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Final Report

Optimization of the UK's future energy mix under diverse policy goals

by

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Abstract

Traditional assessments of renewable energy based on Levelized Cost of Energy (LCOE) fail to capture the critical system-level costs and benefits that determine the true viability of different renewable generators. This thesis develops a multi-zone PyPSA (Python for Power System Analysis) dispatch model for the UK to provide a fairer, system-level assessment of intermittent wind and predictable tidal energy. By forcing the model to find the optimal system design under these varying constraints, it becomes possible to quantify the complex trade-offs between generation choice, storage investment, transmission expansion, and energy curtailment.
The key findings validate and expand on existing literature. First, the research quantifies the cost of grid reliability, revealing it to be the dominant financial barrier to decarbonization at £79.9 billion. Second, the model demonstrates the tangible economic value of predictability; technologies like tidal power, which curtail 55.06% less energy than wind (450.893 MWh/MW vs. 1002.978 MWh/MW for onshore wind), reduce the need for costly storage and grid infrastructure, mitigating reliability costs. Third, the analysis uncovers that the optimal system design is non-linear, with the model executing a strategic reversal in its infrastructure choices (e.g., switching from batteries to pumped hydro) as policy ambition increases. Finally, the model shows that a moderate environmental policy can be more economically optimal than a purely economic approach, delivering a £19.7 billion cost saving. Ultimately, this research provides a transparent framework that makes the hidden costs of Variable Renewable Energy (VRE) integration and the economic benefits of predictable generation explicit. It delivers a more sophisticated and data-driven foundation for evaluating renewable energy pathways, informing future energy planning and investment, offering valuable insights for policymakers designing energy policy, and grid operators managing system stability.

1. Introduction

The United Kingdom's Climate Change Act commits the nation to achieving net-zero emissions by 2050 [3], a goal that necessitates a profound transformation of its electricity grid. Central to this transition is the large-scale integration of renewable energy sources. Wind power, with its relatively low cost and widespread deployment, has become a major player in this effort. However, its inherent intermittency introduces significant system-level challenges, including energy curtailment, strain on storage resources [9], and the need for expensive transmission link upgrades [20]. The financial impact of this curtailment is evidenced by the new monthly record set in February 2020, when £40.5 million was paid out by National Grid to wind producers to curtail electricity generation by Scottish wind farms [9]

This challenge highlights the potential of complementary technologies like tidal stream energy. While its upfront costs are currently high [31], tidal power's key advantage is its predictability; its output follows a deterministic pattern based on lunar cycles, making it far easier to forecast than weather-dependent renewables [20]. This predictability offers immense value to the grid by lowering the requirement for new transmission infrastructure [20], reducing the need for backup generation [31], and easing the burden on storage [20] . The core problem, and the central focus of this thesis, is that traditional evaluation metrics like the Levelized Cost of Energy (LCOE) are insufficient for fairly comparing these two fundamentally different technologies, as LCOE ignores the system-level costs and benefits that are critical in a renewable-heavy grid [6].

To address this research gap, this project develops a multi-zone power system dispatch model of the UK using the open-source PyPSA framework and the EVOLVE dataset [10]. The model is designed to move beyond simple cost optimization by simulating a range of scenarios where different policy objectives—such as greenhouse gas reduction, land use restrictions, and system reliability—are prioritized.

The following sections outline the construction of the model, the data and assumptions underpinning it. The results then examine the dominance of reliability costs, the economic value of predictability, the reversal in optimal strategies under different policy ambitions, and the benefits of moderate environmental policy. These findings are discussed in relation to existing literature. The thesis concludes with implications for future energy planning in the UK and an evaluation of the model's limitations.

1.1 Literature Review

Moving to a decarbonized electricity grid is a complex challenge that goes beyond just techno-economic factors. While the integration of renewable energy is paramount for climate goals, it introduces significant trade-offs across technical, economic, environmental, and social domains that must be holistically addressed to ensure a just and sustainable outcome [8]. In particular, marine renewable energies like tidal and wave power, while promising, come with considerable environmental and ecological uncertainties due to the limited deployment of commercial-scale projects to date [1, 5]. Potential stressors include habitat alteration, changes to coastal sediment transport, acoustic noise, and the effect of electromagnetic fields on marine life [1, 5]. This highlights an urgent need for planning frameworks that can balance the goal of clean energy against a complex set of potential environmental impacts.

