Optimal Planning of Data Centers with On-Site Generation and Storage

A Case Study in Dublin, Ireland

Master's thesis in Design and Construction Project Management

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Abstract

Data center energy demand is soaring globally. In Ireland, data centers accounted for 21 percent of national electricity demand in 2023 and are expected to represent 31 percent by 2030, with virtually all incremental load in Dublin. These pressures have driven the Commission for Regulation of Utilities (CRU) to require on-site dispatchable generation (and/or storage) for all pending data center approvals and led EirGrid, the Transmission System Operator (TSO) in Ireland, to suspend new data center applications until 2028. To address these challenges, this thesis develops a mixed-integer linear programming model from first principles to size and operate an on-site energy portfolio consisting of photovoltaic panels, onshore wind turbines, small modular reactors, and battery energy storage for a 5 MW data center in Dublin, Ireland. The model minimizes annualized life-cycle cost by co-optimizing capacity investments and hourly dispatch under realistic time-of-use tariffs, wholesale spot prices, load profile, operational constraints, and regulatory requirements. Under 2025 cost assumptions, the cost-optimal mix comprises PV and wind with grid imports. Battery energy storage enters the least-cost portfolio by 2028 on pure energy arbitrage. Including additional revenue streams, such as demand response, would enable BESS deployment as early as 2025. Sensitivity analyses reveal that system scale, resource cost trajectories, spot price volatility, and demand response participation can substantially reshape investment decisions: SMRs become competitive in the 50 MW scenario; wider intraday price spreads alone justify significant storage capacity; and dynamic demand response revenues can more than double BESS earnings compared to arbitrage. These results demonstrate the model's utility as a decision-support tool for data center developers, investors, and planners navigating complex economic, technological, and regulatory uncertainties.

Keywords: Data centers, energy optimization, mixed-integer linear programming, on-site generation and storage, investment, planning, decision-support tool

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Lukas Ljungblom, Gothenburg, June 2025

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AF	Annualization Factor
ALCC	Annualized Life-Cycle Cost
BESS	Battery Energy Storage System
CapEx	Capital Expenditure
CF	Capacity Factor
CRF	Capital Recovery Factor
CO_2	Carbon Dioxide
DR	Demand Response
ENTSO-E	European Network of Transmission System Operators
FCR	Frequency Containment Reserve
LCOE	Levelized Cost of Electricity
MILP	Mixed-Integer Linear Programming
NOCT	Nominal Operating Cell Temperature
NREL	National Renewable Energy Laboratory
O&M	Operations and Maintenance
PV	Photovoltaics
PVGIS	Photovoltaic Geographical Information System
SEM	Single Electricity Market
SMR	Small Modular Reactor
ToU	Time-of-Use (tariff)
TSO	Transmission System Operator
WACC	Weighted Average Cost of Capital

Nomenclature

Sets & Indices

$\mathcal{T}$	Set of all hours in the planning horizon.
$\mathcal{T}_{\text{day}}$, $\mathcal{T}_{\text{peak}}$, $\mathcal{T}_{\text{night}}$	Subsets of $\mathcal{T}$ defining ToU tariff periods.
ℓ	Technology index $\in \{\text{PV}, \text{W}, \text{SMR}, \text{BESS}\}$.
τ	BESS duration index $\in \{1, 2, 4\}$ hours.

Parameters & Functions

D_t	Demand at hour t [kW]
G_t	Global horizontal irradiance at t [W/m^2]
$T_{2m,t}$	Ambient temperature at t [°C]
T_{NOCT}	Nominal operating cell temperature [°C]
PR	PV performance ratio [–]
γ	PV temperature coefficient [1/°C]
$v_{10,t}$	Wind speed at 10 m at t [m/s]
H_{hub}	Turbine hub height [m]
α	Wind-shear exponent [–]
$f_{\text{curve}}(v)$	Turbine power-curve function (piecewise cubic) [–]
π_t	Wholesale spot price at t [€/kWh]
λ_t	ToU network tariff at t [€/kWh]
ι, ρ	Export incentive and tax rebate [€/kWh]
F_{sub}	Annual grid subscription fee [€]
r	Discount rate (WACC) [–].
LT_ℓ	Lifetime of technology ℓ [years]
$\text{AF}(r, \text{LT})$	Capital Recovery Factor [–]
c_ℓ^{cap}	Unit capital cost of ℓ [€/kW or €/kWh]
c_ℓ^{opex}	Fixed O&M cost of ℓ [€/kW-yr or €/kWh-yr]
f_{fuel}	SMR fuel cost [€/kWh]
η	BESS round-trip efficiency [–]
C^{grid}	Grid connection capacity [kW]

Intermediate Calculated Inputs

OCC_ℓ	Overnight capital cost of ℓ [€], $c_\ell^{\mathrm{cap}}\, x_\ell$
$P_t^{\max}$	PV capacity factor at t [–]
$W_t^{\max}$	Wind capacity factor at t [–]

Decision Variables

$x_{\mathrm{PV}}, x_{\mathrm{W}}, x_{\mathrm{SMR}}$	Installed capacities of PV, wind, SMR [kW]
$P_{\mathrm{BESS}}, E_{\mathrm{BESS}}$	BESS power rating [kW] and energy capacity [kWh]
$g_t^{\mathrm{PV}}, g_t^{\mathrm{W}}, g_t^{\mathrm{SMR}}$	Generation dispatch at t [kW]
c_t, d_t	BESS charge and discharge power at t [kW]
s_t	BESS state-of-charge at t [kWh]
i_t, e_t	Grid import and export at t [kW]
$u_t^{\mathrm{bess}}, u_t^{\mathrm{grid}}$	Binary mode flags for BESS (charge vs discharge) and grid (import vs export)
y_τ	Binary selection for BESS duration $\tau \in \{1, 2, 4\}$ h
y_{SMR}	Binary build commitment for SMR

Model Outputs

Z	Annualized life-cycle cost objective [€/year]
Z^*	Optimal annualized life-cycle cost [€/year]
LCOE	Levelized cost of electricity [€/kWh], $Z^*/\sum_{t\in\mathcal{T}} D_t$

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1
Introduction

The urgency of the Paris Agreement's 1.5 °C goal is underscored by the latest IPCC AR6 Synthesis Report (2023), which confirms that global CO2 emissions must fall by roughly 50% by 2030 and reach net zero around mid-century to avoid breaching this threshold (Romero, Lee, and Otto, 2023). Meeting these targets calls for deep decarbonization across all sectors and rapid deployment of clean energy technologies.

Unabated fossil fuels still generate over 60% of today's electricity, yet under the IEA's Net Zero Emissions by 2050 Scenario that share must fall below 30% by 2030. At the same time, rapid electrification of transport, buildings, and industry pushes electricity's share of final energy consumption from about 20% today to over 50% by mid-century. Meeting these targets will demand a significant acceleration in the deployment of wind, solar, nuclear, and other low-carbon technologies to establish a fully decarbonized energy system (D'Ambrosio and Schoenfisch, 2023).

Despite recent clean energy gains, according to the IEA Report Electricity 2025 - Analysis and forecast to 2027, released in February 2025, electricity demand is projected to grow more rapidly than it has in years, driven by a surge in industrial activity, wider adoption of air-conditioning, faster electrification of end-uses, and the expansion of data centers around the globe (IEA, 2025a). In 2024 alone, global power consumption climbed by 4.3%, and it is expected to sustain an annual growth rate near 4% through 2027. Cumulatively, this translates to an unprecedented increase of roughly 3 500 TWh in electricity usage over the next three years (IEA, 2025a). These trends make clear that without an accelerated shift to zero carbon power, the world cannot stay on a 1.5 °C-consistent pathway.

Data centers account for a significant share of the projected rise in electricity demand and must be prioritized in efficiency and decarbonization strategies. Synergy Research Group ranks Dublin, Ireland, as the world's third largest hyperscale data center hub by operational critical IT load, surpassed only by Northern Virginia, and Beijing (Dinsdale, 2024). Similarly, IEA (2025b) show Dublin as the the top eight data center market by installed capacity, and ranks high as well in the share of capacity under development, see Figure 1.1. Yet, Ireland's facilities serve largely as storage sites, with most of the data they house generated elsewhere (Fitzgerald, 2024)(Gross, 2025).

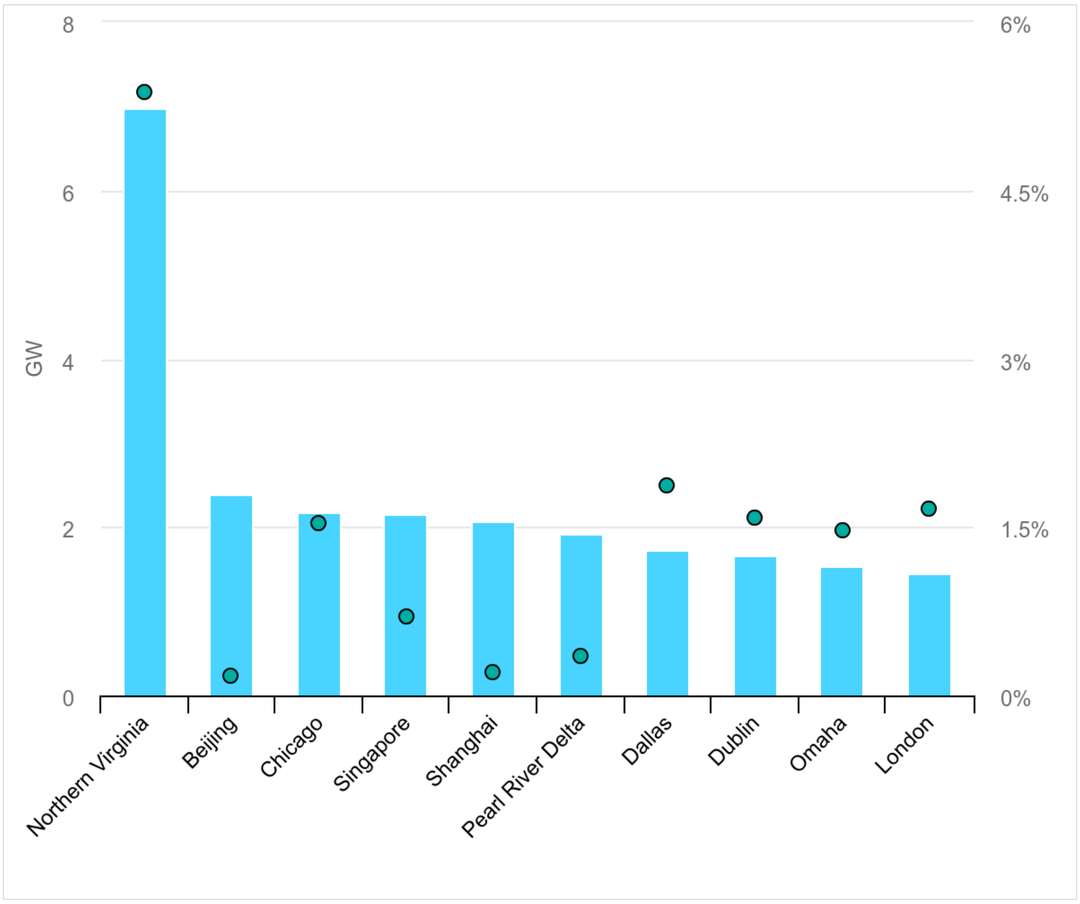


Figure 1.1: Top ten data center markets by installed capacity versus share of capacity under development, 2024. Bars represent installed capacity and dots represent the share of capacity under development (IEA, 2025b)

But why are companies, especially big tech firms, choosing Ireland? As Fitzgerald (2024) notes, Ireland's geographic position puts it at the nexus of transatlantic cables linking the US and Europe, ensuring low-latency access to data from both major economic centers. As an EU member, it also benefits from robust data protection legislation, giving firms a secure regulatory framework. Its mild, temperate climate further lowers cooling costs, which is a significant factor for power hungry data centers. Finally, setting up shop in Dublin enables parent companies to take advantage of Ireland's favorable corporate tax regime, which for larger firms was adjusted to 15% in 2023 (up from 12.5%) (Jackson, 2024).

However, Ireland, and especially Dublin, now faces growing foreign direct investment (FDI) uncertainty for data centers, as investors hesitate over grid capacity constraints, sustainability challenges, and the country's ability to meet its climate targets (Gross, 2025).

1.1 Data Center Energy Challenges in Ireland

According to EirGrid's All-Island Resource Adequacy Assessment 2025–2034, Irish data centers and other new technology loads have secured around 2 000 MVA of capacity at the transmission level, with an additional 300 MVA at the 110 kV distribution level (EirGrid and Soni, 2025).

EirGrid and Soni (2025) forecasts demand to grow extensively, they also have a goal to deliver 80% renewable electricity by 2030. Furthermore, in their median prognosis they forecast electricity demand to increase by 45% by 2034 from 2023 levels, and the largest growth is in data centers and new technology loads which will amount to 31% of all electricity demand by 2030, see Figure 1.2. To further emphasize the big role of data centers in the Irish grid, according to CRU (2025), data center electricity demand amounted to 21% of Ireland's electricity demand in 2023.

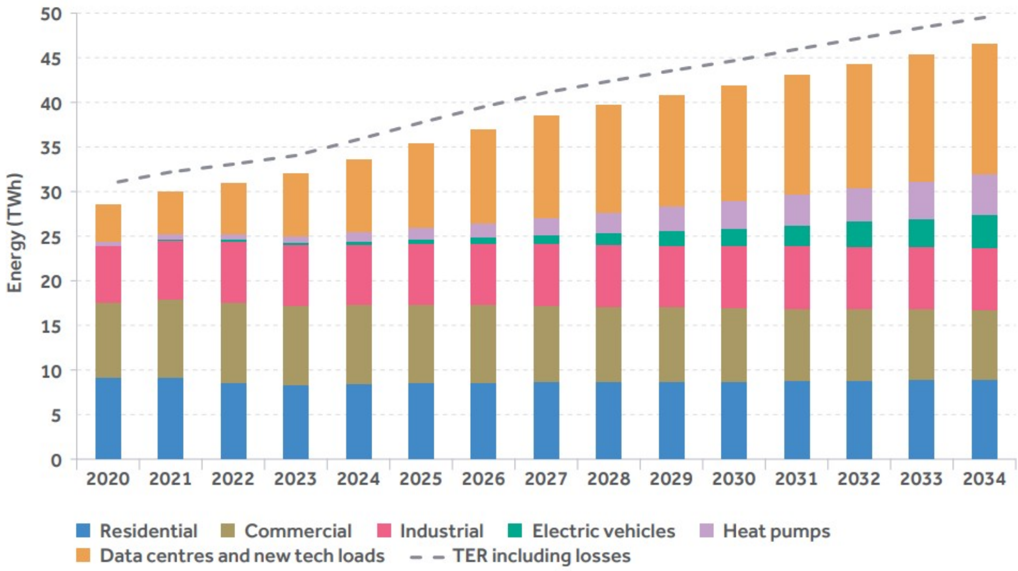


Figure 1.2: Total electricity requirement for Ireland, broken down by sector (EirGrid and Soni, 2025).

EirGrid's All-Island Assessment indicates that demand from data centers is projected to grow further as customers ramp up toward their contracted capacities. Nearly all of this incremental load is clustered around the greater Dublin area and was secured before the Commission for Regulation of Utilities (CRU) issued Direction CRU/21/12426 (EirGrid and Soni, 2025)(Commission for Regulation of Utilities, 2025). Under that direction, any new data center will be assessed based on the "*ability of the data center applicant to bring onsite dispatchable generation (and/or storage) equivalent to or greater than their demand*". As of the All-Island report's freeze date (8 May 2024) commissioned by EirGrid and Soni (2025), no subsequent data center projects have secured grid connections that meet the CRU's requirements.

Nuclear energy, offering carbon-neutral, large-scale, reliable baseload power, has attracted major U.S. tech firms: Amazon, Google, Meta, and Microsoft have all signed offtake agreements and invested in small modular reactor (SMR) developers to supply their data centers (Waltz, 2024). In contrast, Ireland's Integrated Single Electricity Market (I-SEM) prohibits nuclear fission for grid generation under Section 18 of the Electricity Regulation Act 1999 (ISB, 1999). Nonetheless, this thesis includes SMRs in its technology portfolio as a forward-looking option should regulatory barriers evolve.

