

Article

Distributionally Robust Coordinated Maintenance and Dispatch in Multi-Energy Systems with Electricity, Heat, and Hydrogen Carriers: A Wasserstein-Metric Framework

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Abstract

The high energy demand driven by industrial development has transformed the power system from a single energy source to multiple energy systems (MESs). These systems, which involve thermal generators, combined heat-and-power (CHP) units, electrolyzers, fuel cells, etc., with realistic forecast uncertainty, are very operationally challenged. This paper proposes a Distributionally Robust Optimization (DRO) based on a Wasserstein-metric ambiguity set, which simultaneously optimizes the annual maintenance schedules and short-term operational dispatch across MESs. The ambiguity set is constructed using joint samples of forecast errors for the three carriers' demand, allowing for a data-driven worst-case distribution approach that mitigates the excessive conservatism typically associated with conventional robust optimization (CRO). The penalties are explicitly enforced for load and renewable energy curtailments across each of the MESs with source-specific value-of-lost-load coefficients. The Wasserstein radius is improved by sensitivity analysis, obtaining a θ value of 0.20 as the cost reduction radius for a 40% RES penetration. Five RES penetration levels are implemented here on the IEEE 39-bus New England network, with CHP, electrolyzer, fuel cell, thermal storage, and hydrogen storage. The DRO reduces the total annual system cost by 56% compared to CRO, while reducing the unbalanced energy.

Keywords: multi-energy system; Distributionally Robust Optimization; Wasserstein distance; maintenance scheduling; combined heat and power; hydrogen storage; electrolyzer; thermal storage



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1. Introduction

The energy sector worldwide is experiencing an operational shift driven by technological advancements, decarbonization targets, and the exponential growth in renewable energy resources (RESs) [1]. In conventional power systems, planning and operation are based on a single energy carrier model; however, the increased implementation of various RESs as a part of deregulation has given rise to the concept of multi-energy systems (MES) [2]. In a MES, multi-energy carriers (MECs) and storage technologies work in coordination to meet the heterogeneous demands in an economically feasible manner [3]. A deregulated power system (DPS) introduces additional operational complexity by decentralizing decision-making, thereby complicating optimal generator scheduling and coordinated maintenance planning, particularly in the presence of integrated energy storage systems [4]. With the

increasing penetration of renewable energy sources (RESs), ageing conventional generators and heterogeneous energy storage systems can lead to load shedding and renewable energy curtailment if coordinated maintenance scheduling is not performed while accounting for real-time forecasting error constraints [5]. Energy storage systems (ESSs) are emerging as a vital instrument to enhance the operational flexibility of the DPS. ESSs made it possible to bridge the generation–demand gap while generators are out for scheduled maintenance and RES output has to be coordinated [6]. Most recent studies have treated ESSs as only an electrical asset, while neglecting thermal storage systems (TSSs) and hydrogen storage (H2S), which are significant components of MESs. In this way, the coordinated scheduling of different energy carriers in MESs is not satisfactorily addressed in the literature.

The scheduling of MESs is often hindered by uncertainty management challenges, particularly due to the absence of well-defined probability distribution functions in stochastic optimization frameworks [7]. Conventional robust optimization (CRO) generally assures the viability against worst-case scenarios, but with a limitation of being overly conservative and economically extravagant [8]. Distributionally Robust Optimization (DRO), on the other hand, offers a practical balance between consistency and cost-effectiveness by constructing an ambiguity set of reasonable distributions from the available preconditioned data and then optimizing it against worst-case dispersals within the constituting set [9]. DRO based on Wasserstein metrics has been implemented on the system with a single energy carrier, while its application for the uncertainty of the power system with MESs is still lagging.

2. Literature Review

2.1. Deterministic Generator Maintenance Scheduling

Historically, generator maintenance scheduling (GMS) has predominantly relied on deterministic mixed-integer linear programming (MILP) and mathematical programming approaches to minimize maintenance costs under the assumption that all uncertainty parameters are precisely known [10]. These models provided valuable operational insights under normal conditions but were unable to accommodate the stochastic variability introduced by renewable energy sources (RES) and load uncertainty [11]. Extensions to include reliability indices and N-1 contingency constraints improved practical applicability, but the deterministic assumption remained a structural limitation. The critical limitation here is that Deterministic GMS models are structurally incapable of accounting for forecast uncertainty. They systematically underestimate maintenance costs under high-RES penetration, and they cannot capture the cross-carrier interactions that arise in multi-energy systems.

