limitations

This project acknowledges several inherent challenges and limitations, grouped as follows:

- **Model Limitations:** The 0-Dimensional model assumes uniform water levels across the lagoon and treats turbine efficiencies as constants, which may limit predictive accuracy, particularly for larger or irregularly shaped basins. While this simplification enables computational efficiency, it may not fully capture spatial hydrodynamic variations.
- **Data Limitations:** The project relies on historical tidal data from the UK Tide Gauge Network. Any data gaps or inaccuracies could impact simulation reliability. Where necessary, interpolation techniques or fallback synthetic datasets will be used to mitigate data inconsistencies.
- **Computational Limitations:** Resource constraints may restrict the scale of full optimisation experiments, especially during sensitivity analyses. To manage this, experiments will be prioritised based on expected information gain, and computational loads will be phased by adjusting population sizes and iteration counts.
- **Generalisability:** Findings may be specific to the Swansea Bay case study and may not fully generalise to other tidal range structures without adaptation to site-specific conditions.

Despite these limitations, the project design incorporates mitigation strategies to ensure scientific robustness and to maintain the practical value of the findings within the defined scope.

10. Conclusion

This project seeks to enhance the operational performance and economic feasibility of tidal range structures (TRs) through advanced multi-objective optimisation. A 0-dimensional simulation of the Swansea Bay Tidal Lagoon will be developed and optimised using NSGA-II to balance energy output maximisation and unit cost minimisation. The novel application of NSGA-II to tidal power planning addresses a significant gap in current research, offering a more effective alternative to single-objective approaches. The proposed framework will be validated against conventional methods to ensure solution quality, robustness, and reproducibility. By clarifying the trade-offs between energy yield and cost, the study aims to inform the design of scalable, competitive tidal lagoon projects within the UK's clean energy strategy. Results will be grounded in a simplified 0-D model and the Swansea Bay case study and should be interpreted within this context. Future research may extend the work by integrating 2-D hydrodynamic models or applying the framework to other sites to improve generalisability.

References

- [1] Labour Party. *Make Britain a clean energy superpower*. [Accessed: 2025-02-24]. 2024. URL: <https://labour.org.uk/change/make-britain-a-clean-energy-superpower/>.
- [2] Renewables Advice. *Tidal Energy — How it Works, Advantages and Disadvantages*. [Accessed: 2025-04-03]. 2024. URL: <https://renewablesadvice.com/energy/tidal-energy/>.
- [3] New Civil Engineer. *£1.3bn Swansea Bay Tidal Lagoon officially sunk as developer loses planning appeal*. [Accessed: 2025-03-03]. 2022. URL: <https://www.newcivilengineer.com/latest/1-3bn-swansea-bay-tidal-lagoon-officially-sunk-as-developer-loses-planning-appeal-07-12-2022/>.
- [4] Athanasios Angeloudis. *Tidal Range Technologies*. https://thangel.github.io/tidal/tidal_oer_range_technologies.html. Accessed: 2025-05-01. 2024.
- [5] T. Zhang et al. “Optimal operation of a tidal lagoon as a flexible source of electricity”. In: *IEEE* (2024). Accessed: 2025-02-24. URL: <https://arxiv.org/abs/2209.13416>.
- [6] Alternative Energy Tutorials. *Tidal Barrage - How It Works and Types of Tidal Barrage*. Accessed: 7 April 2025. 2024. URL: <https://www.alternative-energy-tutorials.com/tidal-energy/tidal-barrage.html>.
- [7] Sean Petley and George Aggidis. “Swansea Bay tidal lagoon annual energy estimation”. In: *Ocean Engineering* 111 (2016), pp. 348–357. DOI: 10.1016/j.oceaneng.2015.11.022. URL: <http://dx.doi.org/10.1016/j.oceaneng.2015.11.022>.
- [8] Gwlad. *Tidal Energy*. Accessed: 2025-02-24. 2021. URL: <https://gwlad.org/tidal/>.
- [9] The Guardian. *Government rejects plan for tidal lagoon in Swansea*. Accessed: 2025-04-07. 2018. URL: <https://www.theguardian.com/business/2018/jun/25/government-rejects-plan-for-tidal-lagoon-in-swansea>.
- [10] George A. Aggidis and Dario S. Benzon. “Operational optimisation of tidal range power generation schemes”. In: *Renewable Energy* 44 (2013), pp. 1–10. DOI: 10.1016/j.renene.2012.01.101.
- [11] Jingjing Xue, Reza Ahmadian, and Owen Jones. “Genetic Algorithm in Tidal Range Schemes’ Optimisation”. In: *Energy* 200 (2020), p. 117496. DOI: 10.1016/j.energy.2020.117496.
- [12] J. Guo, R. A. Falconer, and B. Lin. “Prediction-free real-time flexible control of tidal lagoons using deep reinforcement learning”. In: *Computers & Industrial Engineering* 167 (2022), p. 108002. DOI: 10.1016/j.cie.2022.108002.
- [13] Kalyanmoy Deb et al. “A fast and elitist multiobjective genetic algorithm: NSGA-II”. In: *IEEE Transactions on Evolutionary Computation* 6.2 (2002), pp. 182–197. DOI: 10.1109/4235.996017.
- [14] Kalyanmoy Deb and Himanshu Jain. “An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints”. In: *IEEE Transactions on Evolutionary Computation* 18.4 (2014), pp. 577–601. DOI: 10.1109/TEVC.2013.2281535.
- [15] Carlos A Coello Coello. “Evolutionary multi-objective optimization: a historical view of the field”. In: *IEEE Computational Intelligence Magazine* 1.1 (2006), pp. 28–36. DOI: 10.1109/MCI.2006.1597056.
- [16] ChatGPT. *Support with proposal structuring, clarification of methodology sections, and reference formatting*. Accessed: May 1, 2025. May 2025.

-
- [17] Túlio Marcondes Moreira, Pedro OS Vaz-de-Melo, and Gilberto Medeiros-Ribeiro. “Control Optimisation Baselines for Tidal Range Structures—CoBaseTRS”. In: *Software Impacts* 14 (2022), p. 100356. DOI: 10.1016/j.simpa.2022.100356. URL: <https://doi.org/10.1016/j.simpa.2022.100356>.
- [18] British Oceanographic Data Centre. *UK Tide Gauge Network: Processed Sea Level Data*. https://www.bodc.ac.uk/data/hosted_data_systems/sea_level/uk_tide_gauge_network/processed/. Accessed: April 8, 2025. 2025.