Furthermore, according to Swinhoe (2022), EirGrid has announced that no new data center applications in Dublin will be accepted until 2028, they are only considering the pending data center connections. This decision reflects concerns over grid capacity constraints and the need for substantial infrastructure upgrades to support continued growth in power demand. Together, these policy shifts underscore that data centers must now factor energy availability and grid integration into their strategic planning (Swinhoe, 2022).

Therefore, it is essential to investigate the role that on-site generation and storage can play in meeting the growing energy demand of data centers and analyze their competitiveness and trade-offs. Doing so equips operators and investors with the insights needed to optimize technology choices, capital allocation, and long-term energy sourcing strategies in a rapidly evolving market and regulatory environment.

1.2 Scope and Objectives

This thesis develops and applies a detailed mixed-integer linear programming (MILP) model to identify cost-optimal on-site energy supply strategies for a 5 MW data center in Dublin, Ireland, with a focus on integrating solar PV, onshore wind, small modular reactors (SMRs), battery energy storage (BESS), and conventional grid imports. The work combines first-principles techno-economic modeling with real-world data and market rules to quantify key performance metrics (annualized lifecycle cost, levelized cost of energy, self-sufficiency) and to translate those results into actionable guidance for data center planners that face uncertain technology costs, volatile electricity markets, and evolving regulatory requirements. The specific objectives are to:

1. Build and solve a MILP model that co-optimizes capacity investments and hourly dispatch for PV, wind, SMR, BESS, and grid exchange over a full year using 2023 weather inputs and 2025 cost inputs.

2. Quantify the value of stacked revenue streams by demonstrating participation in demand response (DR) markets, and compare pure energy arbitrage versus multi-service operation for BESS.

3. Conduct sensitivity studies on wholesale market prices, intraday price volatility, SMR capital cost thresholds, and system scale (including a 50 MW sce-

nario) to assess how these uncertainties reshape the least-cost technology portfolio.

4. Develop practical planning recommendations that enable data center operators and investors to balance grid dependency, cost risk, and regulatory dispatch requirements in the Irish context.

1.3 Delimitations

The following delimitatios were made to not overgrow the project scope while still being able to produce actionable results:

- **Technology scope** Only utility-scale solar PV, onshore wind, small modular reactor (SMR), and lithium-ion battery energy storage systems (BESS) are considered. Other technologies such as diesel generators, geothermal, hydrogen, or large pumped hydro are excluded because they fall outside the target case's size, location, and strategic focus.
- **BESS revenue in base analysis** In the core cost-optimization, BESS value stems solely from energy arbitrage. Capacity, frequency, or ancillary-service revenues are evaluated separately in the DR participation chapter to avoid overcomplicating the primary MILP objective.
- **Data period** All spot price and climate data correspond to calendar year 2023 in Ireland, the most recent period covered by PVGIS. Because spot prices are closely linked to weather conditions, 2024 price data were not paired with 2023 climate profiles. Instead, systematic variations in spot price levels and volatility were applied to capture sensitivities, while the weather inputs remained fixed.
- **Load profile** The data center is assumed to draw a constant 5 MW (or 50 MW in the 10×Scale scenario) 24/7, with no demand flexibility. Real-world variations (daily cycling or server idling) are outside this thesis's scope.
- **BESS sizing constraints** ABB seeks to evaluate the competitiveness of battery energy storage systems sized between 0.5 MW and 20 MW, with durations of 1 hr, 2 hr, or 4 hr. This was the only capacity constraint applied, other resources were modeled without externally imposed size limits.
- **SMR capacity bounds** On-site SMR is limited by a minimum deployable reactor size of 40 MW (based on lower bound reactor design detailed in section 2.2) and a maximum of 300 MW. This thesis ignores multi-SMR coupling or advanced micro-reactor concepts below 40 MW.
- **Modeling framework** The study uses a deterministic mixed-integer linear programming (MILP) formulation, which cannot capture non-linear unit commitment dynamics, multiple dispatch modes, or full stochastic uncertainty. Extensions to MINLP or stochastic optimization are identified as future work.

- **Uniform financing rate** All technologies assume an 8% weighted average cost of capital (WACC). In reality, SMR projects may face higher financing costs due to regulatory or risk premiums, which could raise their effective levelized cost compared to renewables.

2

Background

This chapter first introduces mixed-integer linear programming (MILP) as a rigorous technique for jointly sizing generation and storage assets and optimizing their hourly dispatch under mixed discrete–continuous decision variables. It then reviews the four on-site technologies (solar PV, onshore wind, small modular reactors, and lithium-ion battery energy storage), highlighting recent cost and performance trends. Finally, it examines recent developments in grid connection charges and wholesale spot price dynamics that shape the economics of on-site energy portfolios.

2.1 Mixed-Integer Linear Programming in Energy Systems

Mixed-integer linear programming (MILP) has become a standard approach for simultaneously sizing and operating hybrid energy systems. In a MILP, continuous variables (e.g. generation outputs, storage state-of-charge) are optimized alongside integer or binary variables (e.g. build decisions, on/off status), all under a linear objective and linear constraints.

Hossain, Iftekhar Bin Ashraf, and Ahmed (2024) implement a Pyomo-based MILP for sizing and dispatch of a 20 kW hybrid microgrid, which includes PV, battery, diesel generator and grid interconnection, under multiple market schemes (net-metering, feed-in tariff, zero export price) and, in island mode, with CO_2 emission constraints. Their formulation covers 8 760 hourly steps, employs dozens of binary build and mode selection flags, and incorporates linearized cost and emission penalties. Hossain et al. (2024) demonstrates that:

- Integrated planning and dispatch solves capacity sizing and hourly operation in one unified MILP.
- Global optimality is guaranteed via branch-and-bound despite 8 760 timesteps and 50+ binaries.
- Logical constraints, such as mutually exclusive charge/discharge modes, minimum up/down times and discrete duration choices, are encoded with binary variables without non-convexities.

Beyond these core advantages, subsequent studies have refined MILP formulations to improve tractability and extend their scope. Lyzwa, Wierzbowski, and Olek (2015) compare three different MILP formulations for long-horizon energy-mix planning, showing that the choice and tightness of binary variable encodings (e.g. their AUC, IAUC and novel eMix methods) can reduce solution times by orders of magnitude even when objective and constraints are otherwise unchanged. This underlines that, beyond problem size, careful model formulation is critical to tractability as a system's temporal or spatial resolution grows. Zaree and Vahidinasab (2017) show that MILP can be extended to capture distribution network physics, by linearizing AC power flow via piecewise approximations and embedding reactive power, load shedding and deferrable load constraints, while retaining computational efficiency.

To address input uncertainty, Rahmani-Andebili (2022) integrates fuzzy sets to represent renewable generation forecasts within the MILP, preserving global optimality guarantees while achieving robust dispatch under variable conditions. These enhancements confirm that careful MILP formulation, both in variable encoding and in the inclusion of network and uncertainty features is critical to scaling and realism.

2.2 Small Modular Reactors

Small Modular Reactors (SMRs) are nuclear fission reactors generally producing up to 300 MWe per unit (Boldon and Sabharwall, 2014). Their modular design and smaller footprint offer potential benefits in terms of safety, scalability, and reduced upfront capital commitments relative to traditional large reactors (Bates, Valderrama, Bickford, Chan, Tian, Programs, Shah, and Wagner, 2023). However, their economic competitiveness depends on achieving cost levels that rival other energy sources. SMRs is a crucial technology for the energy system to be able to transition to net-zero emissons. Furthermore, the 92.5% capacity factor of nuclear power is by far the highest of any other energy source (Department of Energy, 2022). This implies that nuclear power plants produce their maximum power for more than 92% of the time throughout the year. SMRs can also quickly be established in brownfield sites where decomissioned coal-fired plant operated (World Nuclear Association, 2024).

Given these characteristics, SMRs are being increasingly considered for a wide range of applications, including distributed power generation and providing dedicated energy sources for specialized facilities such as data centers, which require consistent and reliable power (MarketsandMarkets, 2024).

World Nuclear Association (2024) highlights a rising interest in small and medium-sized reactors due to their lower upfront costs and suitability for off-grid or weak-grid settings. To monitor global SMR progress, the WNA maintains a “near-term deployment” list of 18 reactor designs whose commercialization is highly advanced. The first reactor is expected to come online in 2028, with most deployments occurring in the early 2030s. Developers on the list, including Holtec, GE Hitachi, X-Energy, CGN, OKBM, Kairos Power, and Moltex, are designing units with capacities ranging from about 35 MW to 300 MW (World Nuclear Association, 2024).

2.2.1 SMR Capital Costs

Nuclear power is capital intensive. Approximately 70-80% of the levelized cost of energy (LCOE) comes from initial capital investment (Bates et al., 2023). First-of-a-kind (FOAK) SMRs are estimated to have high overnight capital costs (construction costs excluding financing) in the range of $6,000-$10,000 per kW in the early 2020s. For example, a planned 462 MW (6x77MW) SMR plant in Idaho, USA, saw its construction cost estimate balloon to $9.3 billion, roughly $20,000/kW, causing the projected electricity price to jump from about $55 to $89 per MWh (Schlissel, 2023). These figures are well above the capital costs of many other generation options today.

For context, the U.S. Energy Information Administration (EIA) estimates that a large two-unit AP1000 plant (~2,150 MW) has an overnight cost of around $7,800/kW. While a multi-module SMR plant (~480 MW) is about $8,900/kW (LaRose, Diefenderfer, and Namovicz, 2024). Thus, on a per kW basis, according to these sources current SMRs are approximately in the same ballpark or higher than conventional gigawatt-scale reactors. Worth noting is that total capital required for an SMR project is much lower (e.g. a few billion dollars vs. $5–10+ billion for a large plant), which can make financing and project management easier despite the high unit cost (LaRose et al., 2024).

Likewise, Van Hee, Peremans, and Nimmegeers (2024) evaluated SMR potential and challenges in Europe, reporting an average capital cost of €7 031/kW and an LCOE of €85/MWh (using an exchange rate of: 0.8476 €/$). Their analysis also indicates that SMRs carry a 41% premium in capital cost per kW compared to large reactors.

A critical factor in assessing SMRs as a competitive alternative is the evolution of their costs from FOAK projects to subsequent nth-of-a-kind (NOAK) deployments. FOAK SMRs generally exhibit high overnight capital costs (OCC) due to non-recurring expenses, design uncertainties, and learning curve limitations. However, as more units are built, learning-by-doing and standardization are expected to drive significant cost reductions. Larsen, Abou-Jaoude, Guaita, and Stauff (2024) projects that a “between first- and Nth-of-a-kind” (BOAK) reactor would have a capital cost of $8 000 per kW in their base estimate.

While recent U.S. nuclear construction projects have had OCCs over $10 000 per kW, Bates et al. (2023) estimates FOAK cost of well-executed large nuclear construction project to be around $6,200/kW. And to unlock deployment at scale, Bates et al. (2023) estimates that NOAK advanced nuclear OCCs need to approach ~$3,600/kW after 10-20 deployments depending on the learning rate. This FOAK–NOAK transition is essential to lowering the LCOE and making SMRs competitive with other technologies.

Moreover, a analysis made by Bartak, Bruna, and Cognet (2021) has concluded that light-water based SMRs, which is the most mature of the advanced reactor concepts, can ultimately achieve OCC values similar to, or lower than, large-scale Gen III reactors, in the approximate range of $4,000–$6,000/kW and corresponding

LCOEs near \$50–\$80/MWh for NOAK deployments. Non-light-water based designs promise even more dramatic cost reductions by eliminating high pressures and certain major components. (Bartak et al., 2021).

2.2.2 SMR Operation & Maintenance Costs

Once built, SMRs have relatively low fuel and variable costs, similar to existing nuclear plants. Fuel costs (including used fuel disposal fees) in the order of \$7–\$10 per MWh, comparable to large reactors (Nuclear Energy Institute, 2021). LaRose et al. (2024) estimates fixed O&M at \$122/kW-year (plus about \$3.2/MWh variable O&M) for a 6×80 MW SMR plant. For a plant running at high capacity factor, that translates to roughly \$15–\$20/MWh in O&M expenses. This is slightly lower per MWh than a large reactors O&M (a large PWR is ~\$156/kW-year, or ~\$25/MWh), showing SMRs could achieve O&M savings by design. Furthermore, SMR vendors plan to reduce staffing levels via simpler, safer designs and even operate multiple modules with one team, which would dilute fixed costs (Lewis, MacSweeney, Kirschel, Josten, Roulstone, and Locatelli, 2016). Until this is proven, critics note that if each small reactor requires its own crew and support systems, the operating cost per MW could be up to 190% higher than running an equivalent large unit (Lewis et al., 2016).

2.2.3 First-of-a-Kind SMR Difficulties

Given high capital costs, initial SMR LCOE is expected to be relatively high. According to Nuclear Energy Institute (2021), an unsubsidized FOAK SMR built in the late-2020s is expected to have an LCOE of roughly \$90–\$100 per MWh for an investor-owned project, substantially higher than the estimated \$40/MWh for combined-cycle gas and \$30–\$50/MWh for wind power in the same period. In practice, the first expected U.S. SMR deployment confirmed this order of magnitude: the NuScale and Utah Associated Municipal Power Systems (UAMPA) project's target price was ~\$89/MWh (in 2022 \$), that included sizable government incentives of more than \$4 billion, consisting of a \$1.35 billion contribution from the Department of Energy (DOE) over 10 years for the plant, known as the Carbon Free Power Project, and an estimated subsidy of \$30/MWh in the Inflation Reduction Act (IRA) (Schlissel, 2023)(Gardner and Mishra, 2023). This (novel) project, planned to deliver the six-reactor 462 MW project, was a testimony to the difficulty of executing FOAK SMRs. In November 2023, NuScale with the UAMPA decided to terminate the project due to multiple towns pulling out of the project due to increases of project cost (Gardner and Mishra, 2023).

Similarly, Asuega, Limb, and Quinn (2023) carried out a bottom-up economic assessment of three SMR configurations, a 12 × 77 MWe light-water design, a 4 × 262 MWe gas-cooled module, and a 5 × 200 MWe molten-salt reactor. The study reported LCOEs of \$89.6, \$81.5, and \$80.6/MWh, respectively. Estimates closely mirroring the ballooned NuScale and UAMPS target of $89/MWh (Schlissel, 2023).

2.2.4 Financing and Market Risks in Nuclear Projects

According to Bates et al. (2023) SMRs face high upfront capital costs and lengthy construction periods. This delays cash flow relative to technologies with shorter build cycles. For instance, Bates emphasize that the OCC metric alone does not capture the full spectrum of financial risks incurred during extended construction phases. This underestimation of risk leads many analyses to suggest adjusting the effective cost of capital by applying a higher weighted average cost of capital (WACC) or by annualizing expenditures over the plant's operational life (Dillén, Carlén, Martin, Mellström, Mohlander, Nyström, and Nyström, 2023)(Bates et al., 2023).

On December 20, 2023, the Swedish Government tasked Dr. Mats Dillén with designing financing and risk-sharing frameworks for new nuclear projects. In his August 2024 report, Dillén shows that, assuming a real discount rate of 7%, an overnight cost of 80 MSEK/MW (approximately $8 000/kW), a seven-year construction period and a 60-year lifetime, financing charges account for 62% of the resulting LCOE, compared to just 15% for pure capital expenditure. These findings are broadly consistent with prior analyses by the OECD (Dillén et al., 2023). To reduce the WACC, Dillén recommends a phased financing structure: state-backed low-interest construction loans that convert to market debt, a two-way contract-for-difference to hedge revenue volatility, and an equity floor-and-cap mechanism to share upside and downside risk. His parameters and tools can inform SMR models seeking lower levelized costs.

More generally, the appropriate discount rate for any power project reflects its revenue uncertainty, often called market risk, which arises from unpredictable long term demand trends and shifting supply curves as new generation assets enter or exit the market (Dillén et al., 2023). This market risk premium will vary by technology. Mature, subsidy-backed renewables typically command lower WACC, whereas emerging technologies (like SMRs) face higher financing costs due to greater perceived risk (Dillén et al., 2023).