2.2. Stochastic Programming for Maintenance and Dispatch

The limitations of deterministic models motivated the application of stochastic programming (SP) to GMS, where probabilistic scenario trees represent uncertain RES output and load [12]. Multi-stage SP formulations demonstrated enhanced economic performance by explicitly modelling the temporal evolution of uncertainty. More recently, sample average approximation (SAA) methods have been applied to day-ahead MES scheduling, achieving cost improvements of 8–15% over deterministic baselines [13]. The SP requires accurate knowledge of the true probability distribution of forecast errors, which poses a limitation. In practice, this distribution is unknown and must be estimated from limited historical data. When the training-data distribution deviates from the true distribution—as is common for new RES deployments or under climate-driven non-stationarity—SP solutions overfit to the empirical distribution and incur substantial out-of-sample performance degradation. Standard SP formulations do not address this distributional uncertainty.

2.3. Robust and Distributionally Robust Optimization

Robust optimization (RO) was proposed as a distribution-free alternative, ensuring feasibility against all realizations of uncertainty within a predefined uncertainty set [14]. Two-stage RO formulations, in which maintenance decisions are made in the first stage and dispatch is adjusted in the second stage, have been applied to unit commitment and maintenance scheduling [15]. However, RO's worst-case orientation produces solutions that are excessively conservative and economically extravagant, particularly when the worst-case scenario assigned to all uncertain parameters simultaneously is practically improbable [16]. Distributionally Robust Optimization (DRO) addresses this shortcoming by optimizing against the worst-case distribution within an ambiguity set of plausible distributions, rather than against a single worst-case scenario [9]. Wasserstein-metric DRO, in particular, admits tractable MILP or SOCP reformulations and provides finite-sample out-of-sample guarantees through the theoretical framework of Mohajerin and Kuhn (2018) [17]. Moment-based DRO (using mean-covariance ambiguity sets) has been applied to MES day-ahead scheduling [18], and Wasserstein DRO has been validated for single-carrier power systems [19]. A critical limitation here is that existing Wasserstein DRO studies for energy systems have been limited to single energy carriers [19] or to day-ahead dispatch without annual maintenance scheduling [18]. The simultaneous treatment of multi-carrier joint uncertainty and annual maintenance within a unified Wasserstein DRO framework has not been studied.

2.4. Multi-Energy Systems: Cross-Carrier Integration and Storage

The energy hub concept formalized the modelling of interconnections between multiple energy carriers through conversion and storage technologies [20], and has been extended to include CHP units, heat pumps, electrolyzers, and hydrogen production pathways [21]. Stochastic and robust optimization techniques have been applied to MES scheduling [13,22], and DRO with moment-based ambiguity sets has been explored for MES day-ahead dispatch [18]. Hydrogen has gained increasing attention as a long-term storage medium and industrial decarbonisation pathway [23,24], while thermal storage systems (TSSs) enable the decoupling of heat production from demand [25]. The limitations here are that the vast majority of MES-DRO studies focus exclusively on day-ahead or day-to-day operational dispatch, neglecting the annual maintenance scheduling dimension [18,26]. Furthermore, TSSs and H₂S are rarely integrated within a single maintenance-scheduling framework alongside battery ESSs. This gap means that the cross-carrier synergies between coordinated maintenance windows, hydrogen storage arbitrage, and thermal storage flexibility—which are central to MES operation under high-RES penetration—remain unquantified in the literature.

2.5. Optimization Algorithms for Resource Allocation

Together with the analytical/mathematical techniques for maintenance scheduling and resource allocation, metaheuristic optimization techniques such as Genetic Algorithms (GAs), particle swarm optimization (PSO), and their hybrid model with other optimization techniques have been widely applied [27]. A modified GA implementing adaptive mutation/crossover operators has demonstrated improved convergence for large-scale resource allocation optimization in power systems [28]. When compared to MILP-based DRO techniques, these metaheuristic optimization techniques can be used more effectively for non-convex power system problems, without exact reformulation, but typically lack the finite-sample out-of-sample performance guarantees and global-optimality certificates that Wasserstein DRO provides.

