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SMRΦ: CYBER-PHYSICAL SYSTEM FRAMEWORK FOR MARKET-RESPONSIVE SMR DISPATCH OPTIMISATION VIA MILP-MPC

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ABSTRACT

Global decarbonisation necessitates flexible, low-carbon dispatchable generation to complement intermittent renewables. Small modular reactors (SMRs) offer this capability. However, their typical inflexible baseload operation fails to exploit dynamic market opportunities. This paper proposes and validates a Cyber-Physical System framework that predictively optimises SMR dispatch to minimise operational costs and carbon liabilities while maximising carbon-credit arbitrage revenue. With the levelised cost of electricity £40-60/MWh and the power purchase agreement (PPA) €60-80/MWh, a cyber-physical system (CPS)-model predictive control (MPC) framework exploiting carbon-price signals offers compelling economic value. The methodology integrates autoregressive integrated moving average (ARIMA), random forest and long short-term memory models for hourly forecasting with a mixed-integer linear programming (MILP) optimisation model, dynamically aligning SMR dispatch with electricity demand and carbon-price signals, using historical data from 2022-2025. The MILP model incorporates real-world operational constraints, including ramp-rate limits and minimum up or down times derived from xenon poisoning dynamics. Simulation of the full-horizon MILP (Model II) achieves a 180.32% improvement over the static baseline, rolling-horizon MPC (Model III) is 193.74% and the concatenated MPC (Model IV), which augments the prediction horizon with machine learning forecast over a hybrid window of measured and projected data. These figures reflect the aggregate performance over the full simulation horizon. Results validate the framework's potential to enhance the economic and environmental value of SMRs in modern energy markets.

Keywords: *Carbon-credit arbitrage, rolling-horizon optimisation, digital twin energy market, carbon pricing, nuclear fission, nuclear fusion*

INTRODUCTION

Global efforts to limit anthropogenic warming to well below 2°C and ideally to 1.5°C necessitate rapid decarbonisation of the energy sector [1]. While renewable energy sources (RES) such as solar and wind are central to this transition, their intermittency creates significant challenges for grid stability. Small modular reactors (SMRs) are nuclear units with a capacity of up to 300 MWe and have emerged as a promising technology to provide reliable, dispatchable, and low-carbon power to complement RES [2]-[3]. The symbol Φ in the title denotes the golden ratio ($\varphi \approx 1.618 = \frac{1+\sqrt{5}}{2}$;), reflecting the aspiration toward an optimal balance of flexibility and economic performance.

Despite their technical potential for flexible operation, SMRs are often planned to operate in a traditional, static baseload mode, producing at constant output regardless of grid conditions [4]. This approach is economically and environmentally suboptimal in modern energy markets, which are characterised by volatile, sub-hourly electricity pricing and established carbon-pricing mechanisms: the European Union (EU) Emissions Trading System (ETS) [5]. An inflexible SMR cannot respond to high-price dispatch windows, may generate power when demand and prices are low, and forgoes significant revenue opportunities from carbon-credit arbitrage. This highlights the absence of

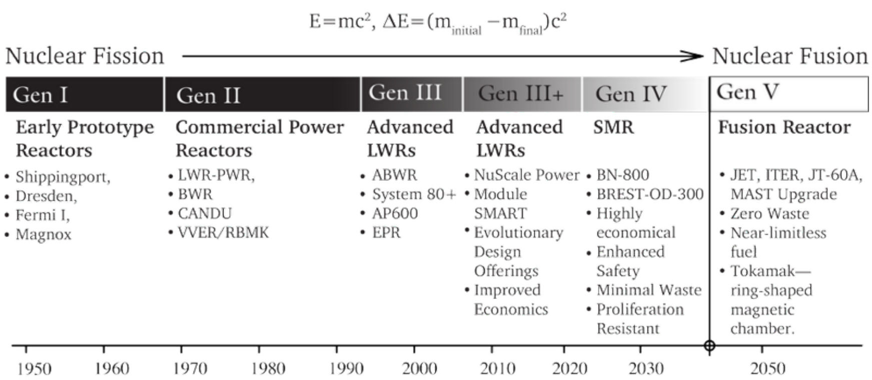


Figure 1 E=mc^2; relationship between energy, mass and speed of light; A century of progress in reactor technologies: from the early prototype fission reactors to fusion reactors
(*Source*: authors [8] adapted from [9])

a coherent, data-driven framework for scheduling SMR operations in response to high-resolution market and grid signals [6]-[7].

The evolution of nuclear technology provides a broader context for this challenge. From early Generation I and II commercial reactors, the industry has advanced to Generation III/III+ designs with enhanced safety, and now to Generation IV SMRs that promise modularity and greater flexibility. Looking ahead, Generation V represents a paradigm shift towards fusion reactors (e.g., International Thermonuclear Experimental Reactor, DEMO), which could offer near-limitless fuel with minimal long-lived waste [9] (Figure 1). SMR deployment offers a practical pathway to low-carbon dispatchable capacity, as fusion reactor technology continues to mature toward commercial viability.

To ground the optimisation model in real-world economics, Table 1 summarises the SMR levelised cost of electricity (LCOE) breakdown contributions based on established United Kingdom Government methodology [10]. This LCOE serves as a baseline against which the carbon-credit arbitrage is evaluated.

Table 1 SMR LCOE case cost breakdown

Cost type	£40/MWh	£60/MWh
Capital (pre-development + construction)	19.5	19.5
Fixed O&Ma (including waste/ decommissioning)	15.5	35.5
Variable O&M	0.0	0.0
Fuel	5.0	5.0
Total LCOE	40.0	60.0#

[a]Operation and Maintenance (O&M)
(*Source*: authors [8], adapted from [10])

Building upon the foundational LCOE analysis for SMRs, this study explores a range of Power Purchase Agreement (PPA) scenarios applicable to SMR deployment within the EU, with particular emphasis on PPA levels from $\frac{€\ 60,70,80}{\mathrm{MWh}}$. These rates, benchmarked against a projected SMR LCOE of approximately €58.50/ MWh ≈ £50/MWh, support investment de-risking in advanced nuclear assets and align with strategic decarbonisation imperatives [11]-[13]. The work further models a carbon price-responsive dispatch strategy whereby the SMR is activated when the European Union Allowance (EUA) price exceeds a threshold of €69 per tonne of carbon dioxide (tCO_2), based on mid-market exchange rates during the work (£1 ≈ €1.14, €1 ≈ £ 0.87; £ 60 ≈ €69), maximising its operational value (Figure 2). In this regime, the SMR's zero-carbon generation profile creates the potential for carbon allowance arbitrage, enabling either a reduction in EUA purchase obligations for the heavy industrial offtakers or the sale of surplus allowances.