From an investment perspective, smaller SMRs may mitigate some of these issues by reducing absolute project size and potentially shortening construction timelines. Many SMR designs seek to maximize off-site fabrication. Bartak et al. (2021) indicates that 60–80% of the plant could be manufactured in a factory setting, thereby lessening labor-intensive on-site construction and minimizing the duration of high-cost capital. The factory-based approach has been shown to shorten construction schedules to approximately 3–5 years. Bartak et al. (2021) argues that the pre-built, standardized SMR design enhances schedule certainty, and since certainty equals lower risk, it reduces lead times and interest rate exposure. This in turn unlocks cheaper debt financing and makes investors willing to accept lower internal rate of returns (IRRs) (Bartak et al., 2021).

2.3 Solar PV

Solar PV technology has seen large developments in the last decade, and according to IEA, n.d. (a), the global PV capacity has tripled from 2018 to 2023 and it is set to become the largest renewable energy source by 2029. In 2023, utility-scale solar PV plants constituted the majority (57%) of global capacity additions, with distributed generation following behind. A significant surge in utility-scale installations, particularly in China, more than doubled its growth in 2023, driven in part by a 50% drop in solar PV module prices, solidifying utility-scale systems as the cheapest electricity source in many regions. Despite this, the increasing difficulty in finding suitable sites and navigating complex permitting for large projects highlights the growing importance of also supporting smaller-scale, rooftop PV systems to achieve the ambitious solar capacity targets of the Net Zero Emissions (NZE) Scenario by 2030, requiring a parallel development of both distributed and utility-scale PV tailored to individual country contexts (IEA, n.d., a).

Solar PV is notably the main renewable technology adopted by the private sector. Private companies contribute to solar PV deployment through investments in distributed, rooftop installations on their premises, which accounted for 25% of total installed PV capacity in 2023. Furthermore, companies are increasingly utilizing corporate power purchase agreements (PPAs) to directly contract with solar PV plant operators for electricity, with solar PV representing almost 70% of renewable PPAs in 2023 (IEA, n.d., a).

Between 2010 and 2023, solar PV experienced a dramatic cost reduction. According to IRENA (2024), the global weighted average LCOE for utility-scale solar PV plants plummeted by 90%, reaching $44/MWh in 2023, with a 12% year-on-year decrease. Globally, the total installed cost of solar PV projects commissioned in 2023 averaged $758/kW, an 86% decrease since 2010 and a 17% decrease from the previous year (IRENA, 2024).

Based on the NREL 2024 Annual Technology Baseline, the CapEx for utility-scale solar PV is projected to continue decreasing through 2050, with average annual reduction rates between 2023 and 2035 ranging from 2.5% to 7.0% in their different scenario (NREL, 2025c). Beyond 2035, CapEx reductions are expected to be moderate across all scenarios. In contrast to the declining CapEx, the OpEx for utility-scale PV is anticipated to remain relatively stable throughout the projection period (NREL, 2025c). IRENA (2024) indicate that the average O&M costs for utility-scale installations in Europe are now approximately USD 10/kW per year. Historical data from Germany reveal an 85% reduction in these costs between 2005 and 2017, eventually reaching about $9/kW per year. This trend translates into a cost reduction of roughly 16–18% with each doubling of the cumulative solar PV capacity installed (IRENA, 2024).

2.4 Onshore Wind

Onshore wind has matured through increases in hub height and rotor diameter, enabling deployment at lower-wind sites and driving rapid capacity expansion (IEA, n.d., b). For the scenario Net Zero Emissions by 2050, wind and solar are the dominant sources of power generation, but the rate of capacity added is not on track with the net zero path, thus both on and offshore wind capacity needs to ramp up significantly (IEA, n.d., b).

2.4.1 Onshore Wind Capital Costs

Distributed wind systems, typically deployed at smaller scales than utility-scale wind farms, are increasingly considered for on-site generation, particularly by facilities like data centers seeking to integrate renewable energy directly at their location (Gao, Zeng, Liu, and Kumar, 2013). Gao argues that by using a network of uncorrelated wind energy sources, distributed data centers can substantially mitigate the challenges of intermittency, thus moving closer to achieving fully green cloud-scale services (Gao et al., 2013). However, their economic viability is largely determined by CapEx, which can vary dramatically depending on the size of the project. While larger turbine models typically incur higher initial costs, they benefit from increased energy production and reduced CapEx per MW for installation and foundations, ultimately lowering the LCOE (International Renewable Energy Agency, 2019).

Due to the inability to leverage the same economies of scale as larger wind farms, smaller distributed wind projects face higher per-kilowatt capital costs. For instance, Stehly, Duffy, and Mulas Hernando (2024) estimates that a residential-scale distributed wind project (approximately 20 kW) incurs a total CapEx of about $8,665/kW with data from 2023. In contrast, commercial-scale projects (around 100 kW) achieve somewhat lower costs at roughly $6,800/kW, while larger industrial or campus-scale distributed installations (approximately 1,500 kW) can further reduce CapEx to about $3,362/kW. This trend underscores that as the size of the system increases, the relative cost per kW decreases as a result of more efficient use of components and shared infrastructure. When looking at utility-scale land-based project, the CapEx would be reduced to $1,968/kW for a 3.3 MW rated wind turbine (Stehly et al., 2024).

To provide a broader perspective on wind project competitiveness, IRENA's 2023 report (IRENA, 2024) shows that the global weighted average total installed cost for onshore wind dropped from about USD 2,272/kW in 2010 to roughly USD 1,160/kW in 2023, a reduction of 49%.

2.4.2 Onshore Wind Operation & Maintenance Costs

According to NREL (2025b) the fixed O&M costs for distributed wind projects are estimated at around $41/kW-year. For "normal" land-based wind projects, they typically range from about $25 to $50/kW-year, with learning rates between 5% and

20%. And 2025 levels amounting to \$30/kW-year, expected to reach \$26/kW-year by 2030. IRENA (2024) provides country-specific O&M cost assumptions for onshore wind. For Ireland, the 2023 O&M cost is estimated at \$33/kW-year. These fixed O&M costs have been declining due to improved turbine reliability and competitive service contracts.

2.5 Battery Energy Storage System

Energy Storage Systems (ESS) are devices used to convert electrical energy generated by power systems into a storable form and subsequently reconvert it to electrical energy upon demand (Wang, Xu, and Qiu, 2020).

Achieving the EU's climate and energy targets and decarbonizing the energy sector require a significant transformation of the energy system to support the rapid deployment of intermittent renewable sources. Today energy storage is dominated by pumped hydro and increasingly by battery energy storage systems (European Commission, n.d., a). Energy storage is essential for ensuring flexibility, stability, and reliability. With renewables projected to account for about 69% of the EU's electricity mix by 2030 and 80% by 2050, the need for system flexibility is set to rise from 11% of electricity demand in 2021 to 24% (288 TWh) by 2030 and 30% (2,189 TWh) by 2050 (European Commission, n.d., b).

Behind-the-meter battery storage installations in the commercial and industrial (C&I) sector are expanding rapidly as costs decline and new value streams emerge. Within this market, where data centers sit in the critical infrastructure subcategory, the C&I segment has become the second-largest for BESS. Forecasts show it growing at about 13% per year, which will add roughly 52–70 GWh of new C&I storage capacity globally each year until 2030 (Jarbratt, Jautelat, Linder, and Wong, 2023).

BESS costs have seen significant recent declines. Global average turnkey energy storage system prices (battery packs + inverter + energy management, excluding site EPC and grid interconnection) dropped 40% from 2023 to 2024, reaching \$165/kWh (Colthorpe, 2025). Behind-the-meter C&I systems, which are often smaller (hundreds of kW to a few MW), can have moderately higher unit costs than utility-scale farms due to less economies of scale and added integration costs (Eia, 2024). For instance, NREL (2025a) estimates, in their moderate scenario, a 0.3 MW/1.2 MWh (4 hour) C&I BESS in the US to have a CapEx of approximately \$1950/kW (or ~\$488/kWh) in 2025.

Battery energy storage systems incur minimal O&M relative to upfront investment. With no fuel costs and few moving parts, fixed O&M, which covers battery monitoring, HVAC, inverter servicing, insurance, software, and periodic cell replacement, typically is 2–3% of the initial CapEx each year (NREL, 2025a). In the NREL ATB, these fixed O&M figures also include provisions for battery degradation over its 15-year lifetime. These levels are in line with US data from Eia (2024) showing fixed

O&M of $60/kW-year for similar sized large commercial battery storage.

2.5.1 Revenue opportunities

Smarma and Bund (2025) emphasizes that BESS operators can flexibly pursue a mix of revenue strategies to maximize value. A smaller BESS operator may outsource real-time optimization, market bidding, and stack management to specialized aggregators or third-party software platforms. Larger operators, such as multi-site C&I portfolios or energy developers with multi-megawatt assets may find it more cost-effective to build their own in-house optimization capabilities.

In practice, every BESS owner blends these high-level strategies into a set of core revenue models:

Table 2.1: Revenue Models for BESS (Smarma and Bund, 2025)(Ratshitanga et al., 2024)

Revenue Model	**What It Is**	**Use Cases**
Energy Arbitrage	Charge during low-cost-off-peak hours and discharges during high-demand, higher-priced periods	Peak-shaving, wholesale trading
Ancillary Services	Grid support functions such as frequency regulation, voltage/reactive power control, black-start capacity, congestion management, oscillation damping	Grid stability, resilience
Capacity Payments	Payments for reserving capacity in grid-operator auctions, ensuring availability during peak demand periods	Peak load management, grid stability
Demand Response	Curtail or shift consumption in response to utility signals or price incentives	C&I bill reduction, grid support

In Q1 2024, German battery-storage returns dipped below €100 /kW-yr, weighed down by a mild winter and weak gas prices, but by Q3 they'd rebounded past €150 /kW-yr on the back of sharper market swings and attractive aFRR payments, showcasing investor appetite for acquiring and developing BESS assets (Smarma and Bund, 2025). In the US, Texas BESS revenues plunged to $55/kW in 2024, down from $192/kW in 2023 and $141/kW in 2022, marking a 61% decline from 2022 levels (Vermillion, 2025).

Mohamed, Best, Liu, Morrow, Pollock, and Cupples (2022), in a distribution network case study for Northern Ireland conducted with Northern Ireland Electricity Networks (NIE Networks), similarly found that single-service participation, particularly pure energy arbitrage, is generally unprofitable by itself. In contrast, participation in ancillary services under Ireland's DS3 System Services, specifically the four volume-uncapped dynamic frequency response products; Fast Frequency Reserve (FFR), Primary and Secondary Operating Reserve (POR and SOR), and Tertiary Operating Reserve 1 (TOR1), deliver the most attractive standalone returns and can yield positive NPVs across all major BESS technologies (Mohamed et al., 2022). Mohamed et al. found, stacking multiple revenue streams unlocks the greatest upside:

- Distribution Network Support (DNS) + Energy Arbitrage (I-SEM): Bundling distribution-network support with day-ahead/intraday arbitrage boosted annual revenues by 54% versus network support alone.
- DNS + I-SEM + DS3: Adding DS3 frequency and reserve response services drives revenues up another 79% on average (a total uplift of 129%), with an average payback of 8 years.

Similarly, Scoltock and Gladwin (2019) uses real Irish grid frequency data to simulate a BESS with a C-rate of 2 (1MWh/2MW) providing the same four EirGrid DS3 dynamic frequency response services; FRR, POR, SOR, and TOR1. Their results show that, depending on how tightly the unit's trigger-frequency margins are set (i.e. its speed of response), the BESS can earn between €83,000 and €136,000 per MW of declared available capacity annually (Scoltock and Gladwin, 2019).

2.6 Grid Cost and Electricity Spot Price Trends

Optimizing a hybrid system that integrates multiple generation sources and storage units requires not only precise cost assessments for on-site generation technologies, but also accurate determination and awareness of grid costs and its developments. This dual focus ensures that the optimization model does not disproportionately favor on-site generation over conventional electricity obtained from the grid connection.

The primary regulatory authority governing electricity in Ireland is the Commission for Regulation of Utilities (CRU). EirGrid, the transmission system operator, also plays a crucial role in managing the national electricity grid (Eirgrid, 2024). Their Statement of Charges 24/25, applicable from 1st of October 2024, is their latest edition and determines the charges for use of the transmission system. According to the statement, distribution connection with Maximum Import Capacity (MIC) of >= 0.5 MW falls under tariff schedule DTS-D1. Under this tariff schedule Eirgrid charges a Demand Network Capacity Charge of €1,601.85 per MW per month, a Demand Network Transfer Charge of €3.4947 per MWh Metered Consumption Energy transferred, and a Demand System Services Charge of € 27.5365/MWh for Metered Consumption Energy transferred (Eirgrid, 2024).

Spot prices are dynamic and traded intraday in globally interconnected markets, but are heavily influenced by local load and generation conditions, making accurate forecasting challenging. Osone and Kodaira (2025) have used quantile regression with general predictors to forecast UK electricity prices. They have estimated multiple quantiles to capture not only the median or average price level but also the potential for extreme high-price occurrences. The results indicate that the baseline spot prices are likely to remain stable or trend downward, primarily due to the increasing penetration of renewable energy sources, e.g. they found that wind power generation increases had a generally negative coefficient in their model, aligning with the argument that growing renewables tend to suppress or lower average prices. However, the market continues to experience significant volatility that can lead to pronounced price spikes under stress conditions (Osone and Kodaira, 2025).

Complementing these findings, Gai, Li, Lu, Li, and Li (2024), which analyzes spot markets in Chinese provinces Shanxi and Shandong, shows that forecasted total new energy output is inversely related to day-ahead clearing prices, whereas an expanded unit bidding space tends to drive prices higher. This highlights that when energy storage, particularly electrochemical storage systems, actively participates in the spot market, they play a dual role: they optimize individual bidding strategies for charging and discharging, and they contribute to narrowing the unit bidding space during periods of high renewable output. This dual interaction can lead to lower clearing prices and more stable market conditions (Gai et al., 2024). Similarly, Yamujala, Koivisto, and Nayak (2025), examining European markets, further adds to these findings by confirming the overall downward trajectory of electricity price levels and demonstrating that the market is subject to significant volatility, including phases of negative pricing driven by oversupply and operational inflexibilities.

3

Methodology

This chapter presents the research approach and justifies the use of mixed-integer linear programming, then details the mathematical formulation and data inputs, and concludes with site selection and ethical considerations to ensure transparency and rigor.

3.1 Research Approach

This thesis employs a quantitative research strategy, centered on the construction and application of a mixed-integer linear programming (MILP) model. Rather than gathering primary qualitative data (e.g., interviews or focus groups), the study relies on numerical datasets, techno-economic parameters and simulation-based optimization to derive generalizable insights.

Quantitative methods are especially appropriate when the objective is to test hypotheses, measure relationships among clearly defined variables, and produce results that can be compared across scenarios and generalized to other contexts. Bell, Bryman, and Harley (2022) note that quantitative approaches support the systematic evaluation of variable relationships through numerical measurement and statistical analysis, thereby it ensures objectivity and replicability. Accordingly, this thesis calibrates the model using hourly data and runs multiple scenarios to produce reliable and comparable numerical results.

3.2 Research Process

The overall research process comprised four iterative phases:

1. **Literature and Background Review.** Research of academic and industry literature characterized:
   - Cost trajectories and performance of PV, wind, SMR and BESS technologies.
   - Regulatory and market environments, including spot prices, tariffs and ancillary service opportunities.
2. **Data Collection and Preprocessing.** Meteorological, market-price and tariff data were sourced from public and proprietary repositories. Time-series

were aligned, cleaned and transformed into capacity factor and price vectors using Python.

3. **Model Development and Calibration.** Following the MILP framework outlined in section 2.1, the sizing and dispatch problem is implemented as a mixed-integer linear program in Python (3.12.3) within a Conda environment, using:
   - Pyomo (v6.8.2) for model formulation (variables, parameters, constraints).
   - Gurobi (v12.0.1) as the solver.
   - pandas and NumPy for time-series preprocessing and parameter initialization.