3. Motivation and Research Gaps

Prevailing MES maintenance studies have a mutual limitation: uncertainty management, maintenance scheduling, and multi-carrier coordination are usually treated as separate problems. Due to this reason, present methods are not able to simultaneously apprehend (i) the effect of long-term maintenance on short-term dispatch, (ii) synchronized employment of electrical, thermal, and hydrogen storage resources, (iii) joint uncertainty among MECs, and (iv) carrier-specific reliability issues. Continuous advancements have been made in MES-DRO formulations; however, several research gaps persist:

- (a) In the literature, generator maintenance scheduling is mostly considered as one problem and is treated independently of dispatch optimization, neglecting multi-carrier coupling effects.
- (b) TSSs and H2S are seldom united into maintenance scheduling frameworks together with battery ESSs.
- (c) The multi-energy carrier Wasserstein DRO is still unexplored as compared to the single-carrier ambiguity set.
- (d) Carrier-specific curtailment penalties have not been combined into an integrated MES-DRO formulation.

These interconnected challenges motivated the development of a combined Wasserstein uncertainty model under a unified distributionally robust framework capable of addressing all four aspects simultaneously. This provided a united maintenance scheduling, which works for all MECs in the power system.

The principal contributions of this paper are:

- (a) An integrated MES-DRO framework is proposed that synchronizes maintenance scheduling of multiple energy carriers—thermal generators, CHP units, electrolyzers, battery ESSs, TSSs, and H2S under joint multi-carrier uncertainty, formulated as a Mixed-Integer Linear Programme (MILP).
- (b) A combined Wasserstein-metric ambiguity set is created over the three-dimensional forecast error space (electricity, heat, hydrogen), allowing rigorous yet non-conservative ambiguity circumventing across all energy carriers concurrently.
- (c) In the objective function, carrier-differentiated load curtailment penalties are integrated, effectively pricing consistency degradation in each energy domain.
- (d) The optimal Wasserstein radius $\theta = 0.20$ is obtained through efficient sensitivity analysis at 40% RES penetration. This can be used as a standard setting for configuring distributionally robust models in MESs.
- (e) DRO reliability is proved over CRO by quantifying simulation results across five RES penetration levels (40–80%), and validated on the IEEE 39 bus New England system.

4. Materials and Methods

4.1. Multi-Energy System Description and Uncertainty Modelling

4.1.1. MES Architecture and Energy Hub

In the paper, three energy carriers: electricity, heat, and hydrogen, act as an energy hub for the proposed MES.

Figure 1 illustrates the topology of the IEEE 39 Bus New England system used in this paper. It consists of 10 thermal generators and 39 transmission lines with a MES hub. This MES hub constitutes CHP units, electrolyzers (ELY), fuel cells (FC), Hydrogen storage (H2S), BESS, and TSSs. These MESs are connected to the central system as shown in Figure 1.