Beyond the environmental concerns, the integration of VRE sources like wind and solar fundamentally alters the technical and economic dynamics of the grid [7]. Foundational economic metrics like the Levelized Cost of Energy (LCOE)—the life-cycle cost of a plant per unit of electricity generated—are now widely considered inadequate and misleading for system planning [6, 12]. The primary flaw of LCOE is that it ignores the temporal value of electricity; it treats a kilowatt-hour generated during a high-demand winter evening as equal to one generated during a low-demand summer afternoon. This is especially problematic for VREs, whose value is intrinsically tied to when they generate power [12]. A more holistic evaluation requires distinguishing between a technology's energy value (the total energy supplied over a year) and its capacity value (its ability to reliably produce power when the system needs it most, particularly during peak demand) [13].

Because VREs have a low capacity value, their integration creates significant integration costs, which are the additional costs imposed on the rest of the system to manage their variability and uncertainty [7, 12]. These costs are not captured by LCOE and can be broken down into three main components: balancing costs to manage short-term forecast errors, grid costs for transmission reinforcement, and profile costs, which are the largest component and arise from the temporal mismatch between VRE supply and load demand [12]. Research shows these integration costs are significant, increase with higher VRE penetration, and can become an "economic barrier" to deployment [12]. Furthermore, the costs passed on to consumers can be much higher than those borne by the system operator [7]. At the project level, this manifests as direct financial risks for developers, who face imbalance penalties and revenue loss from curtailment, making VRE projects often unprofitable without subsidies, even when paired with battery storage [9].

To navigate this complex problem, the state-of-the-art has moved towards using regional economic dispatch models that calculate the Total System Cost (TSC) or System LCOE, thereby capturing the full cost of operating a reliable grid [6, 12]. These models have been instrumental in demonstrating the value of diversifying the renewable portfolio. For example, the EVOLVE project found that including predictable and complementary sources like tidal stream energy could significantly lower total system costs by reducing the need for installed capacity and energy storage, even though the technology itself is more expensive [11]. However, significant gaps remain in these modeling efforts. Simplified dispatch models often omit critical operational constraints like unit commitment and system inertia, which can lead to an overestimation of VRE's potential contribution [10]. This highlights a critical need for frameworks that can better incorporate system-level security requirements to avoid producing overly optimistic and unrealistic scenarios.

This thesis bridges that gap by developing and demonstrating a prescriptive, multi-criteria optimization framework that integrates these complex, system-level challenges directly into the planning process. While many existing models are diagnostic—calculating the costs of a pre-defined scenario [7]—this work is prescriptive, actively designing an optimal energy mix based on a holistic set of weighted priorities. The novel use of a penalty system allows for the operationalization of the System LCOE concept; penalties for reliability and grid upgrades act as direct proxies for the profile costs and grid costs that the literature identifies as critical but difficult to model [6, 12]. Similarly, penalties for biodiversity, land use, and noise provide a mechanism to translate the environmental and social priorities valued by the public into quantitative inputs for the optimizer [2, 8]. By including a predictable renewable like tidal stream energy, the model is equipped to identify the system-wide benefits of a diverse technological portfolio, finding pathways that minimize total system cost and enhance reliability [11]. Ultimately, this framework provides a powerful and transparent policy tool for exploring the trade-offs between economic efficiency, reliability, and broader environmental and social goals, enabling the design of a truly balanced and sustainable energy system.

2. Methodology

This section outlines the power system model created to analyze the trade-offs of renewable energy pathways in the UK. It describes the overall framework, data sources, and key modifications from the EVOLVE project, before detailing the objective function and penalty system that underpin the model design.

2.1 Model Framework

The foundation of this analysis is a multi-zone, capacity expansion, and optimal dispatch model built using the PyPSA framework. Its primary objective is to determine the least-cost combination of generation, storage, and transmission assets required to meet electricity demand under various policy-driven constraints.

The core data and a nine-zone grid topology are adapted from the EVOLVE project [10]. This open-source study provides a 2030 baseline dataset, including zonal demand profiles and time-varying availability factors for renewable generators, which serve as the foundation for the model.

2.2 Model Description

The PyPSA network has several key components:

- Network Topology: The GB grid is represented as a nine-bus system, with each bus corresponding to a distinct geographical zone (z1 to z9). These zones are interconnected by expandable AC transmission links, allowing the model to optimize power flow and determine the required grid infrastructure.
- Time-Series Data: The model operates on a time series of 365 representative snapshots, derived by subsampling the full 8760-hour 2030 baseline data from the EVOLVE project [10]. This approach provides a computationally tractable but statistically representative dataset for a full year of operation. Each snapshot includes zonal demand profiles, time-varying availability factors for all renewable generators and the minimum and maximum availability of Demand-Side Response (DSR).
- Components: The model includes the following physical assets:
    - Loads: The total GB electricity demand is distributed across the nine zones according to fixed fractions from the EVOLVE study [10].
    - Generators:
        - Renewable (Extendable): Onshore wind, offshore wind, and tidal stream generators are included. The model can invest in new capacity for these technologies.
        - Load Shedding (Fixed): A non-extendable "load shed" generator is included at each bus with an unusually high marginal cost. This acts as a last resort to prevent infeasible solutions by representing the cost of unserved energy.
    - Storage Units:
        - Extendable: The model can invest in both lithium-ion batteries (with a two-hour duration) and various pumped hydro storage (PHS) facilities.
        - Fixed: A fixed-capacity DSR unit is included, representing a pre-existing flexibility resource.