   The model integrates:
   - **Investment decisions** (capacity sizing) for PV, wind, SMR and BESS.
   - **Hourly operations** of
     - PV and wind generation (via capacity factors $P_t^{\max}$, $W_t^{\max}$),
     - BESS charge/discharge scheduling, state-of-charge dynamics and discrete duration selection,
     - SMR dispatch within minimum/maximum generation limits,
     - Grid import/export with time-of-use import costs $\pi_t + \lambda^{\text{day/peak/night}}$ and export credits.
4. **Expert Consultation** Throughout model design and interpretation, feedback from industry contacts and thesis supervisors guided the selection of relevant parameters, validated assumptions (e.g. grid fees, connection capacity, scenario selection), and ensured that the case study remained aligned with real-world practices.
5. **Analysis and Validation** The completed MILP was solved with Gurobi for the base case and a range of sensitivity scenarios. Results were analyzed quantitatively, benchmarking cost outcomes against literature values and stress-testing the model under varying technology cost, tariff and load assumptions.

3.2.1 Justification of a Quantitative Approach

A quantitative, model-based approach is well suited to this study because:

- The research question centers on *optimizing* system investments and operations, tasks inherently quantitative and amenable to mathematical programming.
- High-resolution time-series data are available for resources, loads and prices, supporting detailed numerical analysis.
- The outcomes (e.g. levelized cost, capacity mix, CO2 emissions) can be directly compared against published benchmarks and sensitivity ranges.

By foregoing primary qualitative methods, the thesis focuses resources on building a robust, data-driven optimization framework that can be generalized to other behind-the-meter applications (e.g. any industry load) and be applied to sites beyond the investigated site.

3.2.2 Modeling Assumptions

Key assumptions applied consistently throughout the MILP analysis:

- All technologies (PV, wind, SMR and BESS) are annualized using a uniform discount rate (WACC) of 8 %.
- Capital costs, O&M expenses and lifetimes are based on the NREL ATB (2025) data, while SMR capacity limits follow World Nuclear Association classifications.
- Time-series and tariff inputs are aligned on an hourly basis.
- Fixed grid subscription fee of €F_{sub} per year, plus volumetric ToU tariffs.
- Grid connection set to 10 MW for a 5 MW load, matching active industry practices.

3.3 System Overview

The case study models a behind-the-meter energy system for a 5 MW data center in Dublin, Ireland, using 2023 hourly weather inputs from PVGIS and wholesale spot prices from ENTSO-E. A constant 5 MW load is assumed for all hours unless otherwise noted. The candidate resources and their sizing constraints are:

- Grid connection, with maximum import/export capacity fixed at 10 MW in the base case, reflecting the constraint of an actual Irish data center client with a 5 MW load.
- PV and onshore wind each set with maximum installable capacity up to 100 MW, serving as practical upper bounds in the optimization.
- SMR dispatchable generation with capacity treated as a continuous decision variable, bounded between a minimum of 40 MW and a maximum of 300 MW.
- BESS power capacity between 0.5 MW and 20 MW, with selectable energy durations of 1, 2, or 4 hours.

3.4 Mathematical Formulation

In this section the mathematical formulation of the problem is described. First the objective function is stated, then notation, and finally the constraint groups.

3.4.1 Objective Function

The objective of the sizing and operation problem is to minimize the annualized life-cycle cost (ALCC):

$$\begin{aligned} \min\ Z = F_{\text{sub}} \\ &+ \underbrace{\mathrm{AF}_{\mathrm{PV}}\, c_{\mathrm{PV}}^{\text{cap}}\, x_{\mathrm{PV}} + c_{\mathrm{PV}}^{\text{opex}}\, x_{\mathrm{PV}}}_{\text{PV CapEx + O\&M}} \\ &+ \underbrace{\mathrm{AF}_{\mathrm{W}}\, c_{\mathrm{W}}^{\text{cap}}\, x_{\mathrm{W}} + c_{\mathrm{W}}^{\text{opex}}\, x_{\mathrm{W}}}_{\text{Wind CapEx + O\&M}} \\ &+ \underbrace{\mathrm{AF}_{\mathrm{SMR}}\, c_{\mathrm{SMR}}^{\text{cap}}\, x_{\mathrm{SMR}} + c_{\mathrm{SMR}}^{\text{opex}}\, x_{\mathrm{SMR}}}_{\text{SMR CapEx + O\&M}} + \underbrace{\sum_{t\in\mathcal{T}} f_{\text{fuel}}\, g_t^{\mathrm{SMR}}}_{\text{SMR fuel cost}} \\ &+ \underbrace{\mathrm{AF}_{\mathrm{BESS}}\Big(c_P^{\text{cap}} P_{\mathrm{BESS}} + c_E^{\text{cap}} E_{\mathrm{BESS}}\Big) + c_P^{\text{opex}} P_{\mathrm{BESS}} + c_E^{\text{opex}} E_{\mathrm{BESS}}}_{\text{BESS CapEx + O\&M}} \\ &+ \underbrace{\sum_{t\in\mathcal{T}} (\lambda_t + \pi_t)\, i_t}_{\text{Grid import cost}} - \underbrace{\sum_{t\in\mathcal{T}} (\iota + \rho + \pi_t)\, e_t}_{\text{Grid export revenue}} \end{aligned} \tag{3.1}$$

The first two bracketed groups of terms capture the annualized investment and fixed O&M costs for PV, wind and SMR, with capital expenditures converted to equivalent annual payments via their respective capital recovery factors AF_ℓ. The next summation term represents SMR fuel expense over all hours. The following bracketed group similarly annualizes BESS power and energy capacity costs and includes fixed BESS O&M. The positive import-cost summation and negative export-revenue summation reflect hourly grid exchanges under spot and tariff prices.

Each CapEx term is annualized using the capital recovery factor (Eq. 3.2), while OpEx terms are taken directly as yearly charges or hourly costs. This ensures that both investment and operational costs are expressed on a consistent annual basis.

3.4.2 Parameter Computation

Before detailing the operational constraints, we define the key formulas used to generate model inputs from raw data and cost parameters.

Capital Recovery Factor

$$\mathrm{AF}(r, \mathrm{LT}) = \frac{r\,(1+r)^{\mathrm{LT}}}{(1+r)^{\mathrm{LT}} - 1} \tag{3.2}$$

Equation (3.2) converts a one-time capital expenditure into an equivalent uniform annual payment over the asset lifetime LT at discount rate r.

CapEx and OpEx Treatment All investment costs $c_\ell^{\mathrm{cap}} x_\ell$ are annualized using AF, while fixed operation & maintenance charges c_ℓ^{opex} are applied directly on an annual basis.

Tariff and Price Parameters Grid subscription fee F_{sub}, hourly spot prices π_t, time-of-use tariffs λ_t, and export adjustments ι, ρ are loaded as time-series parameters and enter the objective via terms $(\lambda_t + \pi_t) i_t$ and $(\iota + \rho + \pi_t) e_t$.

PV Capacity Factor

$$T_{\mathrm{cell},t} = T_{2m,t} + \frac{G_t}{800}\,(T_{\mathrm{NOCT}} - 20), \tag{3.3}$$

$$P_t^{\max} = \frac{\frac{G_t}{1000}\,\mathrm{PR}\,\Big[1 + \gamma\,(T_{\mathrm{cell},t} - 25)\Big]}{\max_{t\in\mathcal{T}}\{\frac{G_t}{1000}\,\mathrm{PR}\}} \tag{3.4}$$

Equations (3.3)–(3.4) compute the normalized DC output per kW-p by correcting irradiance G_t for cell temperature $T_{\mathrm{cell},t}$, performance ratio PR, and temperature coefficient γ.

Wind Capacity Factor

$$v_{\mathrm{hub},t} = v_{10,t}\left(\frac{H_{\mathrm{hub}}}{10}\right)^{\alpha}, \tag{3.5}$$

$$W_t^{\max} = \frac{f_{\mathrm{curve}}\big(v_{\mathrm{hub},t}\big)}{\max\limits_{\tau\in\mathcal{T}} f_{\mathrm{curve}}\big(v_{\mathrm{hub},\tau}\big)} \tag{3.6}$$

Equation (3.5) lifts 10 m wind speeds $v_{10,t}$ to hub height H_{hub} via exponent α, and (3.6) applies the turbine's piecewise power curve:

$$f_{\mathrm{curve}}\Big(v_{\mathrm{hub},t}\Big) = \begin{cases} 0, & v_{\mathrm{hub},t} < v_{\mathrm{ci}}, \\ \left(\frac{v_{\mathrm{hub},t} - v_{\mathrm{ci}}}{v_{\mathrm{r}} - v_{\mathrm{ci}}}\right)^3, & v_{\mathrm{ci}} \le v_{\mathrm{hub},t} < v_{\mathrm{r}}, \\ 1, & v_{\mathrm{r}} \le v_{\mathrm{hub},t} \le v_{\mathrm{co}}, \\ 0, & v_{\mathrm{hub},t} > v_{\mathrm{co}}. \end{cases}$$

where v_{ci} (cut-in speed) is the minimum wind speed to generate power, v_{r} (rated speed) is the speed at which the turbine reaches its nameplate output, and v_{co} (cut-out speed) is the safety shutdown threshold. This yields the hourly capacity factor $W_t^{\max}$.

Economic Metrics

$$\mathrm{OCC}_\ell = c_\ell^{\mathrm{cap}}\, x_\ell, \tag{3.7}$$

$$\mathrm{LCOE} = \frac{Z^*}{\sum_{t\in\mathcal{T}} D_t} \tag{3.8}$$

Equation (3.7) defines the overnight capital cost as the installed capacity times unit cost, and (3.8) computes the levelized cost of electricity by dividing the optimal annualized cost Z^* by total energy served.

3.4.3 Constraints

Renewable Generation

$$g_t^{\mathrm{PV}} \le P_t^{\max}\, x_{\mathrm{PV}}, \qquad g_t^{\mathrm{W}} \le W_t^{\max}\, x_{\mathrm{W}} \quad \forall t \in \mathcal{T}. \tag{3.9}$$

These inequalities enforce that, in each hour t, PV and wind power dispatch g_t^{PV} and g_t^{W} cannot exceed the available resource scaled by installed capacities x_{PV} and x_{W}, respectively.

SMR Sizing and Dispatch

$$\mathrm{SMR}_{\min}\, y_{\mathrm{SMR}} \le x_{\mathrm{SMR}} \le \mathrm{SMR}_{\max}\, y_{\mathrm{SMR}}, \tag{3.10}$$

$$g_t^{\mathrm{SMR}} \le x_{\mathrm{SMR}} \quad \forall t \in \mathcal{T}. \tag{3.11}$$

Equation (3.10) ties the continuous SMR capacity x_{SMR} to the binary build flag y_{SMR}, enforcing a minimum and maximum size only if the SMR is constructed. Equation (3.11) then caps hourly SMR generation by that installed capacity.

BESS Operation

$$0 \le c_t \le u_t^{\mathrm{bess}}\, P_{\mathrm{BESS}}, \qquad 0 \le d_t \le (1 - u_t^{\mathrm{bess}})\, P_{\mathrm{BESS}}, \tag{3.12}$$

$$s_t = \begin{cases} s_0\, E_{\mathrm{BESS}}, & t = 1, \\ s_{t-1} + \eta\, c_{t-1} - \frac{d_{t-1}}{\eta}, & t > 1, \end{cases} \qquad 0 \le s_t \le E_{\mathrm{BESS}}, \tag{3.13}$$

$$E_{\mathrm{BESS}} = \sum_{\tau\in\{1,2,4\}} \tau\, P_{\mathrm{BESS}}\, y_\tau, \qquad \sum_\tau y_\tau = 1. \tag{3.14}$$

Constraints (3.12) limit charging c_t and discharging d_t by the power rating P_{BESS} and a binary mode-selection flag u_t^{bess}, preventing simultaneous charging and discharging. Equation (3.13) tracks the state-of-charge s_t over time, accounting for efficiency η and enforcing storage bounds. Finally, (3.14) selects exactly one duration option (1 h, 2 h or 4 h) via binaries y_τ, defining the total energy capacity E_{BESS}.

Energy Balance and Grid Exchange

$$g_t^{\mathrm{PV}} + g_t^{\mathrm{W}} + g_t^{\mathrm{SMR}} + d_t + i_t = D_t + c_t + e_t \quad \forall t \in \mathcal{T}, \tag{3.15}$$

$$i_t \le u_t^{\mathrm{grid}}\, C^{\mathrm{grid}}, \qquad e_t \le (1 - u_t^{\mathrm{grid}})\, C^{\mathrm{grid}}. \tag{3.16}$$

Equation (3.15) enforces hourly power balance: total generation plus BESS discharge and grid import must meet demand plus BESS charge and grid export. Constraints (3.16) then restrict import i_t and export e_t by the connection capacity C^{grid} and a binary import/export flag u_t^{grid}.

3.5 Component Data Inputs

In this section the key techno-economic and technical input data for each component is summarized.

3.5.1 Grid

Grid tariffs and charges were provided by a real-world Irish data center operator who requested anonymity. Their facility's constant 5 MW load and 10 MW grid connection capacity match this study's assumptions exactly, allowing direct implementation of the observed tariff structures.

Table 3.1: Emission intensity from SEAI, n.d. and the selected grid connection capacity

Parameter	**Value**	**Unit**
Connection capacity	10	MW
Grid CO_2 intensity	225	gCO_2/kWh

Table 3.2: Regulated ToU Network and Market Charges (5 MW load, 10 MW grid connection)

Charge Category	**Day**	**Peak**	**Night**
Distribution Use of System Charges			
DUoS Capacity Charge	1.368	1.505	0.218
Transmission Use of System Charges			
TUoS Network Transfer	0.335	0.335	0.335
TUoS System Service	1.886	1.886	1.886
Market Charges			
Market Operator	0.066	0.066	0.066
Imperfection Charge	1.152	1.152	1.152
Electricity Tax	0.100	0.100	0.100
Supplier Capacity Charge	1.596	1.596	1.596
Total (c/kWh)	6.5030	6.6400	5.3530
Total (€/kWh)	0.0650	0.0664	0.0535

Table 3.3: Subscription Fees and Annual Charges

Fee Type	**Value per kW**	**Unit**
DUoS Capacity Charge	35.00	€/kW/month
TUoS Network Capacity	1.66	€/kW/month
Total	36.66	€/kW/month
per year	439.86	€/kW/year
10 MW DC Connection:		
Annual subscription	4 398 600	€/year
Standing charge	4 776.39	€/year
Total annual fee	4,403,376	€/year

3.5.2 Load Profile

The load profile is assumed constant at $D_t = 5$ MW for all t, representing the data center operating at full capacity throughout the year. Hourly time steps are used in all simulations to maintain consistency with the meteorological and day-ahead price inputs.

3.5.3 Photovoltaics (PV)

The PV system is simulated using PVGIS-SARAH3 data for the Dublin site (latitude 53.415°, longitude –6.422°, elevation 61 m). An optimally tilted, south-facing crystalline-silicon array is assumed, with a slope of 40° and an azimuth of $-2°$. Hourly inputs include global horizontal irradiance G_t and ambient temperature $T_{2m,t}$, which are converted to a normalized capacity factor $P_t^{\max}$ via NOCT-based temperature corrections, a performance ratio (PR) and temperature coefficient γ. Economic inputs: Capital cost, fixed O&M and lifetime, are taken from the NREL Annual Technology Baseline (NREL, 2025c).

Table 3.4: PV data (NREL, 2025c)(Zdyb and Sobczyński, 2024)(Hudișteanu et al., 2024)

Parameter	Symbol	Value	Unit
Capital cost	$c_{\mathrm{PV}}^{\mathrm{cap}}$	1167	€/kW
Fixed O&M cost	$c_{\mathrm{PV}}^{\mathrm{opex}}$	18.54	€/kW-yr
Lifetime	$\mathrm{LT}_{\mathrm{PV}}$	30	yr
WACC	r	0.08	–
CO_2 intensity (embodied)	$e_{\mathrm{CO2}}^{\mathrm{PV}}$	41	gCO_2/kWh
Performance ratio	PR	0.83	–
Temperature coefficient	γ	–0.0052	1/°C

3.5.4 Onshore Wind

Wind capacity factors are derived from PVGIS wind speed data at 10 m height for the Dublin site (latitude 53.415°, longitude –6.422°, elevation 61 m). These 10 m speeds are adjusted to a turbine hub height of 150 m using the power law exponent $\alpha = 0.14$. A standard piecewise cubic power curve, defined by cut-in, rated and cut-out wind speeds, then converts hub-height wind speeds into a normalized capacity factor $W_t^{\max}$, which scales the installed wind capacity x_{W} in the MILP.