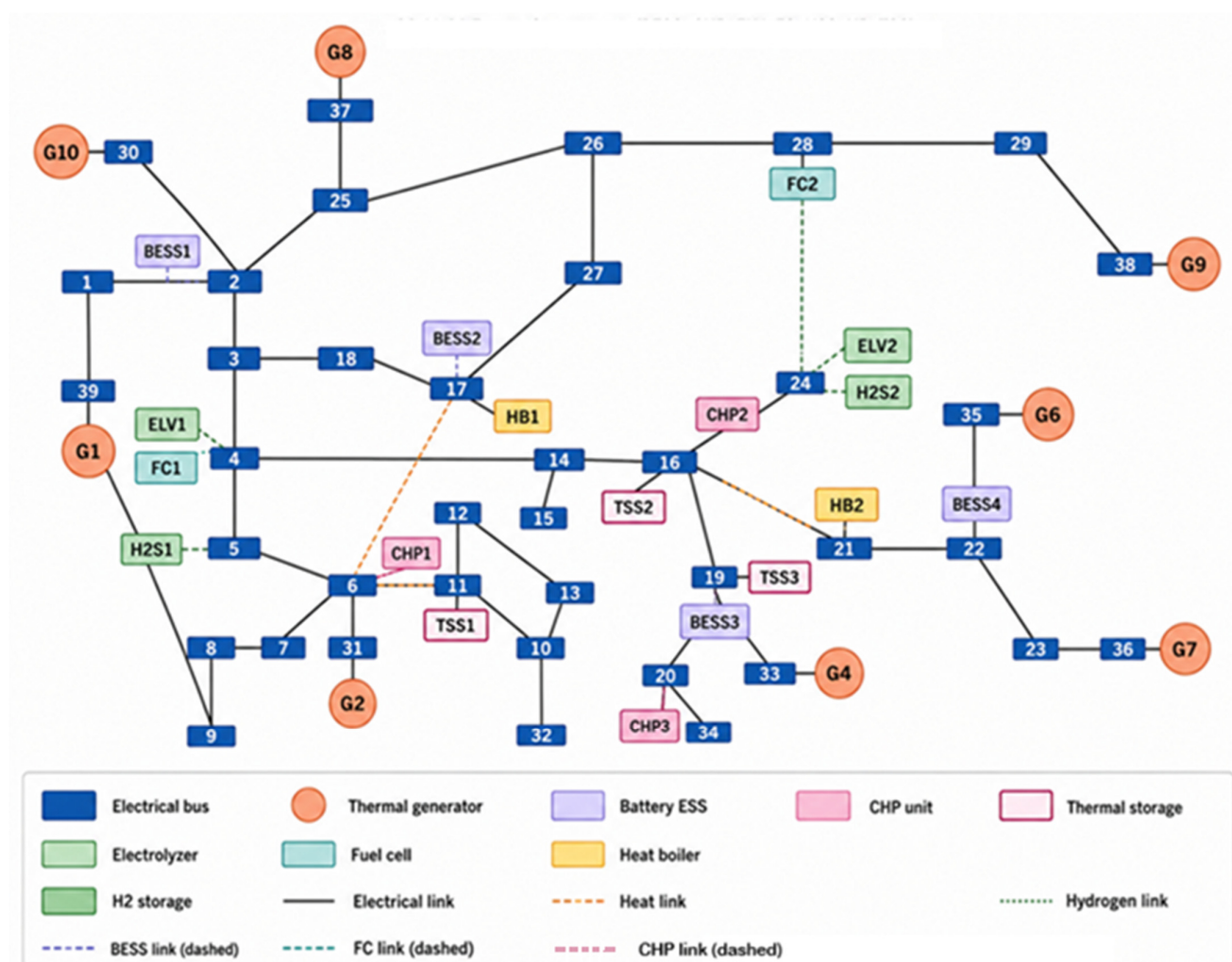


Figure 1. The IEEE 39 Bus New England bus system with integrated MES.

The device categories serving the MES hub are illustrated in Table 1:

Table 1. Component specifications of the MES.

Component	Quantity	Capacity/Output Range	Efficiency/Ratios	Operational Notes
Thermal Generators	10	50–455 MW	Cost: 18–25 \$/MWh	IEEE 39-bus New England system
Battery ESS	4	80–120 MWh	$\eta = 0.95$	SOC bounds [0.20, 0.90]
CHP Units	3	10–80 MW (elec)	$\alpha_{chp} = 0.70$	Heat output: $Q_h = \alpha_{chp} P_e$
Electrolyzers	2	30–40 MW (max input)	$\eta_{ele} = 0.70$	P_{in} to H_2 conversion
Fuel Cells	2	20–30 MW (max output)	$\eta_{fc} = 0.55$	H_2 to electricity conversion
Heat Boilers	2	40–60 MW (max output)	$\eta_b = 0.55$	Natural gas-fuelled backup
Thermal Storage (TSS)	2	40–50 MWh	$\eta_{iss} = 0.92$	Round-trip efficiency
Hydrogen Storage (H2S)	2	60–80 MWh	$\eta_{h2s} = 0.95$	Round-trip efficiency

The operating environment of the proposed model is shown in Figure 2. The multi-energy carrier (MEC) load profiles are created for 52 weeks, 1 representative day per week, for 24 h resolution, encompassing the seasonal variations. From Figure 2, it can be observed

that demand vibrates between 600 MW and 1040 MW, considering both morning and evening peak hrs. Heat demand has a peak between 7 AM and 10 AM, which amounts to 380–450 MW. Hydrogen demand, however, remains comparatively flat and amounts to 40–95 MW with a slight daytime variation. The range of renewable energy can be observed between 0 and 380 MW, which solely depends on the time of day and season. Renewable generation (combined solar and wind) ranges from 0 to 380 MW, depending on time of day and season.