Previous research has explored SMR dispatch optimisation using mixed-integer linear programming (MILP) models, integrating SMRs with thermal storage [9] or analysing their long-term energy mixes [14], and has incorporated carbon pricing, typically with static rather than dynamic forecasted prices [15]. Machine learning (ML) models are widely used for energy forecasting [16], and hybrid nuclear-renewables dispatch has demonstrated

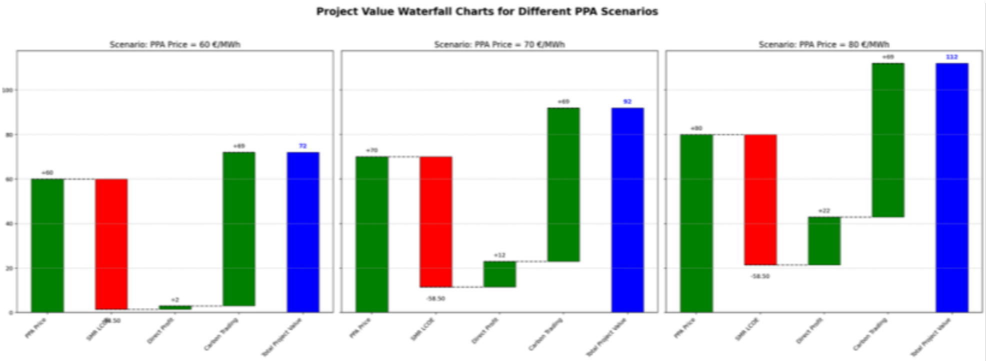


Figure 2 Project value waterfall charts for PPA Scenarios at $\frac{€\ 60{,}70{,}80}{\mathrm{MWh}}$ with Carbon Price at €69/tCO_2 and SMR LCOE at €58.50/MWh ≈ £50/MWh [8]

the economic viability of multi-unit SMR flexible operation [17]-[18] and steady-state SMR modelling with xenon hold-time constraints, including modular safe operation/xenon poisoning constraints, has been validated for multi-timescale operations [7]. Economic co-optimisation of SMR dispatch and maintenance cycles under different penalty cost regimes has been explored [18], while comparative assessment of deep reinforcement learning and MILP for hybrid solar-nuclear dispatch has demonstrated operationally feasible schedules [19]. However, these studies do not integrate high-frequency carbon price forecasting with a rolling-horizon MILP-model predictive control (MPC) dispatch loop, which is the focus of this work.

This paper bridges this gap by introducing a cyber-physical system (CPS) framework that fuses advanced ML forecasting with a detailed MILP optimisation model [20]-[21]. The primary contribution is a holistic, data-driven methodology that enables SMRs to operate as flexible, profitable and grid-supportive assets. The proposed approach builds upon prior findings from the author's master's dissertation [8]. The framework is validated using real-world market data, demonstrating significant improvements over the static dispatch benchmark.

The resulting configuration is particularly salient in the context of hybrid energy-industrial ecosystems, such as those envisioned in Figure 3, which integrates Twin SMRs with a diverse portfolio of energy and industrial systems. Within such integrated industrial environments, the SMR acts not merely as a baseload asset but as a carbon offset enabler whose dispatch is dynamically aligned to carbon market signals and industrial decarbonisation demand.

Figure 3 Great British Nuclear Island Plan [22]

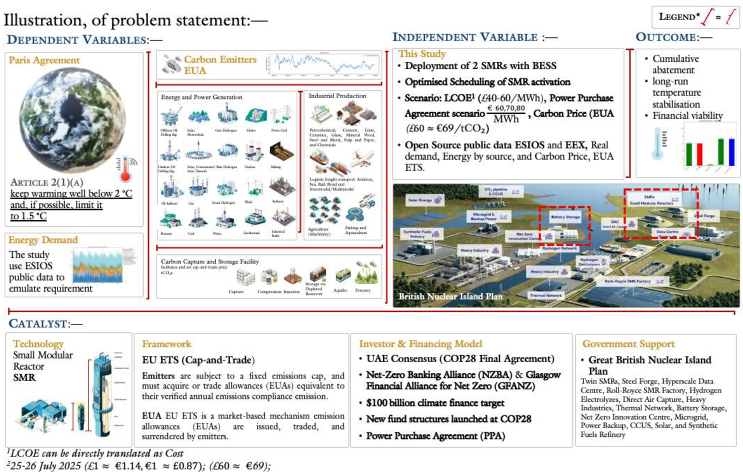


Figure 4 Blueprint illustration and explanation of work relevance [8]

Further depicted is the illustration of the work blueprint in Figure 4.

CPS FRAMEWORK AND METHODOLOGY

The research follows a 14-week Cross-Industry Standard Process for Data Mining (CRISP-DM) workflow, encompassing data understanding, preparation, modelling and evaluation with an additional step to create Model IV MPC Concatenate, as depicted in Figure 5.

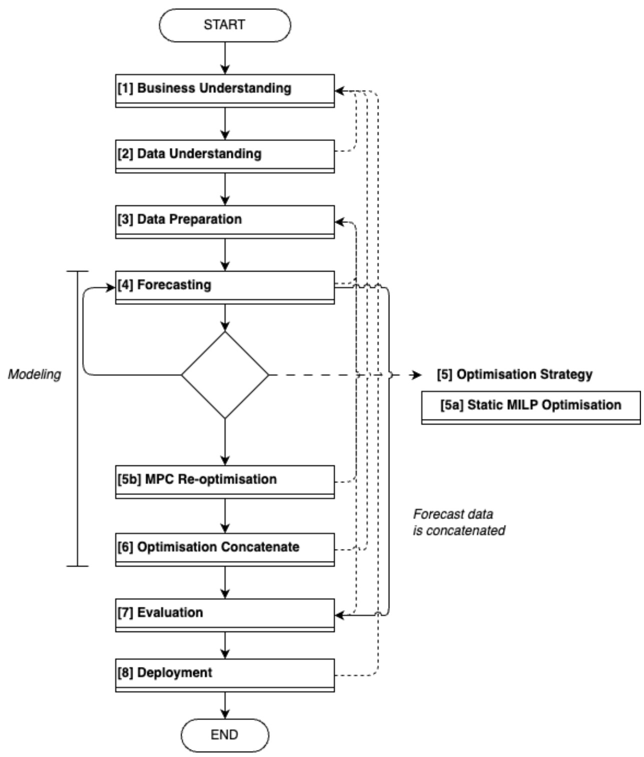


Figure 5 Research process flow; CRISP-DM 1999 framework flow (with additional modelling & evaluation in step 7 for Model IV) [8]

Data Sources and Preparation

Publicly available historical data from 1 January 2022 to 29 May 2025 were used. Energy and Market Data: Hourly electricity market data for the Spanish grid was sourced from ESIOS Red Eléctrica [23]. The dataset includes actual total load, generation disaggregated by source (e.g., Fuel, wind, nuclear), including day-ahead and actual electricity prices. Carbon Price Data; Daily carbon credit auction prices (EUA) were sourced from the European Energy Exchange AG (EEX) [21] (Figure 6). Data preparation involved cleaning, addressing missing values via linear interpolation and feature engineering (Figure 7). Temporal features (e.g., hour of day, day of week) and lagged variables were created to support the forecasting models.

Forecasting Models

Three model classes predict electricity demand and carbon price, covering the spectrum of time series forecasting approaches: autoregressive integrated moving average (ARIMA) as a classical statistical baseline with interpretable parameters; random forest (RF) as a non-linear ensemble method robust to feature interactions and missing data; and long short-term memory (LSTM) recurrent architecture capable of capturing long-term temporal dependencies in demand patterns. This triad enables fair comparison across paradigms (statistical, tree-based, and neural) and informs model selection for the concatenated MPC variant. All models were trained on a portion

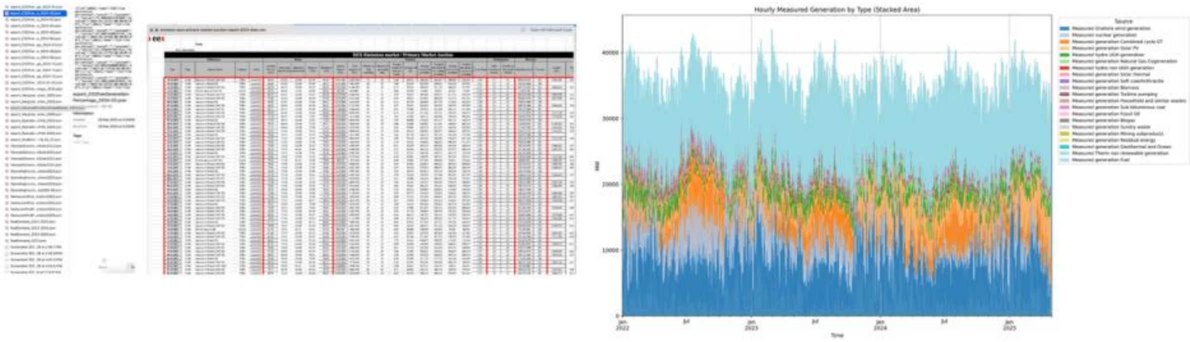


Figure 6 Plot and cleaned hourly measured energy generation by source from 2022 to 2025 [8]

of the historical data and evaluated on a hold-out test set using mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE).