Turbine performance parameters are based on the Vestas V150-4.2 MW, one of the company's best-selling land-based models (Vestas, n.d.). Cut-in speed, rated speed and cut-out speed are taken from the manufacturer's specifications (TheWindPower, 2025). Although the V150 is typically installed at hub heights between 105 m and 166 m, this analysis adopts a 150 m hub height to capture a representative performance profile within that range (TheWindPower, 2025). Economic inputs: Capital cost, fixed O&M and lifetime, are taken from the NREL Annual Technology Baseline (NREL, 2025b).

Table 3.5: Wind data (NREL, 2025b)(TheWindPower, 2025)(Vestas, n.d.)

Parameter	Symbol	Value	Unit
Capital cost	$c_{\mathrm{W}}^{\mathrm{cap}}$	1221	€/kW
Fixed O&M cost	$c_{\mathrm{W}}^{\mathrm{opex}}$	27.1	€/kW-yr
Lifetime	LT_{W}	30	yr
WACC	r	0.08	–
CO_2 intensity (embodied)	$e_{\mathrm{CO2}}^{\mathrm{W}}$	11	gCO_2/kWh
Turbine Parameters			
Hub height	H_{hub}	150	m
Cut in	v_{ci}	3	m/s
Rated	v_{r}	9.9	m/s
Cut out	v_{co}	22.5	m/s
Power law exponent	α	0.14	–

3.5.5 Small Modular Reactor (SMR)

The minimum and maximum capacity bounds for the SMR ($\mathrm{SMR}_{\min}$ and $\mathrm{SMR}_{\max}$) are selected in accordance with the Small Modular Reactor classifications for near-term deployment defined by World Nuclear Association (2024). Capital costs (OCC), fixed O&M, and expected lifetime are sourced from the NREL Annual Technology Baseline, ensuring consistency with the economic assumptions for PV, wind and BESS components.

Table 3.6: SMR data (NREL, n.d.)(Pachauri et al., 2014)(World Nuclear Association, 2024)

Parameter	Symbol	Value	Unit
Capital cost	$c_{\mathrm{SMR}}^{\mathrm{cap}}$	7200	€/kW
Fixed O&M cost	$c_{\mathrm{SMR}}^{\mathrm{opex}}$	122.4	€/kW-yr
Lifetime	$\mathrm{LT}_{\mathrm{SMR}}$	60	yr
WACC	r	0.08	–
Fuel cost	f_{fuel}	0.007	€/kWh
Minimum size	$\mathrm{SMR}_{\mathrm{min}}$	40	MW
Maximum size	$\mathrm{SMR}_{\mathrm{max}}$	3000	MW
CO_2 intensity (oper.)	$e_{\mathrm{CO2}}^{\mathrm{SMR}}$	12	gCO_2/kWh

3.5.6 Battery Energy Storage System (BESS)

All BESS economic parameters, overnight capital cost (OCC), fixed O&M and lifetime, are sourced from the NREL Annual Technology Baseline (NREL, 2025a). NREL provides a combined OCC for a reference 4 h battery, which is disaggregated into separate energy capacity and power capacity costs, allowing the model to select among 1 h, 2 h and 4 h duration options. The admissible ranges for BESS power and energy capacities, as well as the available duration options, are specified by ABB.

Degradation expenses are covered through a fixed O&M cost (FOM) rather than variable operating charges, hence BESS degradation is not specifically modeled in section 3.4. FOM is sized to compensate for calendar and cycle fade, ensuring that the system retains its rated performance over a 15-year lifetime (NREL, 2025a). NREL estimate FOM costs at 2.5% of capital costs per kW.

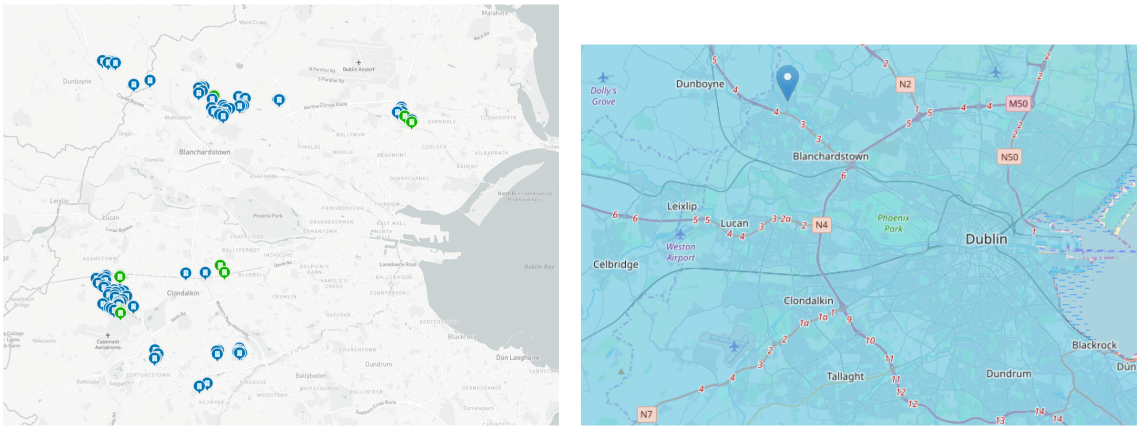
Table 3.7: BESS data (NREL, 2025a)

Parameter	Abbreviation	Value	Unit
Power capital cost	c_P^{cap}	675	€/kW
Energy capital cost	c_E^{cap}	165.6	€/kWh
Power fO&M	c_P^{opex}	16.9	€/kW-yr
Energy fO&M	c_E^{opex}	4.11	€/kWh-yr
Lifetime	$\mathrm{LT}_{\mathrm{BESS}}$	15	yr
WACC	r	0.08	–
Efficiency (round-trip)	η	0.95	–
Duration options	$\tau \in \{1, 2, 4\}$	—	h
Min/Max power	$P_{\mathrm{min}}, P_{\mathrm{max}}$	0.5/20	MW
Min/Max energy	$E_{\mathrm{min}}, E_{\mathrm{max}}$	0.5/80	MWh

3.6 Site Selection

The site for the hypothetical data center was chosen in consultation with ABB to reflect a realistic Dublin deployment. Figure 3.1 (left) maps the locations of existing data centers across the Dublin metropolitan area. To ensure representativeness, the candidate site was placed within the urban envelope where most facilities are concentrated.

Figure 3.1 (right) and Table 3.8 shows the precise coordinates selected for analysis. This point also serves as the origin for all meteorological inputs (hourly wind speeds and solar irradiance from the PVGIS-SARAH3 database of the European Commission). While this choice resembles a typical data center siting, detailed land use restrictions for PV, wind, SMR, and BESS installations in the immediate vicinity were not explicitly modeled.



(a) Data centers currently operating in Dublin (DataCenterMap)

(b) Selected site for climate data extraction (European Commission, n.d., 2024)

Figure 3.1: Overview of data center distribution and chosen site in Dublin, Ireland.

Table 3.8: Selected site attributes

Attribute	Value
Latitude	53.415° N
Longitude	–6.422° W
Elevation	61 m a.s.l.

3.7 Ethical Considerations and Study Validity

All quantitative modeling exercises carry ethical responsibilities around transparency, validity, and fairness. This work draws on publicly available spot price data, weather data, and cost assumptions for each technology. All data sources, parameter selections, and modeling simplifications are fully documented to ensure transparency and guard against undisclosed bias. The technology scope of solar PV, onshore wind, SMRs, and lithium-ion BESS, was selected both for its growing prominence in on-site power applications and to investigate the competitiveness of SMRs and battery storage specifically. Other technologies (diesel generators, hydrogen, geothermal) were excluded from this analysis but are suggested for future research.

Data validity is a key ethical concern. As Bell et al. (2022) observes, the credibility of any quantitative study depends on having sufficient sample sizes and observation durations to capture real-world variability. Relying on a single calendar year of Irish spot prices from ENTSO-E and PVGIS weather profiles therefore carries a risk of overfitting. An unusually windy or calm year could skew optimal capacity recommendations. To mitigate this, spot-price sensitivity and volatility-sensitivity scenarios (section 4.3) explore a range of alternative market conditions, while the 10×Scale case (subsection 4.3.1) tests model behavior under dramatically different load levels.

Another ethical dimension lies in model assumptions that abstract away detailed technical or social factors. The constant 5 MW (or 50 MW) load profile omits any demand-side flexibility available to modern data centers, and the uniform 8% WACC applies the same financing cost to all technologies regardless of their real-world risk profiles. These choices simplify the MILP formulation (section 3.4), but they also introduce blind spots that could mislead planners if taken without scrutiny. By stating these assumptions up front and framing them as deliberate trade-offs, the study aims to respect the ethical imperative of informed decision-making.

Finally, this research was conducted in collaboration with ABB. While ABB and ABB related companies provided access to proprietary data and domain expertise, independent validation, through alignment with NREL projections, academic literature, and Irish market reports, has been pursued at every step. All code, data transformations, and sensitivity sweeps are archived to enable full reproducibility. In this way, the study upholds ethical standards of transparency, accountability, and methodological rigor, ensuring that its conclusions can be fairly evaluated by both industry stakeholders and the broader research community.

4

Results

This chapter presents the MILP-based optimization results in three parts. Section 4.1 compares two benchmark configurations: "Grid Only," in which the 5 MW load is met entirely by grid imports, and "Cost Optimal," which co-optimizes unconstrained investments in PV, wind, SMR, BESS, and grid exchange to minimize annualized life-cycle cost. Section 4.2 illustrates the value of demand response participation, detailing the program assumptions and modeling approach before quantifying BESS-specific revenues and overall system impacts. Section 4.3 then examines the robustness of the Cost Optimal design through six sensitivity studies, evaluating how key uncertainties reshape capacity portfolios, dispatch patterns, cost components, and key metrics (ALCC, LCOE, self-sufficiency, CO2 reduction) under prevailing regulatory and market conditions.

4.1 Benchmark Configurations: Cost Optimal & Grid Only

This section presents the optimal installed capacities, the key economic and technical performance indicators, and a high-level view of system dispatch. The Cost Optimal scenario is the unconstrained ALCC minimization within technology bounds for the 5 MW Dublin data center. Moreover, this scenario is compared to the Grid Only case of supplying the 5 MW load with grid imports only.

Table 4.1: Optimal installed capacities (Cost Optimal case)

Technology	**Capacity**	**Unit**
Photovoltaic (PV)	19.8	MW
On-shore Wind	10.6	MW
Small Modular Reactor (SMR)	0.0	MW
Battery Power Capacity	0.0	MW
Battery Energy Capacity	0.0	MWh

The optimal sizing allocates 19.8 MW to PV and 10.6 MW to wind, with no capacity chosen for SMR or BESS. This indicates that, at current cost and tariff levels, on-site renewables plus grid imports minimize total annualized cost. Introducing firm generation or storage could reduce dependence on grid imports and improve supply security under alternative market conditions.

Table 4.2: Comparison of selected metrics between Grid Only and the Cost Optimal scenario for powering the 5 MW data center load

Metric	**Grid Only**	**Cost Optimal**	**Unit**
ALCC	12.34	10.96	M€/year
LCOE	0.282	0.250	€/kWh
CO_2 Emissions	11 169	6793	tCO_2/year
Self-Sufficiency	0	48.2	%
Initial CAPEX	0	36.1	M€
O&M	0	0.65	M€/year
Grid Fees	12.34	8.61	M€/year
Electricity Imported	38	22.7	GWh/year
Electricity Exported	0	13.3	GWh/year
Peak Grid Import	5	5	MW
Hours with Grid Import	8760	5995	h/year

Table 4.2 compares the Grid Only case with the Cost Optimal scenario, the latter being the configuration that the MILP model identifies as minimizing total annualized cost. Under Grid Only, the system incurs an ALCC of 12.34 M€/year and an LCOE of 0.282 €/kWh, with 38 GWh met entirely by imports and 11 169 tCO2 emitted. In contrast, the Cost Optimal design reduces ALCC to 10.96 M€/year and LCOE to 0.250 €/kWh, cuts CO2 emissions by 39% to 6 793 tCO2, and achieves a 48% self-sufficiency rate, exporting 13.3 GWh of excess renewable generation. These results highlight the economic and environmental advantages of integrating on-site PV and wind, justifying a deeper analysis of price and technology sensitivities in subsequent sections.

Figure 4.1 and Figure 4.2 show the MILP's hourly dispatch for representative spring and winter days, respectively, within the full 8 760-hour annual optimization horizon. The black dots trace the constant 5 MW load. On-site generation (PV in yellow, wind in blue) is plotted "downward" from that 5 MW level, bars from 5 MW down to 0 MW meet the load, while any extension below 0 MW indicates exports back to the grid. Conversely, gray bars above the 5 MW load line show net imports when renewable output is insufficient. Together, these charts give a view of exactly when and how the model calls on each asset to satisfy demand, export surplus, or import shortfalls.

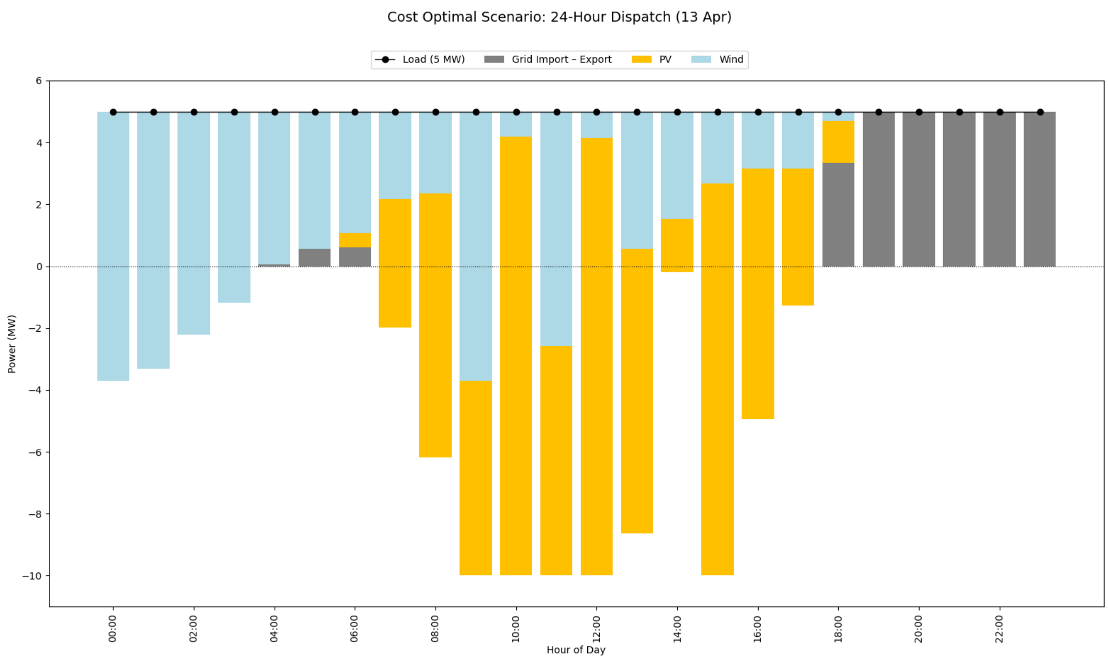


Figure 4.1: Illustrative 24hr dispatch scenario for a typical spring day in Dublin, Ireland.