2.3 Key Modifications from the EVOLVE Project

To focus the analysis on the trade-offs between different renewables, several key modifications were made to the original EVOLVE setup. All core generation, storage, and transmission assets were configured to be extendable, allowing the model to optimize all new capacity investments from a zero-capacity baseline. An exception to this was made for fixed-capacity DSR and load shedding, which were retained as non-extendable assets. This was done to ensure the model's primary objective was to assess the integration of new-build wind and tidal generation rather than to unrealistically scale up existing flexibility services. To reinforce this objective, the marginal cost for load shedding was set to a very high value (£10,000,000/MWh), which ensures the model always prioritizes building sufficient capacity over failing to meet demand.

2.4 The Objective Function and Penalty System

The central innovation of this research is a modified objective function that integrates non-economic policy priorities directly into the power system optimization process. Instead of minimizing the true economic cost, the model is configured to minimize a penalized total system

cost. This allows complex priorities like grid reliability and land use to be quantified and factored into the optimal system design and dispatch.
The objective function, Z, is the sum of the total penalized capital and operational costs across all assets (c) in the network over a given time horizon (t). The penalties are dynamically calculated for each technology based on a set of policy weights unique to each scenario.
The function is expressed as:

$$\text{Minimize} \quad Z = \sum_{c \in C} (\mathrm{CC}_{\text{effective},c} \cdot P_{\text{nom},c}) + \sum_{t \in T} \sum_{c \in C} (w_t \cdot \mathrm{MC}_{\text{effective},c} \cdot p_{c,t})$$

Where:

- Z: The total penalized system cost being minimized.
- C: The set of all components (generators, storage, links) in the network.
- T: The set of all time steps (snapshots) in the optimization.
- CCeffective,c: The effective total capital cost of component c passed to the optimizer.
- Pnom,c: The nominal capacity of component c, a decision variable for investment.
- wt: The weighting of each time step, representing its duration in hours.
- MCeffective,c: The effective marginal cost of component c.
- pc,t: The dispatch of component c at time t, a key operational decision variable.

2.4.1 Penalty System

The effective costs used in the objective function are derived from base economic costs and adjusted by a penalty system that reflects the specific policy priorities of a scenario.

2.4.1.1 Effective Capital Cost

The effective capital cost is calculated using a multiplicative penalty factor. This approach ensures that the penalty is proportional to a technology's capital intensity. The formula is:

$$\mathrm{CC}_{\text{effective}} = \mathrm{CC}_{\text{base}} \times \left(1 + \sum_{p \in P} (\text{Penalty}_{\text{const},p} \times \text{Weight}_p)\right)$$

Where:

- CCeffective: The penalized capital cost used by the optimizer (£/MW).
- CCbase: The unpenalized, base capital cost (£/MW).
- P: The set of all policy considerations (e.g., reliability).
- Penaltyconst,p: The construction penalty score for a technology under policy p (scaled 0-1).
- Weightp: The weight assigned to policy p in the scenario.

2.4.1.2 Effective Marginal Cost

The effective marginal cost is calculated using an additive penalty. This method is essential because many renewable technologies have a base marginal cost of zero. The formula is:

$$\mathrm{MC}_{\text{effective}} = \mathrm{MC}_{\text{base}} + \sum_{p \in P} (\text{Penalty}_{\text{op},p} \times \text{Weight}_p)$$

Where:

- MCeffective: The penalized marginal cost used by the optimizer (£/MWh).
- MCbase: The unpenalized, base marginal cost (£/MWh).
- P: The set of all policy considerations.

- $Penalty_{op,p}$: The operational penalty score for a technology under policy p (scaled 1-10).
- $Weight_p$: The weight assigned to policy p in the scenario.

2.4.2 Calculating the True Economic Cost

After the optimization process, which minimizes the penalized cost, the true economic cost of the resulting energy system is determined. This is done by stripping away the policy penalties and evaluating the optimized system using only the unpenalized base costs.
This true cost is the sum of two components:

1. True Operational Cost: This is calculated by taking the optimized hourly dispatch for every asset and multiplying it by its base marginal cost from EVOLVE study [10].
2. True Capital Cost: This is found by taking the optimized capacity for each new generator, storage unit, and link and multiplying it by its annualized base capital cost.