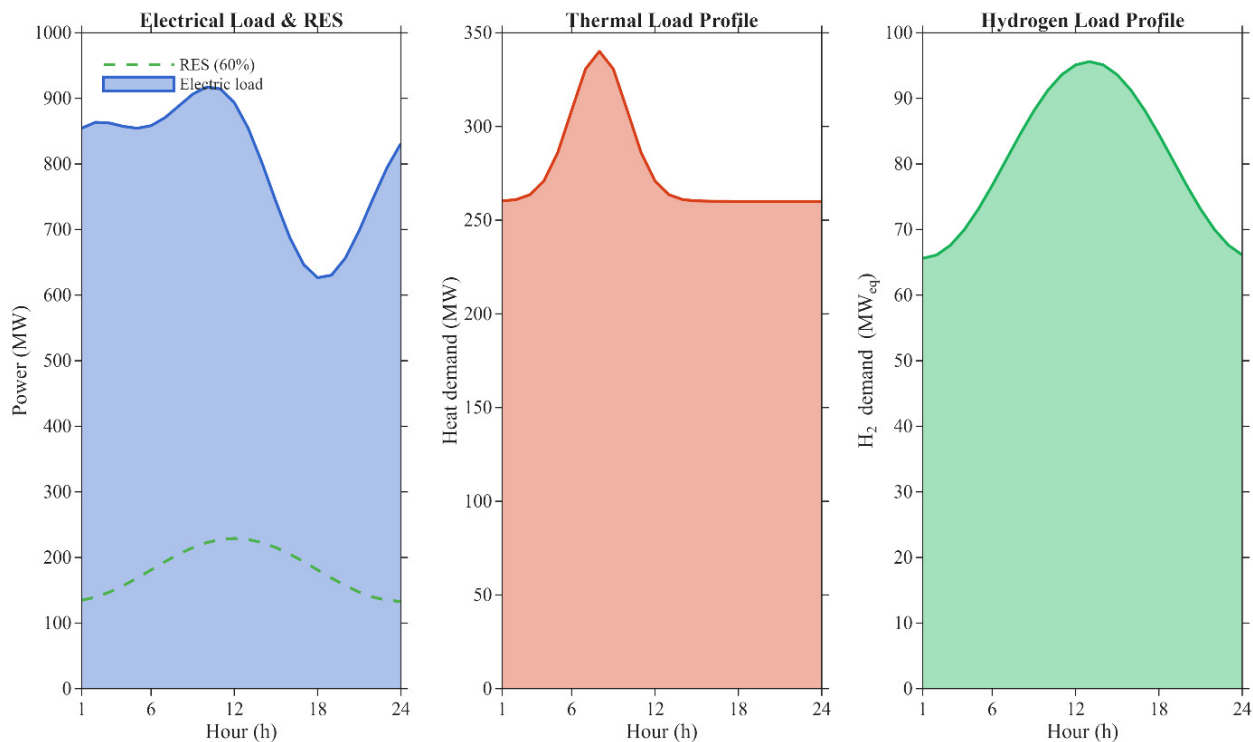


Figure 2. Multi-energy system representative-day load profiles (week 26).

4.1.2. Uncertainty Modelling: Joint Wasserstein Ambiguity Set

In the proposed method, forecast errors occur simultaneously in all three energy carriers, i.e., electricity, heat, and hydrogen. These errors are generally correlated. Therefore, considering each uncertainty separately could not justify the effective dispatch decisions, which will then be either over-conservative or under-protective. The joint Wasserstein ambiguity set is therefore constructed to capture all three forecast-error dimensions together, as a single stochastic vector, rather than as three separate univariate uncertainty sets. The forecast error in different energy carriers, i.e., heat, electricity, and hydrogen, is demonstrated as a joint stochastic disturbance vector.

$$\omega = [\omega_e, \omega_h, \omega_{h2}]^T \quad (1)$$

which is derived from an unknown distribution, $\mathbb{Q}$. Pre-collected forecast error samples are the basis for generating the empirical distribution.

$$\mathbb{P}_n = \left(\frac{1}{N_s} \right) \sum_i \{\omega_i\} \quad (2)$$

where $N_s = 20$ scenarios are generated from a Gaussian distribution for each carrier [29].