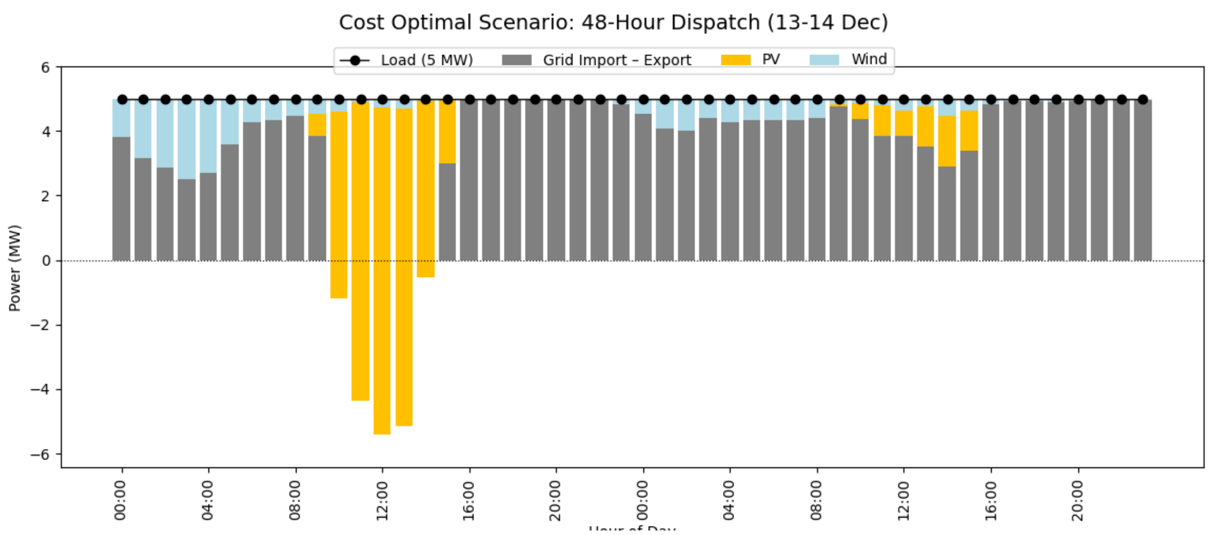


Figure 4.2: Illustrative 48hr dispatch scenario for a typical winter day in Dublin, Ireland.

4.2 Demand Response Program Example

Systems with diverse generation assets, including battery energy storage systems, can earn incremental revenue by reducing their load at the request of the grid operator. However, detailed tariff structures and program rules for demand response (DR) offerings are often not disclosed. DR programs vary by region, but many share similar peak windows and short-notice call requirements. This section uses Arizona Public Service Company's Peak Solutions Day-Of program as a concrete case study. APS's Day-Of program runs between June 1 – September 30 in 2025. Events are issued with 60 minutes of notice, and the events can be called anywhere between 16:00 and 21:00, for a duration of 1 to 5 hours. Participants are compensated for both capacity and energy reductions. The APS-defined peak demand window closely mirrors the peak demand window in Ireland (ToU peak is between 17:00-19:00), making the APS Peak Solutions program applicable to the system investigated in this thesis.

4.2.1 Guidelines and Modelling Assumptions

The APS program allows customers to earn revenue for being available to curtail load on short notice when the grid is stressed. They offer two categories in the program; APS Peak Solutions Day-Of and APS Peak Solutions Day-Ahead. This thesis will demonstrate the potential returns of participating in the former APS Day-Of Program.

Table 4.3: APS Day-Of Program Guidelines and Modelling Assumptions (DOE, 2024)

Parameter	Source	Value
Program Guidelines		
Enrollment period	Official	June 1 – September 30
Notice	Official	60 min prior
Call window	Official	16:00–21:00
Event duration	Official	1–5 h
Max. consecutive days	Official	3
Capacity payment	Official	$40/kW
Energy payment	Official	$0.09/kWh
Penalties	Official	None
Modelling Assumptions		
Number of events	Assumed	20
Fixed BESS power	Assumed	4 MW
Fixed BESS energy	Assumed	16 MWh
Baseline method	Assumed	5-of-10 on *net_import*
Notice reserve	Assumed	1 h of full-power SoC (4MWh)
Event selection	Assumed	Daily highest *net_import*
Currency conversion	Assumed	USD to EUR 0.9

To implement these rules in the model, the BESS is hard-fixed at 4MW/16MWh, and up to 20 events are selected, one per day on the hour of highest net import (no more than three consecutive days in accordance to the guidelines of the program). Each event's start time is drawn from the 16:00–20:00 window and its durations were treated as uncertain and uniformly distributed between 1 h and 5 h, truncated to ensure completion by 21:00, reflecting real world uncertainty in call length. Each event's baseline import is estimated by the "5-of-10" X-of-Y method: Of the ten most

recent non-event observations at the same clock-hour, the five highest are averaged to represent the uncurtailed load (Glass, Suffian, Scheer, and Best, 2022)(Braithwait, 2019). If fewer than ten prior points exist, a simple same-hour mean is used.
To capture APS's 60 min notice, a constraint was developed oulining exactly one hour worth of full power SoC immediately before each potential start, while allowing the battery to arbitrage freely at other times of the day outside the APS window.
Because APS gives only 60 minutes' notice, the model enforces a one-hour headroom reserve immediately before each potential event start: the battery's state-of-charge at notice time must be at least 4 MWh (4 MW for one hour). Outside the 16:00–21:00 DR window it may arbitrage freely, so in practice the BESS often arrives with more than 4 MWh stored. Any energy above the 4 MWh reserve can be deployed during multi-hour calls, which is why some 2–5 h events in the deterministic run (Table 4.4) still yielded capacity and energy payments. However, once that total stored energy (reserve + extra arbitrage) is exhausted, actual import equals the baseline, and if this occurs before a longer call finishes (e.g. only three hours of headroom for a four-hour event), the system cannot participate in the final hour and receives no payment for the event. This "one-hour insurance policy" necessarily sacrifices some arbitrage value in the hour before notice, since the battery could otherwise chase low or negative prices in exchange for guaranteed full-power (4 MW) capacity payment. It balances DR readiness against energy-arbitrage earnings, and explains both the non-zero payouts on longer events (when extra SoC is available) and the zero-payment outcomes when available headroom runs out.

Finally, capacity and energy payments are set at €36 per kW of claimed capacity and €0.081 per kWh of actual curtailed energy (USD rates converted at 0.9). For each event: The capacity payment is computed as

$$\text{€}36 \times \min\Big(\underbrace{\text{baseline import}}_{\substack{\text{expected import if no}\\ \text{curtailment occurs}}},\ \underbrace{\text{physical headroom}}_{\substack{\text{maximum possible load}\\ \text{reduction given available}\\ \text{renewables + BESS}}}\Big).$$

In other words, if the baseline suggests 500kW of grid import, but the battery+renewables can only reduce 400kW that hour, the capacity claim is 400kW.

The energy payment is computed as

$$\text{€}0.081 \times \underbrace{\Big(\text{baseline import} - \text{actual import}\Big)}_{\substack{\text{actual curtailed energy}\\ \text{(kWh) during the event}}}.$$

Here "baseline – actual import" gives the kWh actually reduced in that hour (e.g. if baseline = 500kW but actual import falls to 100kW, then 400kWh was curtailed). Thus total DR payment = (capacity claim × €36/kW) + (curtailed energy × €0.081/kWh).

4.2.2 Results of Participation

Table 4.4 and Figure 4.3 present the outcomes from the 20 selected APS Day-Of calls, showing claimed capacity, energy curtailed, and resulting payments. To evaluate the stability of these results under uncertain event durations, Table 4.5 reports the distribution of total DR revenues from 1 000 Monte Carlo simulations.

Table 4.4: Aggregate DR Participation Results (Single-Run Deterministic Scenario)

Metric	Value
Total events	20
Zero-payment events	10
Average event duration (h)	2.7
Total claimed capacity (kW)	8 543
Total energy curtailment (kWh)	57 503
Capacity payments (€)	307 560
Energy payments (€)	4 658
Total DR revenue (€)	**312 218**

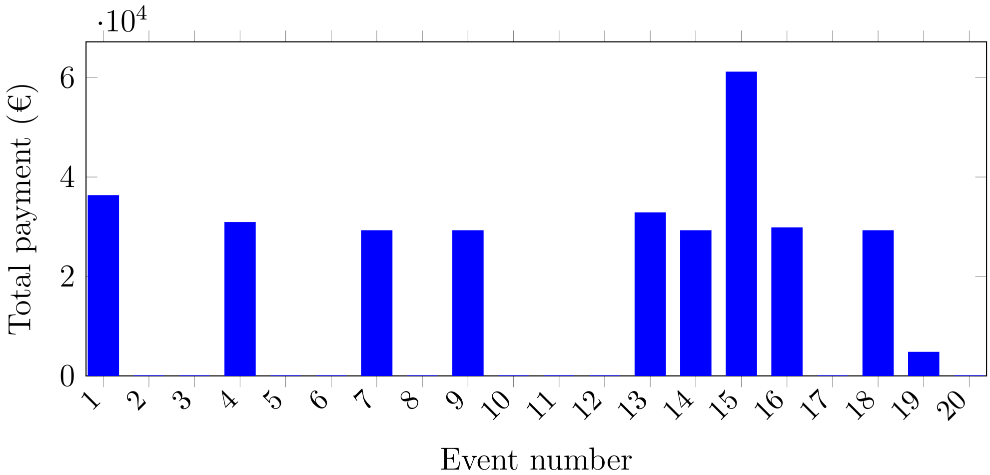


Figure 4.3: Total DR payment per event (capacity + energy).

To quantify the impact of random event durations on total DR revenue, a Monte Carlo sampling of 1 000 runs was performed. In each run, event lengths were drawn uniformly from 1–5 h (then truncated to finish by 21:00) and total revenue recalculated. Table 4.5 summarizes the resulting distribution of total DR revenues. In contrast to the Monte Carlo mean of €461 670 (95 % CI: ±€6 156), the original single-run result of €312 218 falls well below the lower confidence bound. This indicates that the particular sequence of longer, low-headroom events in the deterministic run was an outlier, producing an unusually low revenue. It underscores the importance of a stochastic sensitivity analysis and relying on a single deterministic run can be misleading. Decision makers in similar DR programs should therefore base their planning on the Monte Carlo-estimated mean revenue (~€462 k for this program) rather than on any one scenario outcome.

Table 4.5: Stochastic sensitivity analysis via Monte Carlo sampling (1000 runs): total DR revenue

Statistic	**€**
Mean total DR revenue	461 670
Standard deviation	99 326
95% CI half-width	6 156

In the base (Cost Optimal 5 MW data center) scenario, the optimizer chose 19.8 MW of PV and 10.6 MW of wind, with no BESS or SMR. To evaluate DR participation, remember that a 4MW/16MWh BESS was hard-fixed purely to illustrate the revenue potential of joining the program (i.e. the battery was forced into the mix, not chosen by the model). Under this "forced-BESS" setup, the solver increased PV capacity to 24.1 MW and trimmed wind by just a few kilowatts, ensuring enough headroom (from either surplus renewables or grid import) to top up the battery before DR calls, without substantially altering the overall resource mix.

4.2.3 BESS-Specific Revenue from Program Participation

To reiterate, this illustrative exercise shows how a data center's energy infrastructure can participate in and capture DR payments. The load reduction the system delivers is due to both the available renewables (wind + PV) and the BESS. An interesting aspect of this is to isolate the BESS contribution to program participation, it was done the following way:

1. For each DR call between June 1 and September 30, the model's hourly dispatch output was used to determine the exact energy (kWh) discharged by the BESS and the capacity (kW) it pledged, alongside the contributions from PV and wind.

2. Each event's combined energy- and capacity-payments was split according to the BESS's share of delivered kWh and pledged kW. For example, if the battery supplied 70% of an event's curtailed energy and 80% of its pledged capacity, it was allocated 70% of that event's energy payment and 80% of its capacity payment.

3. Summing the BESS specific payments across all events produced €400 585 of the €461 670 total DR revenue, about 87% of the four-month earnings. If the program would be live for the full year, the annualized payments would amount to roughly €300.5/kW of installed storage capacity.

4.3 Sensitivity analysis

To deepen the insights from the base case (section 4.1) and the APS program results (section 4.2), six targeted sensitivity studies are conducted to explore key uncertainties affecting the optimal on-site energy portfolio. Each analysis isolates one variable:

data center load size, technology costs, market prices, or revenue and cost thresholds, to assess how deviations from base assumptions reshape capacity investments, dispatch patterns, and key metrics such as ALCC, LCOE, and self-sufficiency.

4.3.1 Scale Sensitivity (10×Scale, 50 MW load)

To evaluate how a substantially larger data center would alter the optimal design, a 10×Scale sensitivity was performed: all demand and technology bounds (PV, wind, BESS, grid connection, subscription fees) are multiplied by ten to serve a 50 MW load instead of 5 MW. This "10×Scale" case tests whether a larger demand, near the 40 MW minimum size for SMR, would change the cost-optimal mix. In practice, many commercial and hyperscale data centers far exceed 5 MW, so, examining a 50 MW facility offers an alternative planning scenario for on-site generation and storage.

Table 4.6: Optimal Installed Capacities: 5 MW vs. 50 MW Case

Technology	5 MW Load	50 MW Load	Unit
PV capacity	19.8	0	MW
Wind capacity	10.6	0	MW
SMR capacity	0	150	MW
BESS power	0	0	MW
BESS energy	0	0	MWh

The result is a pure-SMR solution: a 150 MW SMR plant is installed, with no PV, wind, or battery storage selected. Table 4.7 compares this configuration's economic and technical metrics against a baseline "Grid Only" case in which the 50 MW load is supplied entirely via grid imports. For comparison, the table also shows the 5 MW "Grid Only" and "Cost Optimal" results.

Table 4.7: Selected metrics for comparison between the 5 MW and 50 MW case

	5 MW Load		50 MW Load		
Metric	**Grid Only**	**Cost-Optimal**	**Grid Only**	**Cost-Optimal**	**Unit**
ALCC	12.34	10.96	123.37	51.94	M€/yr
LCOE	0.282	0.250	0.282	0.119	€/kWh
CO_2 emissions	11 169	6 793	111 690	15 616	tCO_2/yr
Self-Sufficiency	0	48.2	0	100	%
Initial CAPEX	0	36.10	0	1 080	M€
Fixed O&M	0.00	0.65	0.00	18.36	M€/yr
Grid Fees	12.34	8.61	98.72	43.99	M€/yr
Electricity imported	38.00	22.70	350.0	0	GWh/yr
Electricity exported	0.00	13.30	0.0	863.3	GWh/yr
Peak grid import	5.00	5.00	10.0	0	MW
Hours with grid import	8 760	5 995	8 760	0	h/yr

Table 4.7 demonstrates that scaling the system to ten times its base load delivers substantial operational and environmental benefits, but requires a much larger up-front investment. Under the 10×Scale scenario, the annualized life-cycle cost (ALCC) drops to €51.94 M/yr from €123.37 M/yr (Grid Only) or, by comparison, to €10.96 M/yr in the 5 MW cost optimal case. On a per-MW basis, ALCC falls from roughly €2.19 M/MW-yr (5 MW design) to €1.04 M/MW-yr (50 MW design). Likewise, LCOE halves from €0.250/kWh (5 MW cost-optimal) to €0.119/kWh at 50 MW.

Carbon emissions per year plunge to 6 793 tCO2 for the 5 MW cost-optimal and to 15 616 t CO2 at 50 MW, a roughly 1 359 tCO2/MW-yr in the smaller system and 312 tCO2/MW-yr for the larger system. The 5 MW configuration relied on 19.8 MW of PV and 10.6 MW of wind (CAPEX €36.1 M), exported 13.3 GWh/yr, and imported 22.7 GWh/yr. In contrast, the 50 MW design installs a single 150 MW SMR (CAPEX €1 080 M), exports 863 GWh/yr, and achieves zero grid imports, assuming unconstrained export capability for the SMR.

Thus, moving from 5 MW to 50 MW not only cuts unit cost and carbon intensity by more than half but also shifts the technology mix from a PV/wind-dominated system to a pure-SMR solution. The trade-off is a roughly 30× larger capital outlay (from €36 M to €1 080 M), illustrating both economies of scale and how high load could drive on-site nuclear deployment in a forward-looking Irish data center, assuming future shifts in regulatory policy. In practice, grid connection limits or distribution constraints might restrict how much of that 863 GWh/yr surplus can actually be sold back to the network.