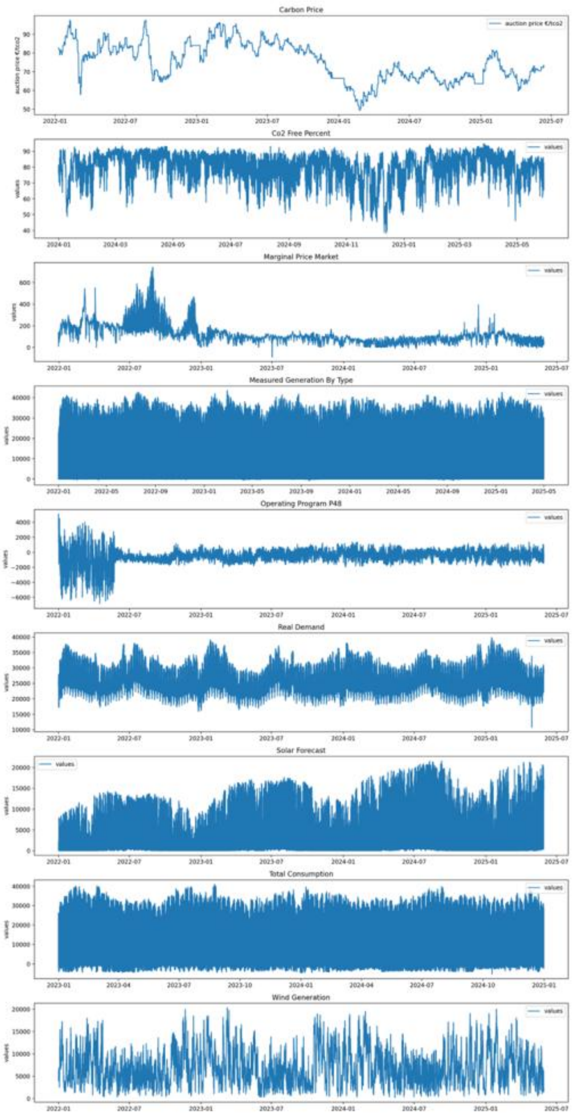


Figure 7 Compiled, cleaned and plotted data source by types from Jan 1, 2022, to May 29, 2025 [8]

MILP Optimisation Model

The core of the framework is a MILP model designed to determine the optimal hourly dispatch schedule for a dual-unit SMR plant integrated with a battery energy storage system (BESS).

Objective Function

The objective is to minimise the total net operational cost over the horizon *T*.

$$min\sum_{t=1}^{T}\left(C_{fuel,t}+C_{su,t}+C_{sd,t}-R_{cc,t}+\sum\nolimits_{k}C_{penalty,k,t}\right) \quad (1)$$

where:

$C_{fuel,\,t}$ is the fuel cost;
$C_{su,t}$ and $C_{sd,t}$ are the start-up and shut-down costs;
$R_{cc,t}$ is the revenue from carbon credits, and
$C_{penalty,k,t}$ represents various penalty costs (e.g., for unmet demand or violating BESS state-of-charge limits).

Decision variables:

$u_{i,t}$ E {0, 1}: On/off status of SMR unit *i* at time *t*;
$p_{i,t} \geq 0$: Power output of the SMR unit *i* at time *t*;
$p^{ch}_{bess,t}$, $p^{dis}_{bess,t}$, ≥ 0: BESS charge and discharge; and
$soc_{bess,t} \geq 0$: BESS state of charge.

Key Constraints

Power Balance: Total generation from SMRs and BESS discharge must meet the forecasted demand at each hour.

$$\sum_{i} p_{i,t} + p^{dis}_{bess,t} - p^{ch}_{bess,t} = Demand \quad (2)$$

SMR Operational Limits:
Generation within a minimum $P_{min} \cdot u_{i,t} \leq p_{i,t} \leq p_{max} \cdot u_{i,t}$, where $\cdot = x$;
$p_{i,t} \leq$ RampUpLimit and $p_{i,t-1} - p_{i,t} \leq$ RampDownLimit;

Minimum up-time and down-time constraints to manage thermal stress and xenon poisoning dynamics; and

Maximum uptime of 40 Hours.

BESS Model:
Constraints governing the state of charge, charge/discharge efficiency, and power limits.

$$soc_{bess,t} = soc_{bess,t-1} + (\eta_{ch} \cdot p^{ch}_{bess,t}) - (p^{ch}_{bess,t}/\eta_{diss}) \quad (3)$$

Carbon Price Logic

The model incorporates a tiered carbon price threshold (e.g., ≥ €69/tCO_2) to influence dispatch decisions, incentivising generation during high-revenue periods.

Xenon Poisoning Mitigation

Xenon-135 (^{135}Xe), produced through the ^{135}I decay chain, is a potent neutron absorber ($\sigma Xe \approx 2.65 \times 10^6$ *barns*) [24]. During shutdown, neutron flux decreases, and xenon concentration rises unchecked as its decay outpaces neutron-induced burnup, creating a temporal reactivity dip "xenon transient" that may inhibit immediate restart [25]. High-fidelity simulations using the Serpent Monte Carlo code within the VTT Kraken framework demonstrate ^{135}Xe buildup and decay oscillations reaching a stationary state after approximately 200 hours [25]. The reactor physics analysis indicates a safe xenon management operating-to-resting ratio of 1:1.375 [8]. The MILP operationalises this through conservative proxy constraints: 11 h downtime (after ≤ 8 h uptime), 24 h (after 8–40 h uptime) and 72 h (after > 40 h uptime), to ensure margins above the theoretical minimum. A maximum continuous uptime of 40 h is set as a precautionary measure to align with xenon transient and thermal stabilisation [8]. These constraints do not directly simulate core physics but pre-empt xenon-induced restart inhibition while maintaining consistent generation capacity. They represent a conservative engineering margin rather than a first-principles reactor physics boundary condition. Future optimisation could replace static up-time and down-time constraints with a dynamic model that more accurately reflects the xenon decay curve based on the reactor's recent power history [25]-[26].

Control Strategy and Evaluation

Four model variants of increasing sophistication are evaluated (Table 2). Model I (Static) applies a fixed schedule representing conventional, inflexible baseload operation. Model II solves the full 168-hour dispatch problem in a single window. Model III (MPC) implements rolling horizon control: the MILP solves over a 168-hour prediction horizon, but only the first 24 hours are executed before the horizon rolls forward with updated state and forecasts. Model IV (concatenated MPC) augments Model III with ML-generated forecasts over a shorter 72-hour prediction horizon, hybridising five days of historical data with two days of projected data to simulate SMR meeting net demand. Models II-IV were implemented in Pyomo and solved using the CBC (COIN-OR Branch-and-Cut) solver. A relative optimality gap of 5% and a per-window runtime limit were set to balance solution quality with computational tractability for rolling-horizon operation.

Models Layered Horizontal Flowchart

Figures 8 to 11 depict the process flowcharts of each model.