ω_e , ω_h , and ω_{h2} represent the forecast errors for electricity, heat, and hydrogen demand, respectively. The proposed joint Wasserstein–DRO algorithm can be represented as:

- Generate $N_s = 20$ Gaussian error samples $\omega^i = (\omega_e^i, \omega_h^i, \omega_{H_2}^i)$ for each energy carrier based on the empirical distribution P_N .
- Apply the generated errors to the nominal demand:

$$P_{\text{realized},r}(t,i) = P_{\text{base},r}(t) + \omega_r^i,$$

where $r \in \{e, h, H_2\}$.

- Define the Wasserstein ambiguity set:

$$\mathcal{B}_\theta(P_N) = \{Q : W(Q, P_N) \leq \theta\},$$

using the L_1 transportation cost on $(\omega_e, \omega_h, \omega_{H_2})$.

- Convert the bilevel min–max optimization problem into a tractable single-level optimization problem by invoking the strong duality theorem as the next step of the algorithm

$$\min_{x,u,\lambda} \left[\sum \text{Deterministic Cost}(x,u) + \theta\lambda + \frac{1}{N_s} \sum_{i=1}^{N_s} \left(\text{Cost}(x,u,\omega^i) - \lambda \|\omega^i\|_\infty \right) \right]$$

subject to the operational constraints, maintenance scheduling constraints, storage constraints, energy carrier balance constraints, and $\lambda \geq 0$.

- Solve the resulting convex (or linear) optimization problem to obtain the optimal maintenance schedule x^* , dispatch schedule u^* , and dual variable λ^* .
- Repeat the optimization for a range of Wasserstein radii θ , and select the optimal value θ^* based on the trade-off between the total operating cost and the unbalanced energy.
- Return the optimal maintenance schedule x^* , optimal dispatch schedule u^* , minimum operating cost, and corresponding unbalanced energy at $\theta = \theta^*$.

The 20 scenarios are selected from statistical presentation and computational traceability. The testing has been done using 10, 20, 30, 40, and 100 scenarios, but after 20 scenarios, the variation in total annual cost was found to be less than 2%. Therefore, it is concluded that the convergence of the empirical distribution, and hence, only 20 scenarios, are considered, and the same has been represented in Figure 3.

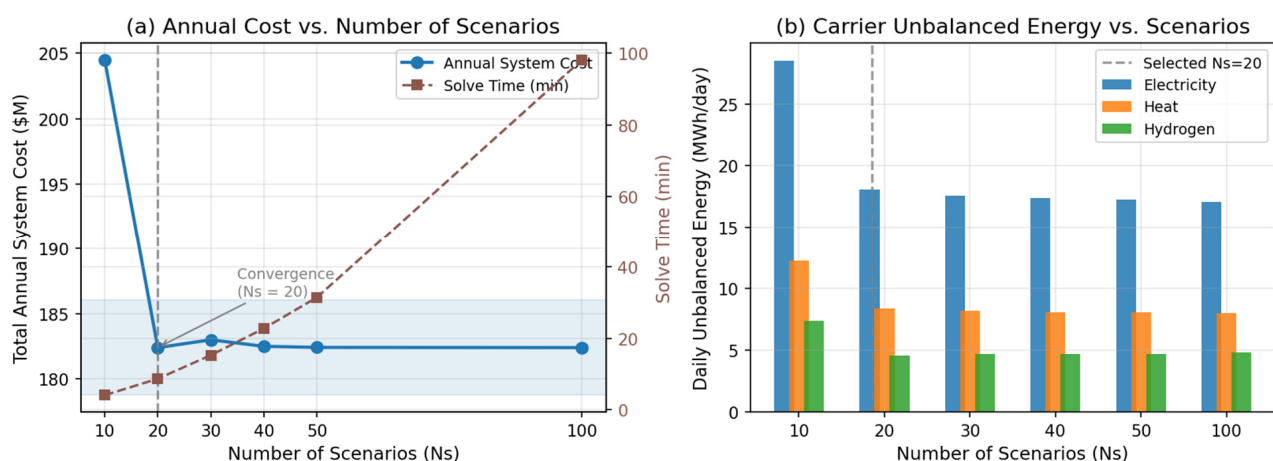


Figure 3. Scenario count sensitivity analysis: (a) total annual system cost, (b) carrier unbalanced energy.