4.3.2 BESS Adoption under Projected Cost Trajectories

In the base Cost Optimal scenario, using 2025 overnight cost of capital (OCC) and fixed O&M for PV, wind and BESS, and for the SMR using the earliest NREL ATB estimate of $8 000/kW and $122.4/kW-yr, only PV and wind enter the least-cost portfolio. This chapter asks:

> *If one were to commission the project in each year from 2025 through 2030, will BESS become part of the cost optimal mix, if so, in which year?*

All technologies follow the NREL ATB cost trajectories; SMR costs remain fixed at the 2030 NREL values of $8 000/kW OCC and $136/kW-yr O&M since this is the earliest value introduced in the NREL data (NREL, 2024). Table 4.8 summarizes OCCs and fixed O&M costs used in this analysis.

Table 4.8: Projected cost assumptions for PV, wind and BESS (2025–2030) (NREL, 2024).

Year	PV		Wind		BESS	
	OCC ($/kW)	fO&M ($/kW-yr)	OCC ($/kW)	fO&M ($/kW-yr)	OCC ($/kW)	fO&M ($/kW-yr)
2025	1297.0	20.6	1357.0	30.1	1486.0	37.2
2026	1228.0	19.8	1319.0	29.4	1433.0	35.8
2027	1160.0	19.0	1281.0	28.6	1379.0	34.5
2028	1091.0	18.2	1242.0	27.8	1325.0	33.1
2029	1022.0	17.4	1204.0	27.0	1272.0	31.8
2030	953.0	16.6	1166.0	26.3	1218.0	30.5

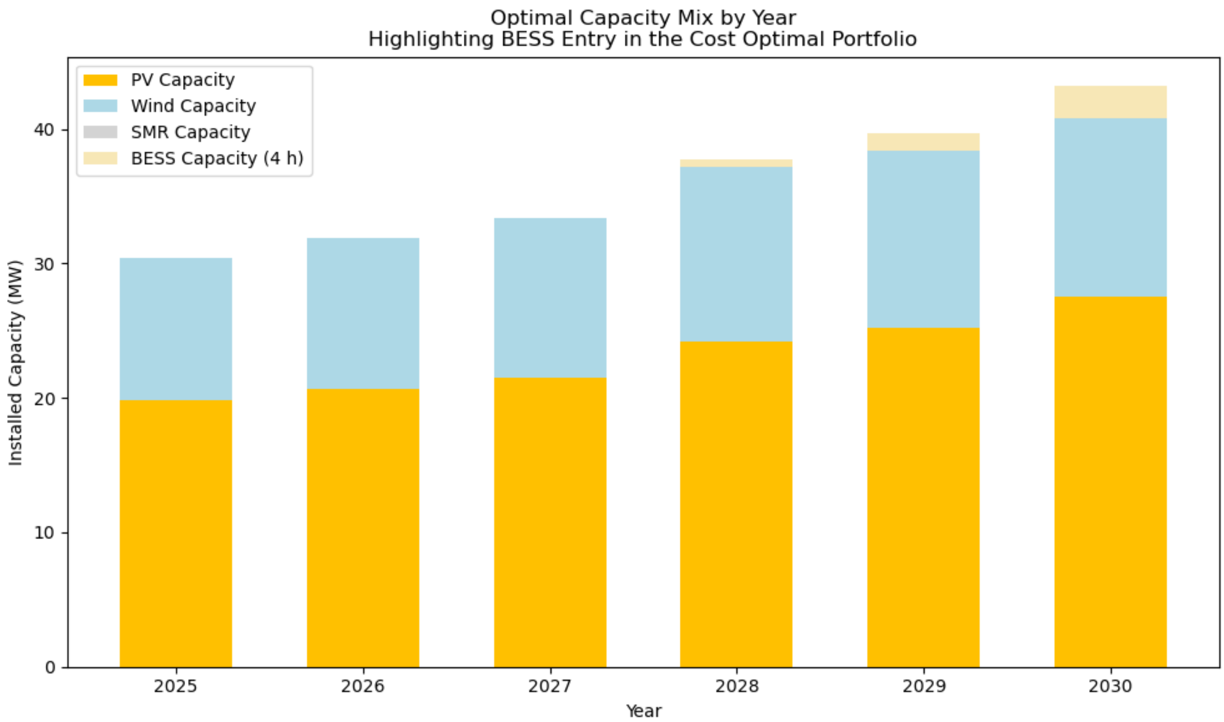


Figure 4.4: Optimal investment capacity mix assuming a new build in each year from 2025–2030, showing the cost-minimizing PV, wind, SMR and BESS power ratings under projected resource cost trajectories.

Figure 4.4 shows the evolution of the cost-optimal capacity mix (i.e. the combination of PV, wind, SMR and BESS that minimizes the annualized life-cycle cost) from 2025 through 2030 under NREL ATB cost trajectories. In this analysis, all overnight cost of capital (OCC) and fixed O& M inputs are stepped forward according to their projected cost rates, so investors can see not only if but when BESS finally "breaks through," and also how the falling costs of PV and wind reshape the least-cost portfolio over time. In particular, although PV and wind continue to grow each year, it is only in 2028, when battery costs have fallen by roughly 10.8% from their 2025 levels, that BESS enters the capacity mix (0.56 MW/2.26 MWh). Thus, Figure 4.4 signals 2028 as the earliest year in which grid connected battery storage becomes economically justified under the combined cost trends. [in discussion: Keep in mind, the BESS revenue stack only includes energy arbitrage in this scenario].

Table 4.9: Optimal installed capacities with 2028 cost levels

Technology	Capacity	Unit
Photovoltaic (PV)	24.20	MW
Onshore Wind	13.00	MW
Small Modular Reactor (SMR)	0.0	MW
Battery Power Capacity	0.56	MW
Battery Energy Capacity	2.26	MWh

Adding BESS increases system self-sufficiency by approximately five percentage points, climbing from about 48% in the 2025 cost optimal scenario to roughly 53% under 2028 cost assumptions.

To show how each asset is dispatched "under the hood", Figure 4.5 presents a representative 48-hour winter dispatch for the 2028 cost-optimal mix, building on the spring and winter examples in Figure 4.1 and Figure 4.2.

In this plot:

- Pale-yellow bars above the 5 MW load line indicate BESS charging (drawing from the grid or on-site surplus).

- Pale-yellow bars below the line show BESS discharging into the load.

Notice that between 08:00–10:00 on the 12th, the battery charges from PV/wind surplus, whereas during 01:00–04:00 on the 11th, when spot prices dip, the MILP chooses to charge the BESS from the grid.

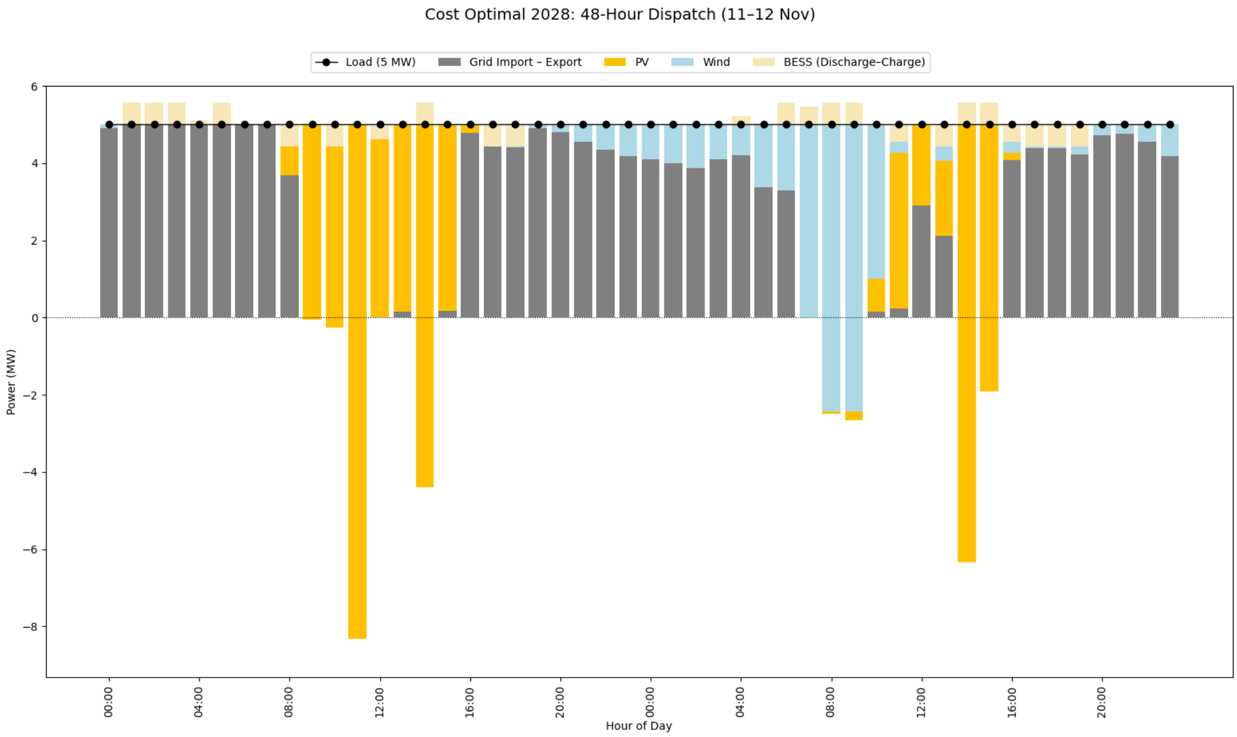


Figure 4.5: Cost optimal capacities in 2028, showcased in a winter period of 48 hours with climate data from 2023 in Dublin, Ireland.

4.3.3 Spot Price Sensitivity

To assess how varying wholesale prices alter the cost-optimal asset mix from section 4.1, first any negative hourly spot prices are set to zero and then multipliers ranging from 50% to 200% of 2023 Irish spot levels are applied. For each multiplier, the MILP re-optimizes the mix of PV, wind, SMR, and BESS, minimizing annualized life-cycle cost. Figure 4.6 displays the resulting installed capacities for each price factor.

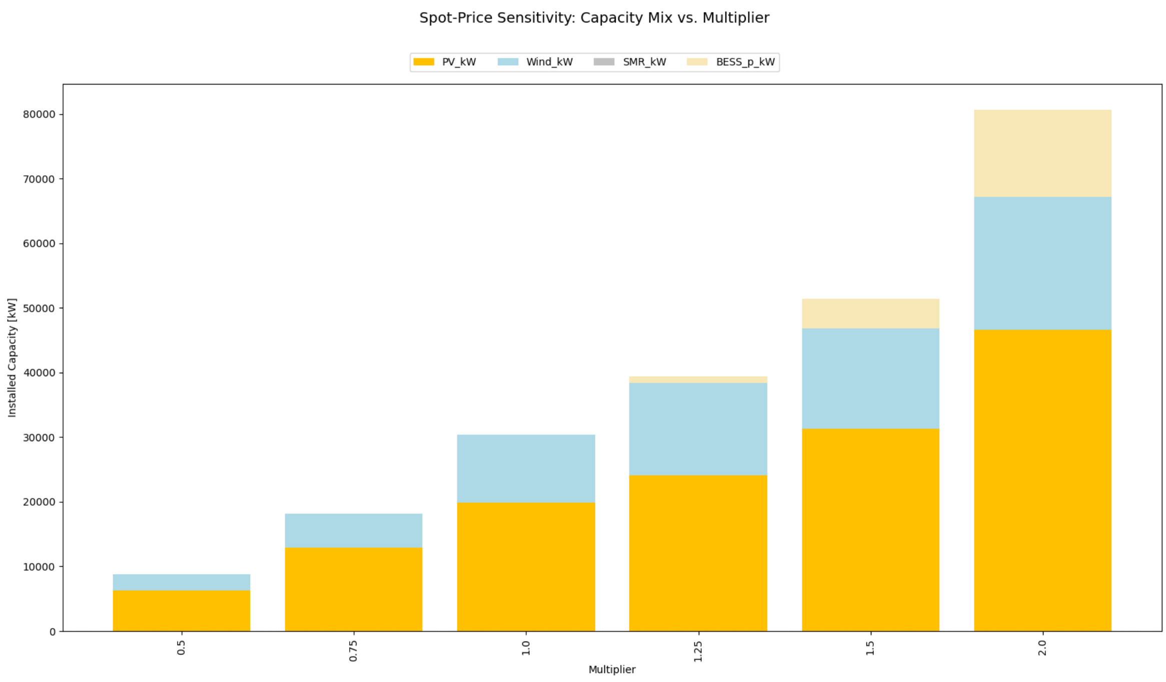


Figure 4.6: Optimal capacity mix (PV, wind, SMR, BESS) under spot price multipliers of 0.5×–2.0× relative to 2023 Irish wholesale prices for a 5 MW constant load.

Under lower price scenarios (0.5×–1.0×), only renewables and grid import appear, with no SMR or storage. At roughly 1.25×, a small battery (~1 MW/4.1 MWh) becomes economical. Beyond 1.5×, BESS capacity grows rapidly, to 4.6 MW at 1.5× and 13.4 MW at 2.0×. THis indicates that storage only pays its way when the price spread is large enough to cover its capital cost.

Table 4.10 summarizes the corresponding ALCC and LCOE under each multiplier.

Table 4.10: ALCC and LCOE under zero-floored price scenarios

Multiplier	ALCC (M€/yr)	LCOE (€/kWh)
0.50	9.57	0.219
0.75	10.44	0.238
1.00	10.96	0.250
1.25	11.20	0.256
1.50	11.18	0.255
2.00	10.35	0.236

Up to 1.0×, adding only PV and wind drives ALCC upward from 9.57 M€/yr (0.5×) to 10.96 M€/yr (1.0×). At 1.25×, introducing a 1 MW/4.1 MWh BESS raises ALCC to its peak of 11.20 M€/yr (and LCOE to 0.256 €/kWh). As the multiplier increases to 1.50×, arbitrage revenues begin offsetting storage costs, nudging ALCC down to 11.18 M€/yr (LCOE 0.255 €/kWh). At 2.00×, a larger 13.5 MW/53.6 MWh battery becomes justified, pulling ALCC to 10.35 M€/yr and LCOE to 0.236 €/kWh. In summary, battery storage can reduce total cost but only once spot prices surpass the threshold needed to justify progressively larger BESS investments.

Note: All figures assume zero-floored prices and account solely for energy arbitrage revenue coming from the battery storage. Demand response or ancillary service payments are excluded in this sensitivity.

4.3.4 Spot Price Volatility

Building on the Cost Optimal case from Section 4.1, this subsection examines how scaling the intensity of hourly price swings, while holding the annual average constant, affects optimal capacity choices. A mean-preserving spread transformation multiplies deviations from the historical mean by 50%, 150% and 200% (with all negative prices floored at zero), and the model is re-solved for each volatility level to update the PV, wind, SMR and BESS mix.

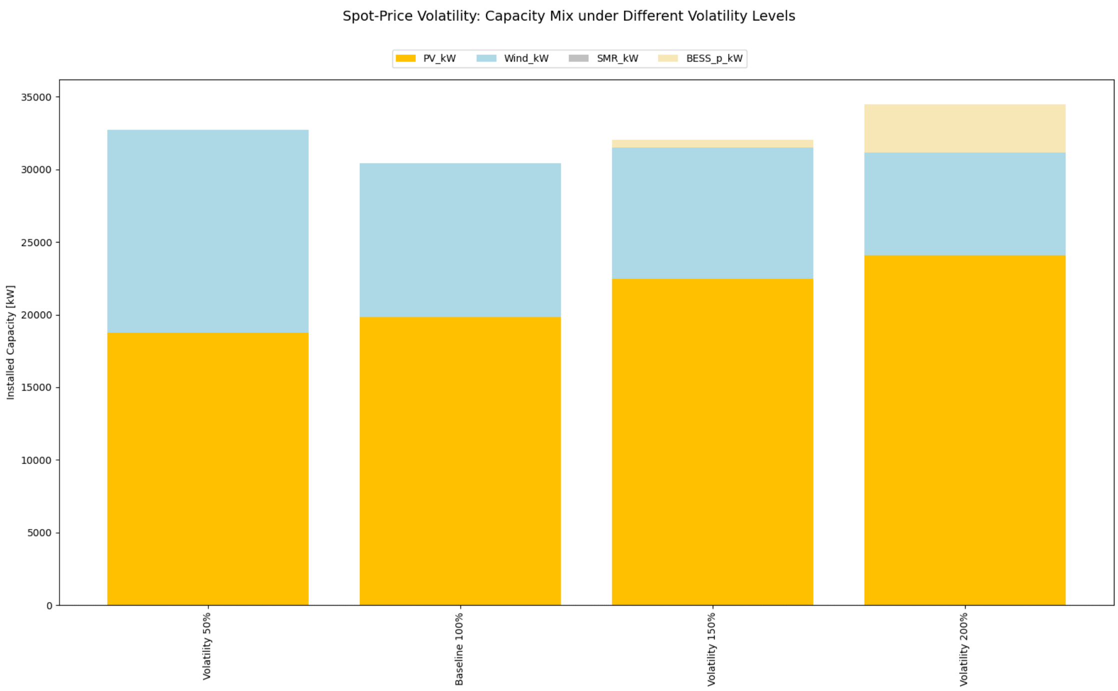


Figure 4.7: Optimal capacity mix (PV, wind, SMR, BESS) under each volatility level.