Table 2 Simulation parameters

	Model			
Feature	I[a]	II	III	IV[b]
Parameter	Static	MILP	MPC	MPC + Concatenate
Optimisation Approach	Fixed Schedule	Single Window	Rolling Horizon	Rolling Horizon Concatenated
Horizon/Window	168h	168h	168h Pred. 24h Ctrl.	72h Pred. 24h Ctrl.
Solver Time Limit	200s	200s	220s per windowc	300s per window[c]
Optimality Gap	5%	5%	5%	5%

[a] 7 days from 7:00 am May 22 to 6:00 am May 29, 2025 | emulates conventional)
[b] 7 days (5 days of actual data + 2 days of forecasted data) from 7:00 am May 24 to 6:00 am May 31, 2025
[c] The solver time limit variable is set to the fastest timeframe the model can solve

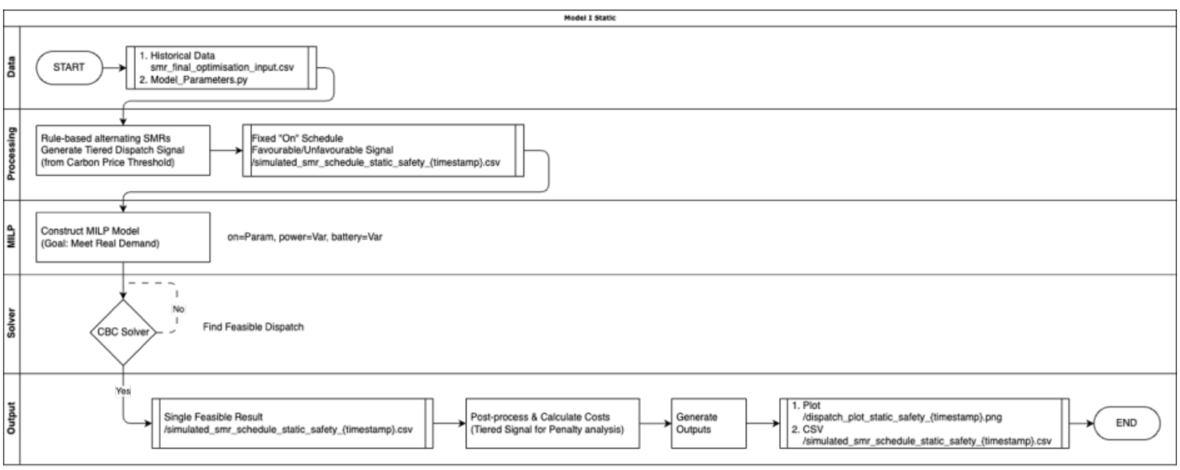


Figure 8 Model I (static) layered horizontal flowchart [8]

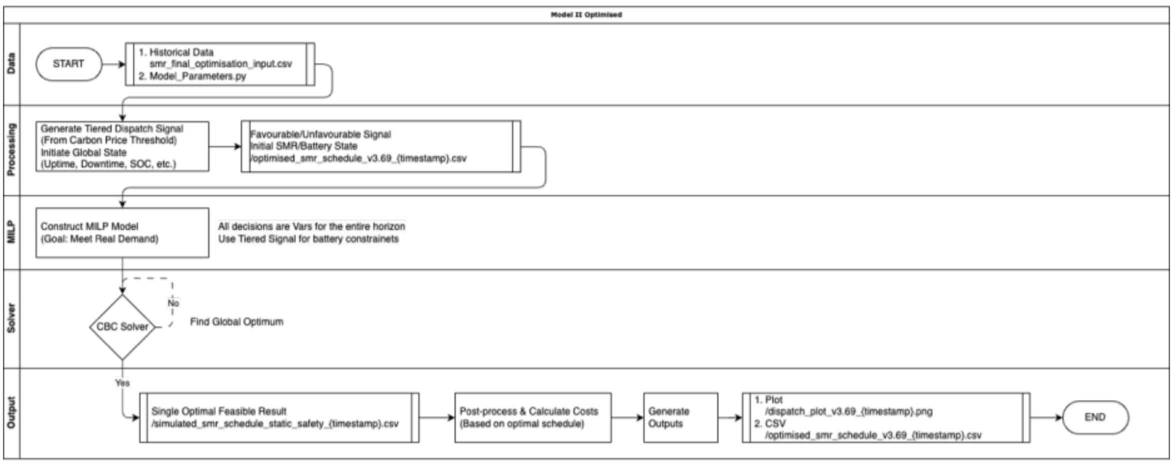


Figure 9 Model II (MILP) layered horizontal flowchart [8]

Evaluation Metrics

Total Net Cost

To quantify the financial benefits of the proposed control strategies, the percentage improvement in Total Net Cost of each model is calculated relative to the Static Model I baseline. The Total Net Cost in Equation 4 values for each model are derived from the simulation,

$$\text{TotalNet Cost} = \Sigma \text{ Operational Cost} + \Sigma \text{ Penalty} - \Sigma \text{ Reward credits} \tag{4}$$

where:

Operational costs include the cost of generating electricity and the costs associated with starting up and shutting down the SMR unit. Penalties encompass all costs incurred due to undesirable outcomes, such as not meeting demand, generating excess power, battery State of Charge (SOC) deviations (too low, too full, critical levels, or charging at unfavourable times), simultaneous SMR/battery operations (if disallowed), initial charge deficits, and violations of SMR uptime/downtime rules. Rewards and Credits include: financial incentives for beneficial actions, such as discharging the battery during favourable periods and earning carbon credits for low-emission generation. Rewards and credits refer to financial incentives for positive actions, such as discharging the battery during favourable periods and earning carbon credits for low-emission electricity generation.

Percentage of improvement

A negative value for Total Net Cost indicates a favourable financial outcome (i.e., profit or significant cost reduction); a greater negative value signifies a more effective strategy.

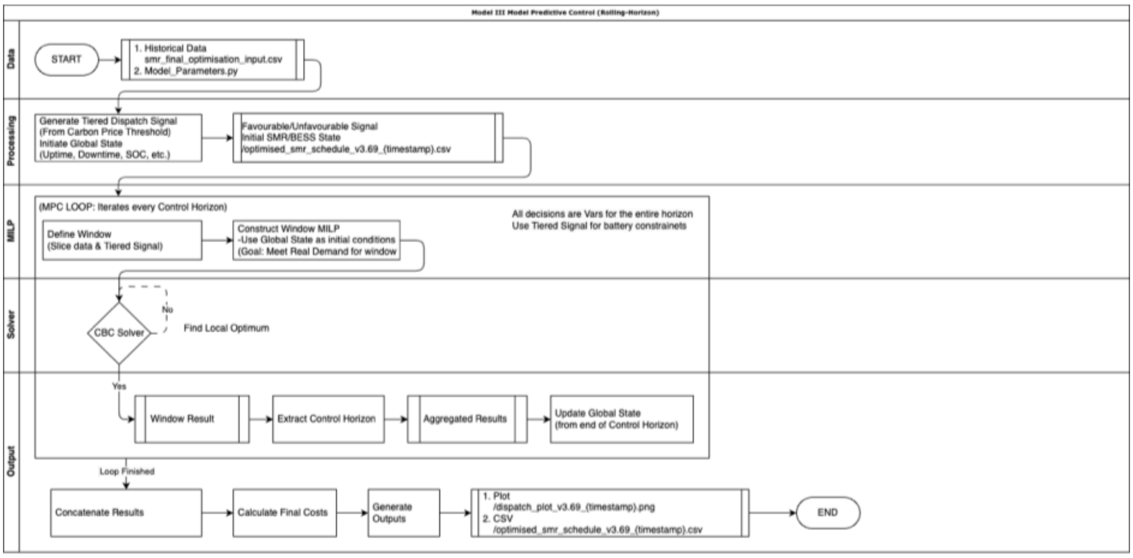


Figure 10 Model III (MPC) layered horizontal flowchart [8]