To ensure a fair comparison between the one-time capital investments and the ongoing operational costs, the total capital cost is converted into an equivalent annual figure. This is achieved using the Capital Recovery Factor (CRF) formula.

$$\mathrm{CC}_{\text{annualized}} = \mathrm{CC}_{\text{lifetime}} \times \frac{r(1+r)^L}{(1+r)^L - 1}$$

Where:

- $CC_{annualized}$: The equivalent annual cost (£/year) used in the economic analysis.
- $CC_{lifetime}$: The total upfront base investment cost (£).
- r: The discount rate (e.g., 0.05 for 5%).
- L: The economic lifetime of the asset in years. For this analysis, a lifetime of 25 years is assumed for new assets, in line with common practice for energy infrastructure projects in the UK [14].

2.5 Data and Assumptions

The validity of the model's outputs is contingent upon the quality and justification of its input data. This section details the sources for the base costs and the rationale behind the penalty scores

2.5.1 Base Marginal Costs

The base marginal costs (£/MWh) for all technologies are sourced from the EVOLVE model setup [10].

2.5.2 Base Capital Costs

The base capital costs were derived from several sources using specific project size assumptions. Onshore wind costs were calculated based on a 50 MW project, converting a total cost of £60 million [14] to £1,200,000/MW. Similarly, offshore wind was modeled on a 1,000 MW project, converting a £1,810 million total cost [14] to £1,810,000/MW. For tidal energy, a 15 MW project size was assumed, converting a £74 million total cost [14] to approximately £4,933,333.33/MW. Battery storage costs, assuming a 2-hour duration, bundled power and energy costs (~$250/kWh and ~$300/kW) [16], which were then converted from 2022 USD

(£0.81/$1) to approximately £648,000/MW. The 2020 cost for hydroelectric pumped hydro of $2,623/kW [15] was assumed to be stable to 2030 and was converted from 2020 USD (£0.78/$1), resulting in £2,045,940/MW. Lastly, the capital cost for AC transmission was based on an average link length of 100 km, converting the £1,190/MWk lifetime cost [17] to £119,000/MW.

2.5.3 Penalty Scores

Scale	Construction Penalties Range 0-1					Operational Penalties Range 1-10	
Technology	GHG	Land Use	Reliability	Biodiversity & Noise	Grid Upgrades	Land Use	Biodiversity & Noise
Onshore Wind	0.15	0.90	0.85	0.18	0.60	6	5
Offshore Wind	0.20	0.25	0.65	0.20	0.70	2	6
Tidal Stream	0.40	0.10	0.10	0.45	0.20	2	8
Battery	0.30	0.15	0.05	0.05	0.10	2	2
Pumped Hydro	0.25	0.95	0.05	0.30	0.30	7	6

Table 1: Penalty scores for model components by policy criteria

This section outlines the rationale for penalty scores assigned during model optimization. These scores quantify the environmental, social, and operational effects not captured in direct financial costs. Within this framework, penalty scores have been assigned to each technology using the foundational data from the cited sources.

2.5.3.1 Construction Phase Penalties

These penalties are applied as a one-time capital cost adjustment to reflect impacts associated with manufacturing, transportation, and construction. The scores are normalized on a scale from 0 to 1.

For Reliability, batteries and pumped hydro storage (PHS) receive the lowest penalty as they are fully dispatchable, providing grid stability and rapid response services [27, 18]. Tidal energy also receives a low penalty, as its output is predictable [20]. In contrast, offshore wind is assigned a significant penalty due to the inherent variability of wind resources, while onshore wind receives the highest penalty, justified by historical data showing that real-world capacity factors have often fallen significantly below planning estimates [19].

In terms of Grid Upgrades, batteries have a low penalty because facilities can often be sited near existing demand centers, minimizing the need for extensive new transmission infrastructure [26]. Tidal benefits from high predictability, which can lower integration costs for other variable renewables in the system [20]. While providing valuable balancing services, PHS facilities are often in remote locations [22], requiring substantial transmission capacity. The intermittency of onshore wind imposes significant "system costs" for grid reinforcement and backup capacity [31], but offshore wind receives the highest penalty due to the combined expense of managing intermittency and the high capital cost of subsea transmission infrastructure [31].

For Lifecycle GHG Emissions, the ranking of wind technologies is consistent with harmonized Life Cycle Assessment (LCA) data for gCO_2e/kWh, with onshore wind and offshore wind having among the lowest carbon footprints of electricity generation technologies considered [23].

PHS reflects emissions from the large quantities of concrete and steel required for dam and reservoir construction [28]. The higher penalty for batteries is due to carbon-intensive mining and manufacturing processes [24], and tidal receives the highest penalty in this category due to its extreme material intensity, requiring massive steel and concrete structures [25] to withstand harsh marine environments.