Under reduced volatility (50%) the result mirrors Section 4.1, with only PV and wind built. At baseline volatility (100%) the original cost optimal capacities reappear. As volatility rises to 150% and 200%, battery storage becomes attractive, a small battery (0.5MW/2MWh) appears at 150%, growing to 3.3MW/13.2MWh at 200%. Solar capacity also increases while wind declines, reflecting that sharper daytime price peaks favor a combination between solar and storage. This demonstrates that, even if average prices stay the same, greater price volatility by itself can justify investments in flexible resources.

Table 4.11: Cost metrics under zero-floor spot price volatility

Volatility	ALCC (M€/yr)	LCOE (€/kWh)
50%	10.77	0.246
100%	10.96	0.250
150%	11.07	0.253
200%	11.08	0.253

Table 4.11 shows that increasing price volatility has only a modest impact on overall system cost. ALCC rises from 10.77 M€/yr at 50% volatility to a peak of 11.08 M€/yr at 200%. Likewise, LCOE increases slightly from 0.246 €/kWh to 0.253 €/kWh, reflecting the small capital cost of adding flexible storage relative to the additional arbitrage value captured. These results confirm that while higher volatility does justify incremental storage investment, the effect on average cost and unit energy price remains contained within a narrow spectrum.

4.3.5 BESS Revenue Threshold Analysis

The absence of any battery in the Cost Optimal case could stem from a narrow revenue stack (energy arbitrage only) or insufficient spot price spreads in 2025. In reality, BESS operators combine arbitrage with capacity, frequency and demand response services (see subsection 2.5.1). Rather than selecting a specific revenue stack, this sensitivity simply asks:

> *How much total annual revenue must a battery earn to become economic in the 2025 Cost Optimal 5 MW data center model?*

A uniform per-unit cost offset (i.e. a "credit") is applied to both power and energy capex, with the credit gap halved at each iteration until the model first installs a battery. The resulting credit level represents the break-even subsidy required to trigger any storage build. The obtained break-even point resulted in:

Table 4.12: Break-even total BESS revenue threshold for the 2025 Cost Optimal case

Metric	Value	Units
Break-even "other services" credit	75.0	€/kW-yr
Model selected BESS power	784	kW
Model selected BESS energy	3 134	kWh
Energy arbitrage revenue (base case)	55 101	€/yr
Total revenue required (€/yr)	**113 873**	€/yr

At the break-even point the battery earns 70.3 €/kW-yr from arbitrage plus 75 €/kW-yr of other services, for a total of 145.3 €/kW-yr (~€114 k/yr for a 784 kW unit).

This result provides a clear target: If the sum of the BESS revenue stack (capacity payments, frequency or reserve revenues, demand response earnings and arbitrage) generates at least €145 per kW-yr, a storage asset becomes cost-optimal. Otherwise, the Cost Optimal model will continue to omit BESS under 2025 market conditions.

4.3.6 SMR Cost Threshold Analysis (10×Scale)

Building on the 10×Scale scenario (subsection 4.3.1), with 50 MW load, a gap-based binary search was used to identify the highest SMR overnight capital cost (OCC) at which any SMR capacity remains economic. Starting from a base OCC of €7 200/kW and an upper bound of 3× that value, a uniform cost "gap" was applied and then halved at each iteration. At every step the model was resolved and the gap narrowed until SMR capacity dropped to zero. The final gap value therefore defines the break-even OCC threshold for economic viability.

Table 4.13: Break-even SMR capital cost and resulting capacities

Metric	Value
Base SMR OCC	€ 7 200/kW
Break-even SMR OCC	€ 13 219 /kW
Installed capacities at break-even	
PV capacity	198 MW
Wind capacity	106 MW
SMR capacity	0 kW
BESS power / energy	0 kW / 0 kWh
Grid connection capacity	100 MW

Once SMR OCC exceeds roughly € 13 219/kW, the solver abandons SMR entirely and allocates all firm capacity to renewables (with no battery), relying on the 100 MW grid connection. This threshold quantifies the upper capital cost limit at which SMR can still outcompete large scale PV and wind under the tenfold demand (50 MW) and grid fee assumptions for a data center in Dublin, Ireland.

5

Discussion

The optimization results in chapter 4 shed light on how a 5 MW data center in Dublin can be powered most cost-effectively, both under the base case assumptions and under alternative scenarios (50 MW load, market volatility, demand response participation, and SMR cost shifts). This chapter critically examines those findings in light of the theoretical foundations and assumptions laid out in chapter 2 and chapter 3. In doing so, it assesses the robustness of each result and identifies practical implications for data center operators and policymakers.

5.1 Robustness of the 5 MW Data Center Findings

In the 5 MW base-case, the cost-optimal solution selects 19.8 MW of PV plus 10.6 MW of wind in combination with grid imports. This configuration reduces the ALCC from €12.34 M/yr (grid-only) to €10.96 M/yr, and the LCOE from €0.282/kWh to €0.250/kWh (see section 4.1). Carbon emissions fall from 11 169 t CO2/yr to 6 793 t CO2/yr. These improvements demonstrate clear advantages of on-site generation.

5.1.1 Drivers Behind SMR and BESS Omission

In our base run, neither SMR nor BESS capacity is built. Two main factors explain this outcome:

1. **Battery revenue stack is too limited** BESS was modeled solely on hourly energy arbitrage. In reality, batteries can also earn from ancillary services (frequency regulation, reserves, capacity payments). As found in Mohamed et al. (2022), energy arbitrage alone often fails to justify BESS capital expenditures. Our threshold analysis (subsection 4.3.5) revealed that a 0.784 MW/3.134 MWh BESS would require approximately €145/kW-yr (€113 873/yr total) in combined arbitrage and ancillary revenues just to break even. At 2025 cost levels, that threshold greatly exceeded the arbitrage revenues, so batteries remain uneconomic without a richer revenue stack. Participating in demand response program (or ancillary services) as seen in subsection 4.2.3 far would have exceeded the €145/kW-yr threshold.

2. **SMR minimum size and cost assumptions** The minimum SMR capacity was set at 40 MW (World Nuclear Association, 2024)(NREL, n.d.). Hav-

ing lowered the SMR capacity limit further could have tilted the result to the SMR being chosen in the cost optimal capacity mix. However, most early SMR capital cost data gathered in section 2.2 correspond to plants with multiple reactors exceeding at least 200 MW, which benefit from lower per-kW overnight capital costs (OCC). The base OCC assumption of €7 200/kW reflects a 300 MW design, a standalone 40 MW unit would likely face substantially higher costs, around $9 000–$20 000/kW as indicated by Schlissel (2023) and LaRose et al. (2024). Increasing the OCC to these levels for a 40 MW minimum would further undermine the economics of SMRs at a 5 MW site. Conversely, lowering the minimum size (e.g., to 10–20 MW) could reduce generation mismatch but probably incurs even steeper OCC due to lost scale economies.

Because of these constraints, the MILP naturally gravitates toward PV + wind at 5 MW. The assumptions were verified by cross-checking NREL's cost data, PVGIS profiles, and Irish spot prices, and the sensitivity sweeps reproduce break-even thresholds consistent with the literature (e.g. Scoltock and Gladwin (2019) for BESS).

5.2 Battery Storage Economics and Threshold Analysis

Although no BESS is selected in the base (2025) run, battery storage enters the cost-optimal mix by 2028 when accounting for projected cost declines across PV, wind, SMR, and BESS. Moreover, optimal BESS sizing continues to grow as 2029–2030 cost assumptions take effect. This suggests that data center operators should begin securing permits and laying the groundwork for on-site battery deployment well before 2028.

5.2.1 Required Revenue vs. Market Benchmarks

In subsection 2.5.1, average BESS revenues in a representative US market are shown to decline sharply from $192/kW-yr in 2023 to an estimated $55/kW-yr in 2024 (Vermillion, 2025). The cost-optimization model, by contrast, indicates that a 0.784 MW battery would require approximately €114k/yr (or €145.3/kW-yr) in order to enter the optimal capacity mix in 2025. Put differently: 2023 US revenues ($192 / kW-yr) would have comfortably exceeded the break-even threshold for BESS deployment, while the 2024 US revenues fall well below the €145.3/kW-y target. For a European comparison, German BESS revenues in 2024 exhibited significant intra-year variation. In Q1, average earnings remained under €100/kW-yr, but by Q3 they had rebounded above €150/kW-yr, just surpassing the modelled threshold. This highlights the volatile environment in BESS earnings and why proper planning and revenue stack awareness need to be in place when making these investment decision. Either through in-house expertise or outsourcing the energy optimization.

Moreover, recall Scoltock and Gladwin (2019) who used real Irish frequency data, found that a 2 MW/1MWh battery could earn €83 000–€136 000/MW-yr. Our derived €113 873/yr for 0.784 MW (i.e. €89 276/MW-yr) sits comfortably in that same range. This alignment with independent studies increases confidence that our BESS threshold analysis is realistic.

5.3 SMR Cost Uncertainty

SMR technology is still emerging and unit costs remain uncertain. When a base SMR capex of €7 200/kW (NREL 2030 projections) is assumed, then it is found that SMR only becomes competitive in the 50 MW load scenario. However, recent levels for SMR projects (e.g. NuScale at $20 000/kW (Schlissel, 2023), or $8 900/kW for multi-module plants (LaRose et al., 2024)) suggest a wide range where SMR capital costs may end up. As noted in section 2.2, a first-of-a-kind to nth-of-a-kind (FOAK to NOAK) reactor can see costs settle around $8 000/kW. If SMR projects remain above €13 000/kW (BOAK) according to the SMR threshold analysis in subsection 4.3.6, they will not beat PV + wind at this scale, so decision makers should track when announced SMRs approach or fall below that break-even threshold. Also, when e.g. 5-10 MW micro-reactors can be built in the €7 200–€13 000/kW range, it will be time to seriously consider them for data center power supply.

5.4 Demand Response Participation

In the Demand Response scenario, a 4 MW/16 MWh battery was added to the PV+wind system specifically to participate in the APS Peak Solutions program (section 4.2). Over the four-month event window, that combined system earned approximately €462k in DR payments. By contrast, our BESS break-even analysis (subsection 4.3.5) showed that a smaller 0.784 MW/3.134 MWh battery would need about €114 000/yr in combined arbitrage + ancillary revenues just to justify its cost.

A detailed attribution of payments reveals that the BESS alone claimed €400 585, approximately 87% of the total DR earnings. Annualizing the battery's four-month return yields about €300.5/kW-yr, more than double the €145/kW-yr break-even BESS revenue threshold.

These results demonstrate that, under 2025 cost assumptions, a battery storage system designed to capture DR revenues can generate several times the revenue needed to cover its capital and fixed O&M costs. In contrast, a smaller battery relying solely on energy arbitrage would fall short of its economic hurdle.

5.5 Spot-Price Volatility and Levels

Section 2.6 notes that wholesale markets are expected to remain stable or decline, punctuated by periodic volatility and price spikes (Osone and Kodaira 2025; Gai et al. 2024). The sensitivity runs show that multipliers of 1.25–2.0× on spot prices induce BESS deployment even when mean prices remain unchanged. Regarding spot price volatility, and given that the literature points to periodic volatility, the interesting takeaway is that spot price volatility only has a marginal effect on ALCC and LCOE. This is due to the optimization model dynamically adapting to whatever price signals prevail. This shows the importance of taking the right strategic direction in energy infrastructure investments and why an optimization model like the one created can help paint future scenarios and aid in capacity mix decisions. If, for instance, you expect prices to become more volatile, a model-driven approach to resource sizing and dispatch can keep both ALCC and LCOE from rising, and in some cases even improve cost outcomes.

6
Conclusion and Future Work

This thesis presented a mixed-integer linear programming model built from the ground up to optimally size and dispatch an on-site energy portfolio (PV, wind, SMR, BESS) for a 5 MW data center in Dublin. By minimizing annualized life-cycle cost under realistic time-of-use tariffs, spot prices and operational constraints, the model identifies least-cost combinations of generation, storage and grid import.

In the 2025 baseline case for a 5 MW load, the cost-optimal solution installs approximately 19.8 MW of PV and 10.6 MW of wind, with no battery or SMR capacity chosen. This configuration yields an annualized life-cycle cost of €10.96 M and a levelized cost of energy of €0.250/kWh, while cutting CO2 emissions by 39% relative to a grid-only supply.

By bringing together site-specific resource profiles, evolving technology cost trajectories, financing parameters and Ireland's emerging requirement (Direction CRU/21/12426) that data centers must secure on-site dispatchable generation or storage, this modeling framework fills a critical gap in complex energy planning. With EirGrid having paused new data center applications until 2028, tools that co-optimize investments and operations are indispensable for developers and investors navigating an uncertain regulatory landscape.

The sensitivity analyses further illustrate that there is no single "right" design, but rather trade-offs across multiple dimensions:

- **Scale** At 50 MW load, SMRs become competitive. At 5 MW, utility-scale PV + wind still dominate.
- **Cost trajectories** As capital and fixed O&M costs decline per NREL ATB projections, BESS joins the mix by 2028 on pure arbitrage.
- **DR in revenue stack** Demand response participation can more than double BESS earnings relative to its break-even threshold, enabling its deployment in the cost optimal mix in 2025.
- **Price volatility** Even with average spot prices held constant, wider intra-day price spreads alone can justify substantial storage investments, while altering system ALCC and LCOE only marginally.

These scenarios highlight the many assumptions and uncertainties such as technology costs, market prices, and regulatory rules that must be weighed in by decision-makers. The developed model provides the ability to drill into "what-if" questions and extract precise insights for any combination of parameters or geographic setting.

In closing, behind-the-meter PV and wind should be the first priority for 5 MW data centers in Dublin, with BESS capacity configured to capture demand response and ancillary-service revenues rather than relying solely on energy arbitrage. Regulators and investors should monitor the declining cost trajectories of storage and SMRs, especially as SMR overnight capital costs approach the range of €7 200 to €13 000 per kW. That insight can guide incentive design and help anticipate when small modular reactors become competitive. By aligning technology deployments with these evolving cost and revenue signals, data centers can achieve significant reductions in lifecycle cost, strengthen operational resilience, and substantially lower carbon emissions.

Future work

Future research could integrate financial performance metrics such as IRR and LCOS, so that capacity sizing decisions align directly with common investment benchmarks. The model could also co-optimize participation across multiple ancillary-service markets (frequency restoration reserve, spinning reserve, capacity products), to capture the full value of system flexibility. Incorporating stochastic representations of PV and wind forecast errors along with load variability would support dispatch strategies that balance revenue opportunities against calibrated safety margins. Additional resource options (e.g. geothermal, small-scale hydro, and hydrogen storage) could be incorporated to assess their value in the portfolio. Also, expanding the objective function to reflect reliability requirements for Tier 1 to tier 4 data center operations by including cost penalties or explicit service-level constraints would clarify trade-offs between energy supply design and uptime guarantees. Finally, applying the framework across diverse geographic settings would validate its scalability and uncover location-specific synergies among renewables, storage and grid services.

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