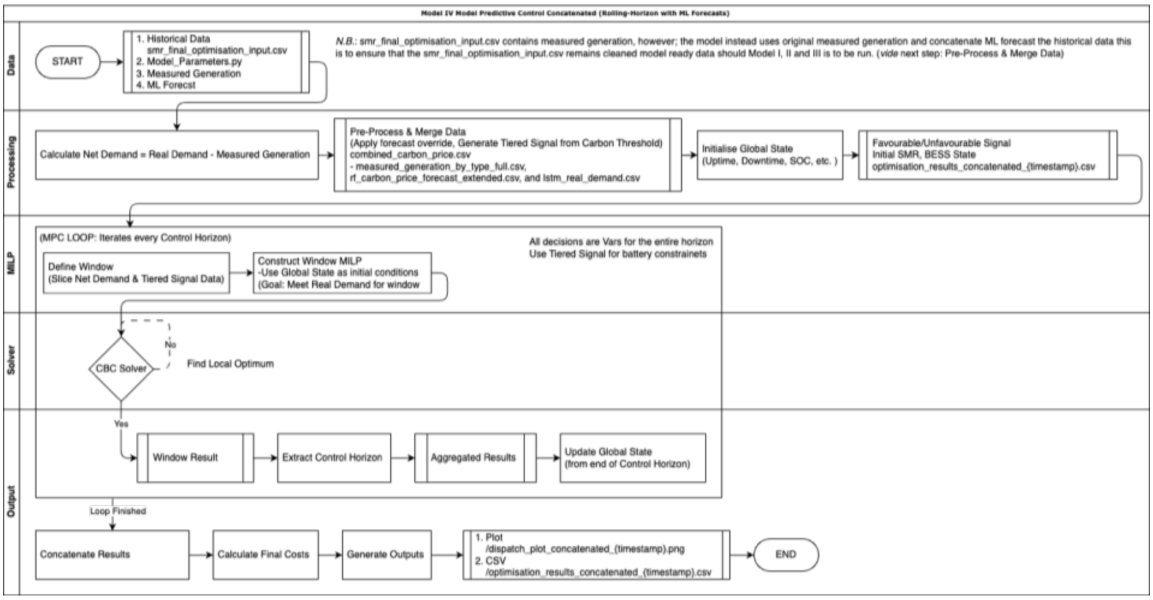


Figure 11 Model IV (MPC concatenate) layered horizontal flowchart [8]

The percentage improvement is computed using Equation 5, where the static Model I cost is the baseline, and the costs of the other models are the improved costs.

$$\text{Percentage of Improvement} = \frac{(\text{Baseline Cost} - \text{Improvement Cost})}{\text{Baseline Cost}} \times 100\% \quad (5)$$

where:

Baseline Cost refers to the Total Net Cost of the reference model (Static Model I); and

Improved Cost refers to the Total Net Cost of the alternative model being evaluated.

Total Project Value

To precisely quantify the financial performance of an SMR under the dynamic conditions, the following formula is utilised:

$$\text{Total Project Value} = \text{PPA Price} - \text{SMR LCOE} + \text{Potential revenue from carbon trade} \quad (6)$$

Equation 6 quantifies SMR LCOE profit dispatch with a carbon threshold at €69/tCO_2, SMR LCOE at £50 and PPA at €70/MWh.

RESULTS AND DISCUSSION

Simulation Parameters and Forecasting Performance

Individual ML models were trained on a 52-week representative window offering seasonal diversity (Figure 12). Table 3 presents simulation parameters and forecasting model performance on the hold-out test set. LSTM achieved the best demand forecasting accuracy (MAPE: 3.00%), while RF demonstrated strong carbon price prediction (MAPE: 2.47%). ARIMA, as a univariate baseline, showed higher error (MAPE: 16.09%), consistent with its inability to capture non-linear feature interactions. The trained models forecast demand and carbon prices over a 48-hour rolling window appended to Model IV to guide the prediction horizon.

Table 3 ML simulation and forecasting model performance

Parameter	Value		
Simulation Timeframe	192 hours (8 days)		
MPC Prediction Horizon	72 hours		
MPC Control Horizon	24 hours		
Forecasting Model	MAE	RMSE	MAPE
ARIMA	3370.4	4500.20	16.09%
LSTM (Real Demand)	716.67	1020.86	3.00%
RF (Carbon Price)	1.66	2.06	2.47%

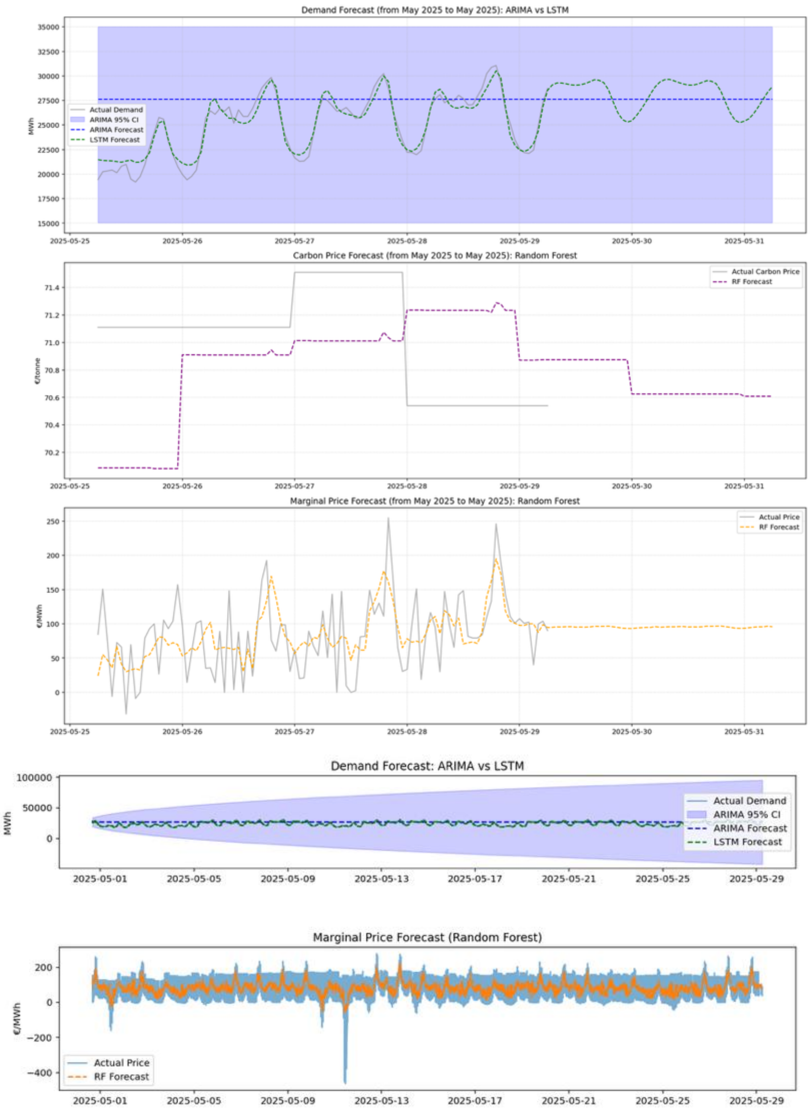


Figure 12 Forecasted demand using ARIMA, LSTM and RF for real demand, carbon price and marginal price; top, timeframe (TF): 1 month, bottom TF: 7 days daily [8]

Economic and Operational Performance

An important contextualisation applies. These financial outcomes are derived from a simulation environment with deliberately significant penalty costs, designed not to forecast precise, real-world profit and loss, but to create a rigorous testing ground that forces ML and MILP models to learn and strictly adhere to complex operational constraints (e.g., startup/shutdown protocols, BESS limits, ramp rates). Reported improvements (180-227%) should therefore be interpreted primarily as a validation of the framework's decision-making logic under these demanding, constraint-driven conditions. The framework holds potential for real-world financial estimation, provided actual price signals of operations and scenario-specific economic valuations are used in place of the synthetic penalty values.