Regarding Biodiversity & Noise, the penalty reflects the severity of ecological impacts during construction. Batteries have a minimal direct impact, though upstream mining activities are destructive [24]. Onshore wind is penalized for risks to avifauna and noise disruption to terrestrial wildlife [30]. Offshore wind construction noise, particularly from pile driving, is known to harm marine mammals [5]. PHS is penalized for the large-scale, irreversible habitat destruction caused by flooding land for reservoirs [28]. Tidal receives the highest penalty due to concentrated construction risks, like blade strikes and noise, in ecologically sensitive coastal areas [1, 5].

Finally, Land Use penalties are based on the direct and indirect land area consumed. Tidal and offshore wind have a minimal onshore land footprint [25, 21]. Battery storage is typically compact [4]. Onshore wind receives a very high penalty because the total required spacing area between turbines is extensive [29]. PHS is assigned the highest penalty as it requires the permanent flooding of vast land areas for its reservoirs [28].

2.5.3.2 Operational Phase Penalties

These penalties reflect ongoing impacts of running these technologies and are added to the marginal cost of operation (£/MWh). The scores are rated on a scale of 0-10. Direct GHG emissions are not penalized as they are negligible for these technologies during operation.

For Biodiversity & Noise, batteries receive a low penalty for the constant but localized hum from cooling systems and inverters. Onshore wind has a mid-range penalty reflecting the continuous noise and visual impact on local communities and birds [30]. Offshore wind is assigned a significant penalty due to operational noise affecting sensitive marine mammals and ecosystems [1], a similar penalty to PHS for the major and permanent disruption to river ecosystems and fish migration from daily operations [28]. Tidal receives a very high penalty, reflecting the major disruption that operating turbines cause in ecologically concentrated tidal zones [5].

In terms of Land Use, offshore wind, tidal, and batteries receive a very low penalty as the land footprint is minimal [21, 4, 25], often limited to a small onshore substation. Onshore wind has a moderately high penalty due to the large land area turbines occupy, even with the possibility of multi-use (e.g., agriculture) [29]. PHS receives a high penalty reflecting the permanent loss of vast land areas from flooding for two large reservoirs [28].

2.6 Model Design and Verification

To verify the core functionality of the adapted PyPSA model, the key notebooks from the original EVOLVE study [10], GB 2030 LTW v7.ipynb and GB 2030 LTW v7 0GW marine.ipynb, were re-run and the results were successfully replicated. This step confirmed that the model's fundamental setup was correctly implemented before moving on to the customized penalty system. The model's final configuration is the result of an iterative development process. Initial experiments included gas generators to represent a realistic backup source, but this consistently prevented new renewable capacity from being built. Similarly, efforts to force a minimum build of renewables were found to distort results. To force the model to explore renewable pathways, these choices were abandoned in favor of a highly penalized load-shedding mechanism. The penalty weighting system was also revised after initial tests showed that if all penalties summed to 1, it rendered the penalties redundant when the weights were equal. The final approach, which assigns a specific weight to a primary policy priority while distributing the remainder, ensures that policy considerations meaningfully influence the model's investment decisions across all scenarios. Finally, while the core objective function solves a linear problem, alternative quadratic and exponential penalty functions were explored. These nonlinear functions significantly increased computational time without altering the fundamental trade-offs or key insights, as they only affected the overall scale of the total system cost rather than the relative proportions of each technology. These choices were critical to ensuring the model balanced computational tractability with a realistic representation of the UK power system and produced meaningful insights.

3. Results

This analysis provides empirical evidence on four key findings related to the economic dynamics of a decarbonized energy grid.

3.1 Dominance of Reliability Costs

Ensuring grid reliability is the single greatest economic factor in a decarbonized grid. The model shows that the cost of guaranteeing stability in a fully renewable grid incurs significantly higher costs than other environmental policies. For example, the Sweep_reliability_w100 scenario, which focuses on reliability, incurs a total annualized system cost increase of £46 billion above the economic baseline of £33.92 billion (Figure 1). This rise is driven by a portfolio that requires substantial infrastructure additions relative to the economic baseline. These include a need for 153.7 GW of additional storage, 92.6 GW of grid upgrades, and 94 GW of tidal capacity. This also results in a strategic shift in the generation mix, with a reduction of 98.9 GW in onshore wind and 70.5 GW in offshore wind compared to the baseline.