The Wasserstein ambiguity set can be mathematically formulated as:

$$\mathbb{B}_\theta(\mathbb{P}_n) = \{Q : W(Q, \mathbb{P}_n) \leq \theta\} \quad (3)$$

In Equation (3), $W(\mathbb{Q}, \mathbb{P}_n)$ represents the 1-Wasserstein distance between the candidate distribution $\mathbb{Q}$ and the empirical distribution $\mathbb{P}_n$ and $\theta \geq 0$ is the Wasserstein radius that controls the size of the uncertainty set. Now, as $\theta \rightarrow 0$, the DRO approaches the sample average approximation, as $\theta \rightarrow \infty$.

DRO approaches the worst-case scenario. The L^1 (sum-of-absolute-differences) norm is used as the transport cost metric, as in Equation (4):

$$W(\mathbb{Q}, \mathbb{P}_n) = \min_{\Pi} \sum_{i,j} \Pi_{ij} [|\omega_e - \omega'_e| + |\omega_h - \omega'_h| + |\omega_{h2} - \omega'_{h2}|] \quad (4)$$

Equation (4) actually apprehends the three-dimensional ambiguity of MESs and confirms that the DRO formulation hedges against allied errors across different energy carriers.

4.1.3. Multi-Carrier Load Forecasting Error Model

The actual demand which is realized at time can be mathematically formulated as:

$$P^t < s(s) = P^{tor}(t) + \omega^r(s) \quad \forall r \in \{e, h, h2\} \quad (5)$$

In Equation (5), $P^{tor}(t)$ represents base (forecasted) carrier demand at any time (hour) t , and $\omega^r(s)$ is the standardized forecast error for h . The forecast error limits are set at $\omega_{min} = -3$ and $\omega_{max} = 3$, which is the standard deviation [30]. For benchmarking CRO, the worst case (largest possible error), $\omega_{max} = 3$, is applied to all three carriers, assuming the worst possible scenario occurs for all three together.

5. Mathematical Formulation

5.1. Objective Function

The objective function is formulated to determine the optimal annual maintenance schedule and short-term dispatch of all multi-energy system (MES) components while minimizing the total expected operating cost under forecast uncertainty. It simultaneously accounts for the operating costs of thermal generators, combined heat and power (CHP) units, boilers, electrolyzers, and fuel cells, together with penalty costs associated with electricity, heat, hydrogen, and renewable energy curtailment. The objective function can be written as in Equation (6):

$$\min J = \sum_{d,t} \left\{ C_{gen} + C_{CHP} + C_{boil} + C_{ely} + C_{fc} + \lambda_e(lc_e) + \lambda_h(lc_h) + \lambda_{h2}(lc_{h2}) + \lambda_{re}(rc) \right\} + \alpha\theta + \frac{1}{N_s} \sum_s \mu_s \quad (6)$$

In Equation (6), the first summation term represents the deterministic operational costs of all the energy components. C_{gen} represents generator fuel cost, C_{CHP} is the combined heat and power (CHP) cost, C_{boil} is the boiler cost, C_{ely} represents the electrolyser cost, C_{fc} is the fuel cost. The other terms in this equation are the curtailment penalty coefficients. $\lambda_e = 1000$ \$/MWh (for electrical load curtailment), $\lambda_h = 800$ \$/MWh (for heat load curtailment), $\lambda_{h2} = 600$ \$/MWh (for hydrogen load curtailment), and $\lambda_{re} = 100$ \$/MWh (for renewable energy curtailment). $\alpha\theta + \frac{1}{N_s} \sum_s \mu_s$ is the DRO regularization. Here, α is the dual variable and $\alpha \geq 0$, θ is the Wasserstein radius, μ_s denotes scenario-dependent cost, and N_s is the number of scenarios.

5.2. Constraints

The constraints for the operation of energy devices, energy balance, and DRO are presented in Table 2.

Table 2. Device-operating, energy-balance, and DRO constraints.