The MPC models demonstrated intelligent battery cycling, charging the BESS when SMR generation was cheap and discharging to capture high-value market opportunities. Model I (Static) inflexible schedule led to chronic under-utilisation or over-depletion of the BESS (Figures 15-18). All models, including the highly optimised MPC variants, successfully adhered to all SMR operational constraints, with zero incurred costs for violations of maximum uptime, minimum downtime, or ramp rates. This demonstrates the robustness of the MILP formulation in enforcing xenon management and reactor stability protocols. The progressive performance improvements from Model I to IV (Tables 4 and 5) reflect increasing sophistication of the decision-making methodology, not differences in model calibration or penalty weighting, as all models share the same objective function, penalty terms and constraints.

Simulation of Digital Twin

The final validation phase demonstrates MPC logic within a real-time simulated closed-loop environment through a functional Digital Twin (Figures 19 and 20). The Digital Twin serves as the CPS validation layer, integrating the proven optimisation engine with simulated SMR physical dynamics to validate real-time, hour-by-hour operation decision-making of the Realtime MPC Controller class, moving beyond static and batch simulation. The architecture comprises three core elements, where:

Physical Layer (Simulated)

The SMR Physics Model and BESS Physics Model components, which dynamically update their state (e.g., core temperature, SOC, Xenon concentration) based on commanded power setpoints and environmental

Table 4 Comparative performance of dispatch models

	Model			
Metric	I Static Model	II Full Horizon MILP	III MPC Model	IV Concatenate MPC
Total Net Cost (€)[a]	32,735 mil	-26,294 mil	-30,686 mil	-41,732 mil
Total SMR Generation (MWh)	11,186.64	11,563.80	11,205.22	12,843.46
Total Carbon Credits (€)	0.318 mil	0.329 mil	0.319 mil	0.366 mil
Total Battery Discharge (MWh)	30,445	32,454	32,246	43,429
Unmet Demand Cost (€)[c]	0.00	0.00	0.00	0.00
Critical SOC Cost (€)	4.51 mil	0.15 milb	0.15 milb	0.15 mil[b]

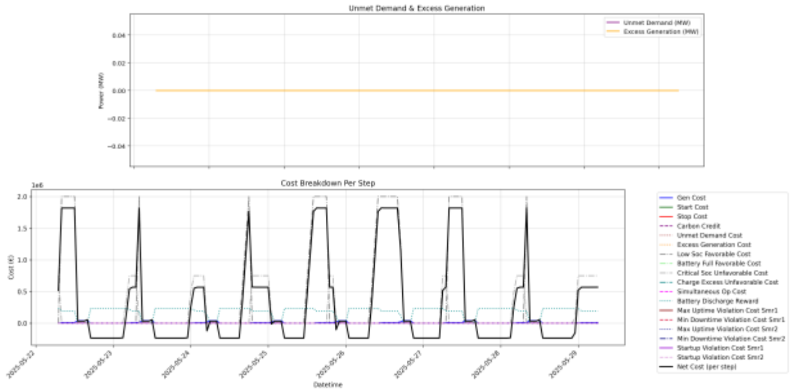
[a] Simulated Metric; red = unfavourable, green = favourable.
[b] Initial penalty encountered relates to ensuring the BESS achieves a minimum 100 MWh charge level.
[c] *see* Figures 13 and 14.

Table 5 Comparative performance improvement of dispatch models

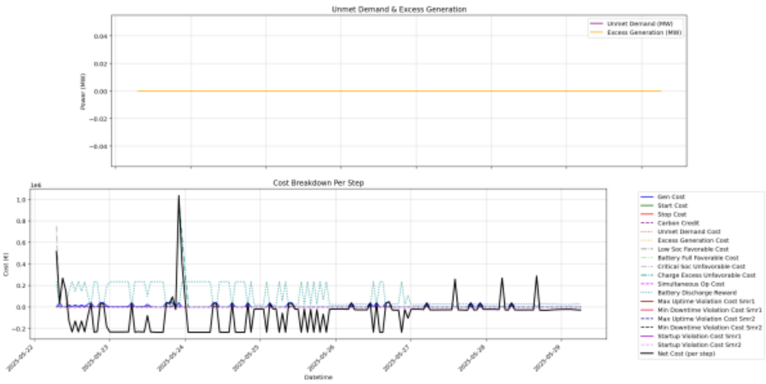
	Model			
Metric	I Static Model	II Full Horizon MILP	III MPC Model	IV Concatenate MPC
Percentage of Improvement	N/Aa (baseline)	180.32%	193.74%	227.48%

[a] N/A; Not Applicable, Static Model is used as the control referenced model

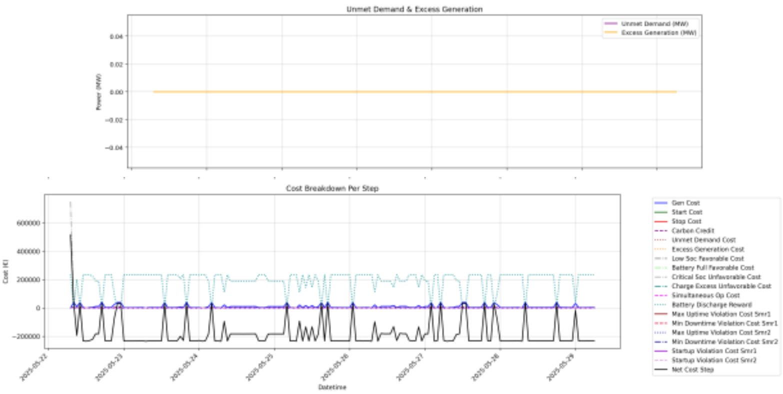
Model I (Static)



Model II (MILP)



Model III (MPC)



Model IV (MPC Concatenate)

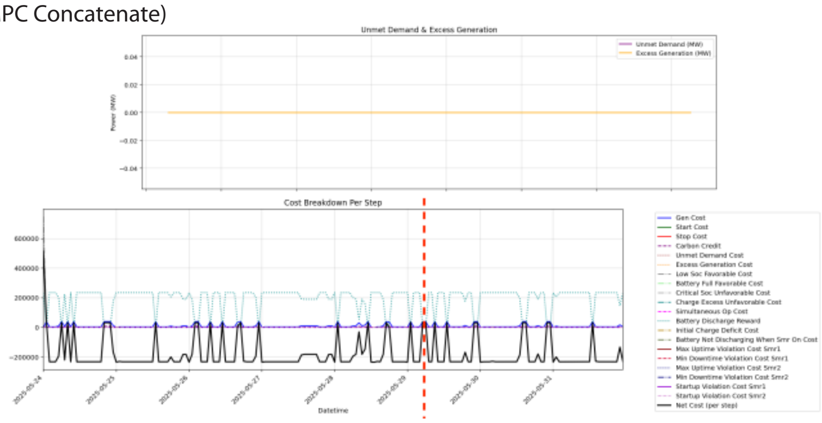


Figure 13 Selected result Model I – IV, unmet demand and excess generation, and cost breakdown (*See* Figure 14 for full plot of each model) [8]