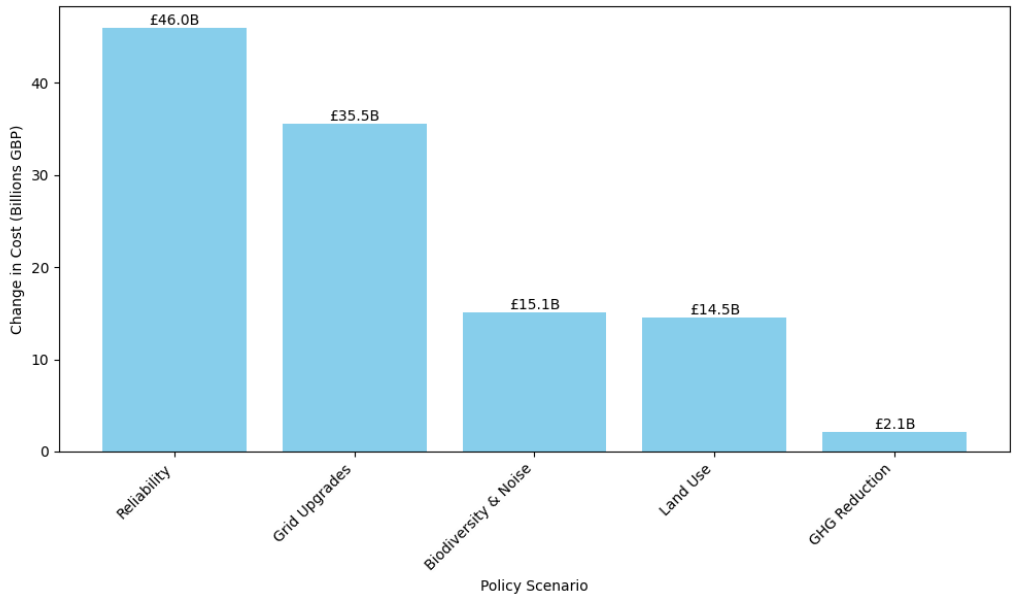

Figure 1: Change in cost for extreme scenarios (weight 100) relative to economic baseline (Source: df_part1_analysis)

3.2 Value of Predictable Generation

Predictable power sources, like tidal energy, reduce the need for costly support infrastructure. As shown in Table 2, the Sweep_land_use_w100 scenario demonstrates the complementary value of tidal energy. In this scenario, the model strategically selects 23.59 GW of tidal power, which allows the system to accommodate a 31.85% increase in offshore wind capacity. This portfolio simultaneously reduces required storage capacity by 36.24%, lowers total curtailment by 30.85%, and decreases system cost by 10.20%.

Scenario	Economic System Cost (Billions £)	Installed Offshore Wind (GW)	Installed Onshore Wind (GW)	Installed Tidal (GW)	Installed Battery (GW)	Total Curtailment (TWh)
Sweep_ghg_w0	53.9	109.4	4.5	19.4	684.1	6,637.3
Sweep_land use_w100	48.4	144.3	0	23.6	436.2	4,589.5

Table 2: Comparative outcomes for land use and GHG scenarios (Source: allsweepsresults.csv)

This reduction in curtailment is a direct result of tidal’predictability, which is further quantified in Figure 2. The plot shows that, on average across extreme policy scenarios, tidal power curtails 55.06% less energy per unit of capacity than onshore wind (450.893 MWh/MW vs. 1002.978 MWh/MW). This operational efficiency confirms that a technology's value is not just in its LCOE, but in its ability to reduce system-wide inefficiencies.

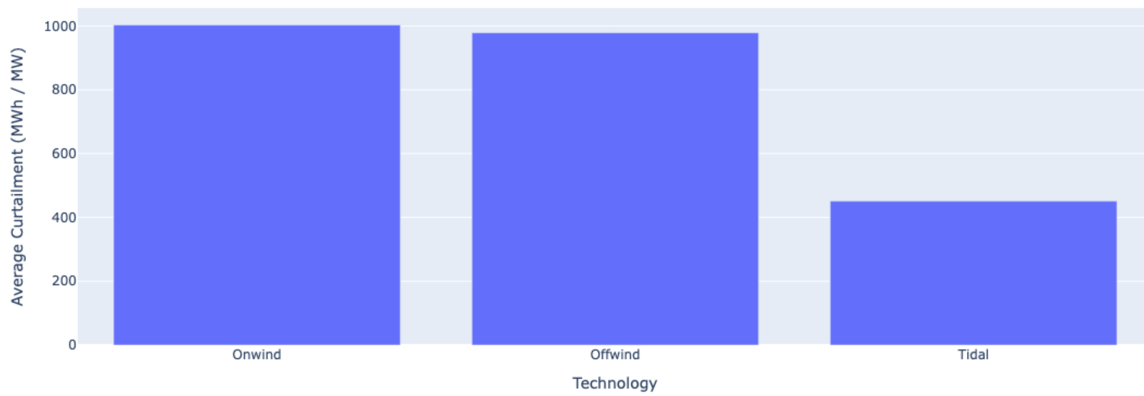

Figure 2: Average normalized curtailment per unit of capacity (MWh/MW) (Source: allsweepsresults.csv)

3.3 Optimal Strategy Reversal

The model's shift from battery storage to pumped hydro storage as the primary storage solution under increasing GHG penalties (Figure 3) can be directly explained by the penalty system. As detailed in the methodology, batteries receive a higher capital cost penalty for lifecycle GHG emissions due to carbon-intensive mining and manufacturing processes, while pumped hydro storage's GHG penalty is slightly lower despite the use of concrete and steel. This makes pumped hydro a more economically attractive option for the optimizer when GHG constraint is introduced. This demonstrates a non-linear tipping point where the introduction of a new policy constraint fundamentally changes the system's preferred infrastructure.

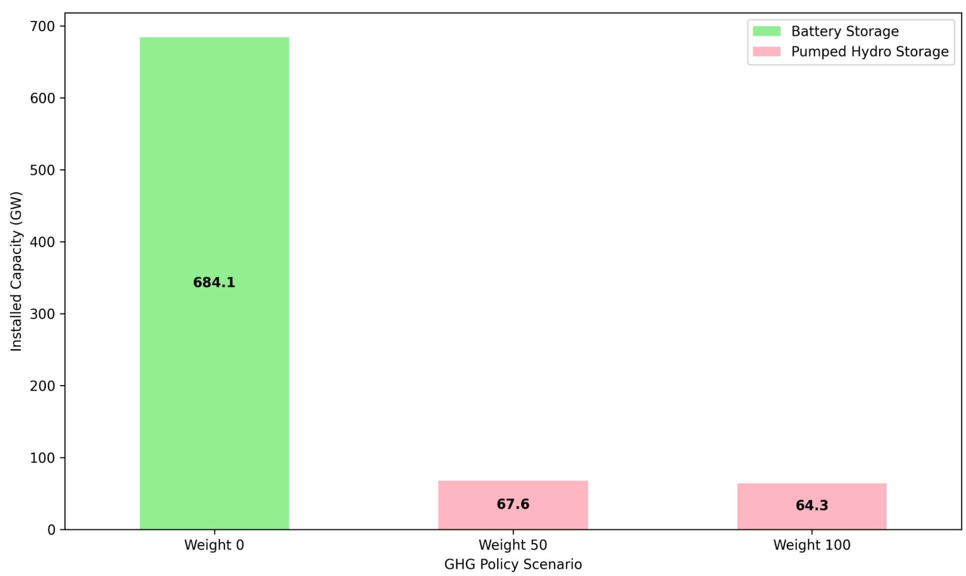

Figure 3: Shift in battery vs. pumped hydro storage with increasing GHG weighting (Source: allsweepsresults.csv)

3.4 Economic Benefits of Moderate Environmental Policy

Implementing a moderate environmental or reliability policy can lead to a more economically optimal outcome than a purely economic one. The transition from a 0 GHG weighting to a 50 weighting results in a total system cost reduction of £19.70 billion. Similarly, even within a reliability-focused strategy, the system cost decreases by £2.76 billion when moving from a 0 to a 50 reliability weighting. This suggests that incorporating a moderate focus on non-economic factors can lead to more efficient and resilient system designs.