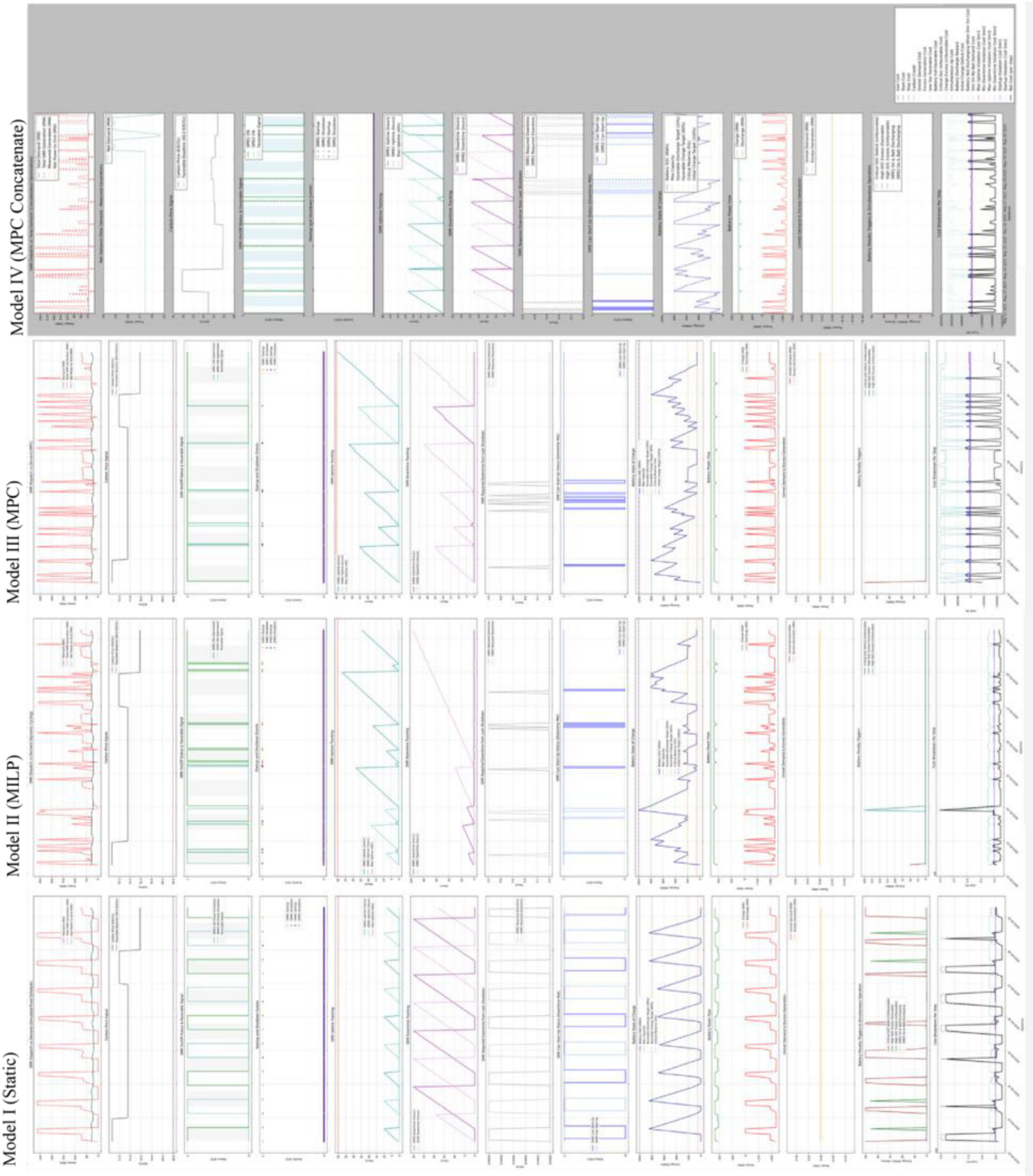


Figure 14 Full simulation output for Models I-IV (as viewed horizontally, from left to right: Static, Full MILP, MPC, and MPC concatenate [8]

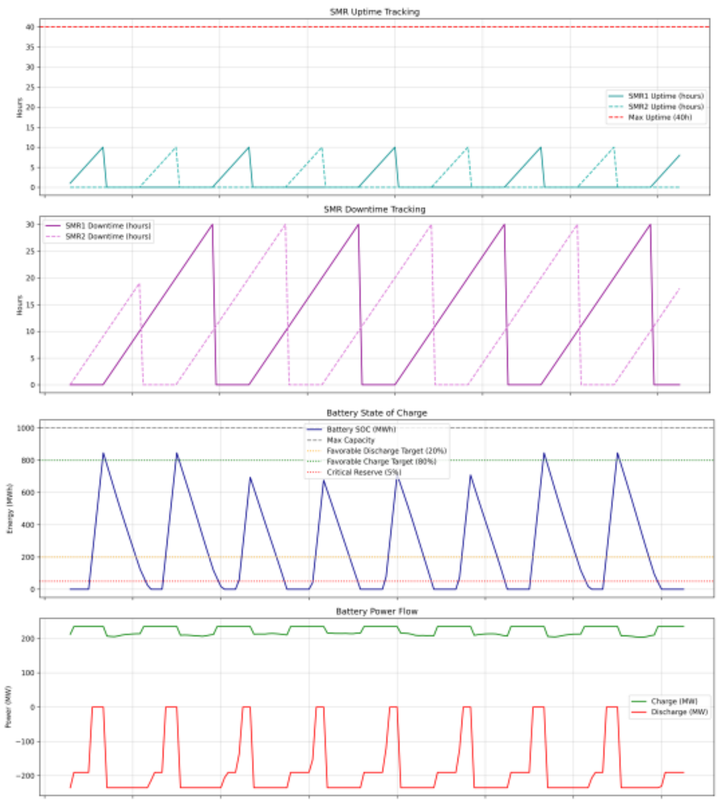


Figure 15 Selected results Model I (Static) activation with inflexible battery use, (i) SMR uptime, (ii) SMR downtime, (iii) battery state of charge, (iv) battery power flow [8]

Figure 16 Selected results Model II (MILP) optimised model aggressive battery use (i) SMR uptime, (ii) SMR downtime, (iii) battery state of charge, (iv) battery power flow [8]

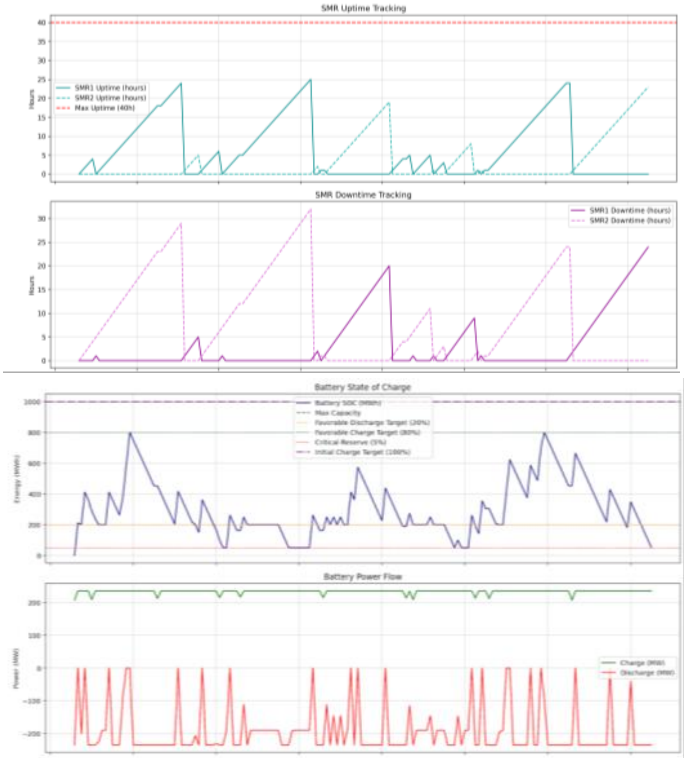


Figure 17 Selected results Model III (MPC), strategic battery cycling (i) Uptime, (ii) downtime, (iii) battery state of charge, (iv) battery power flow [8]