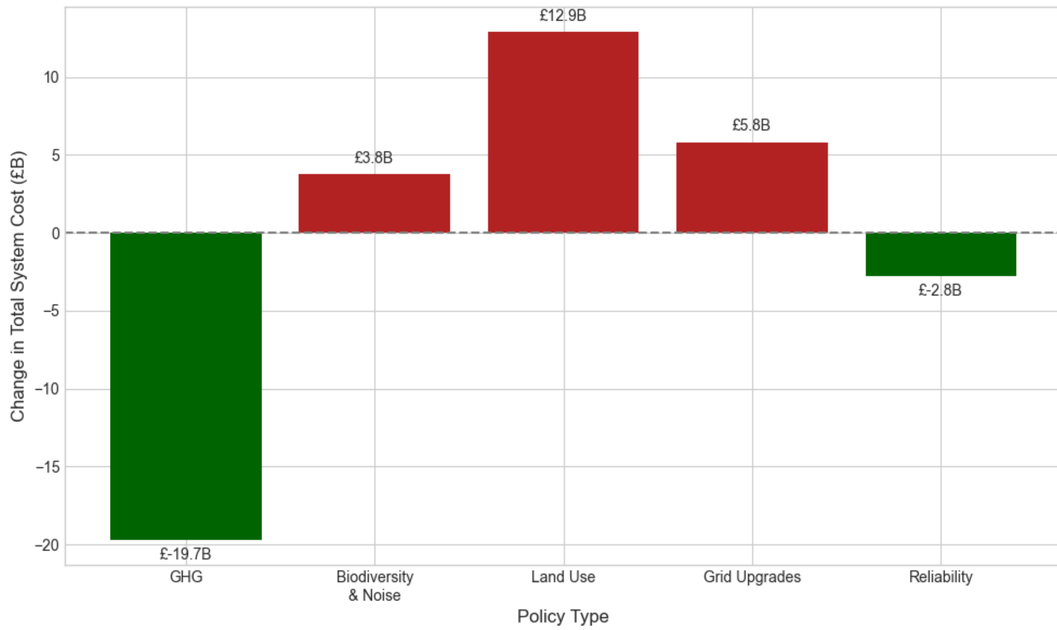

Figure 4: Impact of moderate policy implementation (0% to 50% Weighting) on total system cost (Source: analysis_part3_results)

4. Discussion

While this research focuses on the UK power system, the core findings and principles are broadly applicable to other regions with high VRE penetration and similar decarbonization goals. This research moves beyond identifying "integration costs" as a theoretical barrier to quantifying them as the primary economic driver of system design. By showing that reliability costs are significantly greater than other policy-driven costs, the findings challenge the adequacy of traditional metrics like LCOE [6, 12], which fail to account for these system-wide dynamics. The results confirm the need to account for integration costs at the system level for effective planning [7]. The analysis also provides an empirical basis for the value of portfolio diversification. Choosing a predictable energy source like tidal power, even though it costs more to produce each unit of energy (its higher LCOE), shows that a technology's true value is more than just its price tag. Its real worth comes from its ability to lower the total costs of the entire energy system [11]. This highlights how a technology's capacity value —its ability to reliably generate power when the grid needs it most [13]—can be a powerful tool for cutting costs across the system. The observation that reliability costs are the dominant economic driver in a decarbonized grid and that predictable energy sources provide tangible system-wide value are fundamental dynamics that extend beyond geographical boundaries.

Furthermore, the model's finding that the optimal technology mix can reverse under increasing policy ambition has critical implications for policymakers. It demonstrates that a linear, "more of the same" approach is not a viable long-term strategy. Instead, a staged policy implementation must recognize that the fundamental logic of system design can shift dramatically at a tipping point, a dynamic not captured by simpler diagnostic models [7, 10].

Finally, the surprising finding that a moderate environmental policy can reduce total system costs challenges the conventional assumption that environmental constraints invariably add costs. This suggests that a purely economic optimization can become trapped in a "local optimum"—for instance, by overbuilding the cheapest generation without the necessary complementary infrastructure. By forcing portfolio diversification, a moderate environmental constraint can push the system toward a more balanced and economically efficient mix. This provides a powerful, data-driven argument that proactive environmental planning, which translates public priorities into quantitative inputs [8], should not be viewed solely as a cost center but as a catalyst for greater economic and system efficiency. This is a potent lesson for energy planners globally. The framework's ability to quantify these complex trade-offs provides a powerful tool for energy planners worldwide who are tasked with designing robust and cost-effective energy systems in the face of climate goals and increasing VRE integration.

5. Conclusion

The results, which highlight the importance of system-level costs, confirm the need for holistic planning that accounts for integration costs, a gap identified in the literature [7]. The key findings demonstrate that reliability costs are the dominant economic driver in a decarbonized grid, making them the central challenge of VRE integration [7, 12]. Furthermore, the predictability of a generator is a quantifiable and valuable tool for mitigating high integration costs, thereby confirming the economic benefit of portfolio diversification [11, 20]. The optimal pathway to decarbonization is not linear; strategic choices can reverse as policy ambition increases. A moderate environmental policy can also lead to a more economically efficient system by promoting a balanced technology mix and helping the system avoid suboptimal configurations. Ultimately, these findings provide a data-driven argument for moving beyond simplistic metrics like LCOE and adopting a Total System Cost approach that accounts for the complex, interconnected dynamics that must be considered for effective policy making.

6. Model Limitations

A key limitation of this research is that due to lower per-MW capital costs of transmission links, the model often prioritizes extensive grid transmission capacity over energy storage (e.g., 334 GW Installed AC over 0.71 GW battery + 224.49 GW hydroelectric in Sweep_reliability_w100). While this represents a valid cost-optimal solution within the model's framework, such large-scale grid expansion may be impractical due to physical, regulatory, or environmental constraints not modeled. Consequently, reported system costs are likely conservative, lower-bound estimates. Future research should incorporate granular transmission constraints, such as land use or regulatory limits, to yield more realistic cost projections

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