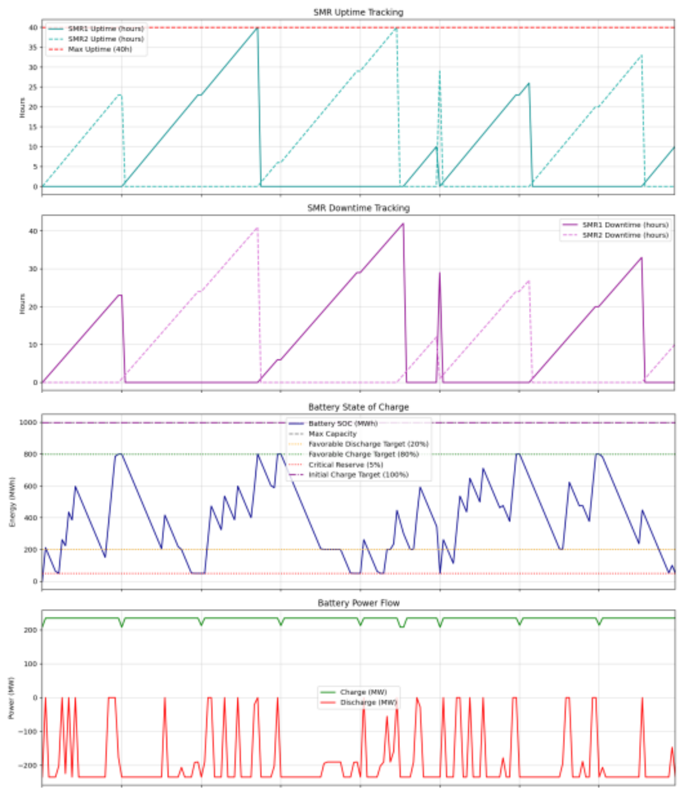


Figure 18 Selected results Model IV (MPC concatenate) Model hybrid of historical and concatenated ML-based forecast (i) SMR uptime, (ii) SMR downtime, (iii) battery state of charge, (iv) battery power flow [8]

factors. This emulation provides physics-informed state evolution without requiring access to proprietary reactor simulation codes, ensuring reproducibility.

Data Layer
A simulated data stream that feeds the SMR states, current time, and real-time market data (current carbon price, demand) into the control module.

Cyber Layer (Control Module)
The MPC solver, which receives the current state, runs the optimisation to generate a new 72-hour plan (re-optimising every 24 hours per the control horizon), and issues the control setpoints for the next hour back to the Physical Layer.

CONCLUSION

This paper validates a CPS framework for predictive optimisation of SMR dispatch in dynamic electricity and carbon markets. By integrating machine learning forecasting with rolling-horizon MILP, the framework transforms SMRs from inflexible baseload units into responsive and economically optimised assets. Results show significant net cost improvements: 180.32% for full horizon MILP, 193.74% for standard MPC, and 227.48% for concatenated MPC under real-grid scenarios. The framework also enables carbon-credit arbitrage and enforces critical operational constraints, including xenon poisoning management, providing a practical foundation for future flexible and decarbonised nuclear energy systems. Future work should incorporate stochastic optimisation, multi-module and hybrid-system extensions, digital-twin and cyber-resilient architectures, and validation across grid contexts beyond the ESIOS/European Energy Exchange AG (EEX) case studied. The open-source CBC implementation supports reproducibility.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

AUTHORS' CONTRIBUTION

Kamarularifin Azman conceptualised the study, collected and analysed the data and drafted the manuscript. Fasee Ullah reviewed and edited the manuscript critically for intellectual content. All authors have reviewed and approved the final version of the manuscript.

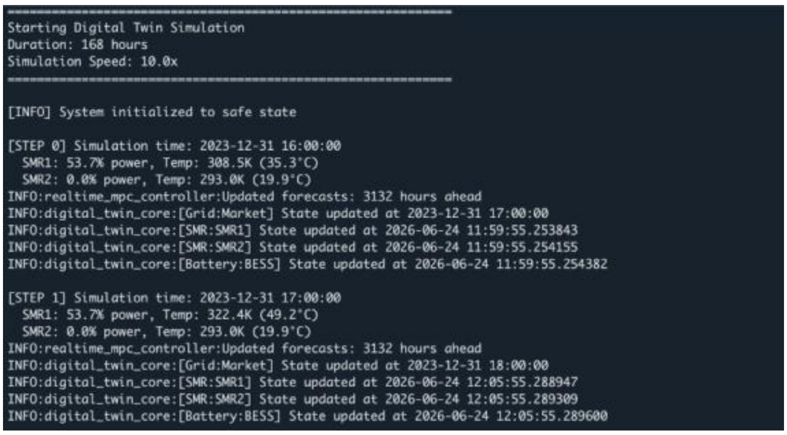

Figure 19 STEP digital twin simulation of SMR of optimised model [8]

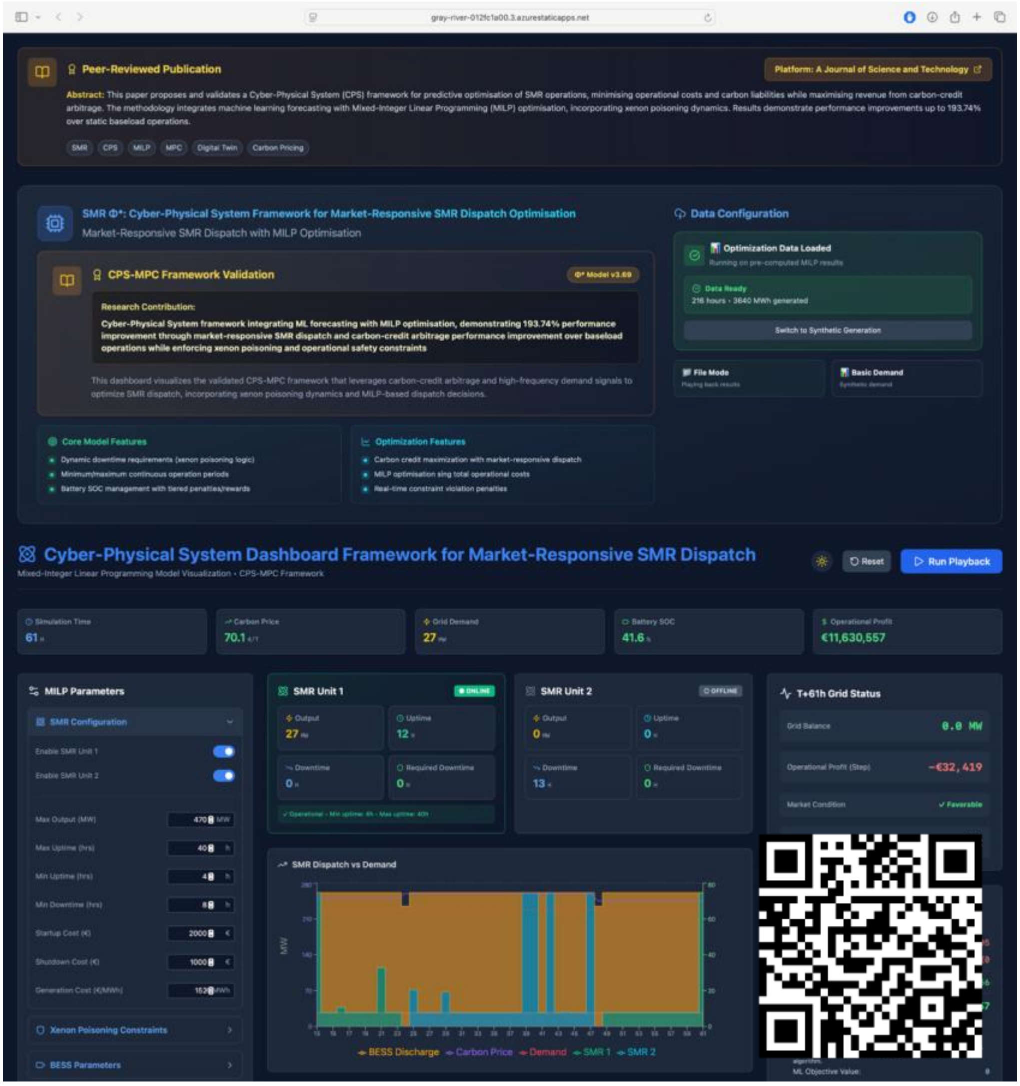

Figure 20 Deployed dashboard (Azure, React + Vite) of simulation and QR code to dashboard (https://gray-river-012fc1a00.3.azurestaticapps.net / https://smr-digital-twin.vercel.app/) [8]

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