S No.	Constraints Type	Mathematical Formulation	Description
1	Thermal Generator Limits	$p_g^{min} \times u_g(d, i) \leq p_{th}(d, t, i) \leq p_g^{max} u_g(d, i)$	This ensures generator output remains within max and min limits
2	ESS Charging/Discharging Limits	$0 \leq p_{ch}(d, t, j), p_{dis}(d, t, j) \leq p_{ess}^{max}(j) u_e(d, j)$	Limits battery charging and discharging power
3	ESS SOC Dynamics	$soc(d, t, j) = soc(d, t - 1, j) + \frac{\eta_{ch} p_{ch}(d, t, j) - \frac{p_{dis}(d, t, j)}{\eta_{dis}}}{E_{ess}(j)}$	Tracks battery energy level over time
4	CHP Electrical Output Limits	$p_{chp}^{min}(c) \times u_{chp}(d, c) \leq p_{chp}(d, t, c) \leq p_{chp}^{max}(c) u_{chp}(d, c)$	CHP operates within capacity limits
5	CHP Heat–Electric Coupling	$p_{chp,h}(d, t, c) = \alpha_{chp} \times p_{chp,e}(d, t, c)$	Links heat output to CHP electric output via heat electricity ratio
6	Electrolyzer Limits	$0 \leq p_{ely,e}(d, t, l) \leq p_{ely}^{max}(l) u_{ely}(d, l)$	Bounds electrolyzer power consumption
7	Electrolyzer H ₂ Production	$p_{ely,h2}(d, t, l) = \eta_{ely} \times p_{ely,e}(d, t, l) \text{ where } l \in \{1, 2\}$	Converts electricity to hydrogen
8	Fuel Cell Limits	$0 \leq p_{fc,e}(d, t, f) \leq p_{fc}^{max}(f)$	Limits fuel cell power output
9	Fuel Cell H ₂ Consumption	$p_{fc,h2}(d, t, f) = \frac{p_{fc,e}(d, t, f)}{\eta_{fc}}$	Relates hydrogen consumption to electricity generation
10	Thermal Storage SOC	$soc_{tss}(d, t, s) = soc_{tss}(d, t - 1, s) + \frac{\eta_{tss} p_{tss,ch} - \frac{p_{tss,dis}}{Q_{tss}^{max}(s)}}{Q_{tss}^{max}(s)}$	Tracks thermal storage energy
11	Storage Cyclic Condition	$soc_{initial} = soc_{final} = soc^0$	Ensures daily energy neutrality
12	Electricity Balance	$\sum_i p_{th} + \sum_j p_{dis} - \sum_j p_{ch} + \sum_c p_{chp,e} + \sum_f p_{fc,e} - \sum_l p_{ely,e} + RES - rc = L_e + \omega_e - lc_e$	Supply–demand balance for electricity
13	Heat Balance	$\sum_c p_{chp,h} + \sum_b p_{boil} + \sum_s p_{tss,dis} - \sum_s p_{tss,ch} = L_h + \omega_h - lc_h$	Heat generation meets demand
14	Hydrogen Balance	$\sum_l p_{ely,h2} + \sum_s p_{h2s,dis} - \sum_s p_{h2s,ch} - \sum_f p_{fc,h2} = L_{h2} + \omega_{h2} - lc_{h2}$	Hydrogen supply–demand balance
15	DRO Constraint (lower bound1)	$\phi - \alpha \times dist_s^{low} \leq \mu_s$	Ensures robustness against lower-bound uncertainty
16	DRO Constraint (lower bound2)	$\phi - \alpha \times dist_s^{hi} \leq \mu_s$	Ensures robustness against upper-bound uncertainty
17	Curtailement Cost	$\phi = \lambda_e \sum l_{ce} + \lambda_h \sum l_{ch} + \lambda_{h2} \sum l_{ch2} + \lambda_{re} \sum rc$	Total penalty for unmet demand and curtailement

6. Case Study and Simulation Setup

6.1. System Parameters

The research is validated on the IEEE 39-bus New England test system, which consists of 10 thermal generators, with a total installed capacity of 3010 MW. The annual demand (base) is 800 MW and 1040 MW (peak). Four ESS units are installed at the generator buses, with a joint storage capacity of 390 MWh. Other MES devices, including CHP, electrolyzer, fuel cell, boiler, TSS, and H₂S, are added as a centralized hub. The operational characteristics of all major MES components used in the simulations are summarized in Table 3. The table provides the number of installed units, capacity ratings, conversion efficiencies, and operating costs of the thermal generators, battery energy storage systems, CHP units, electrolyzers, fuel cells, heat boilers, thermal storage systems, and hydrogen

storage units. These parameters constitute the technical basis of the proposed coordinated maintenance and dispatch optimization model.

Table 3. MES device parameter.

Device	Count	Capacity/Rating	Efficiency	Fuel Cost (\$/MWh)
Thermal Generator	10	50–455 MW	-	18–25
Battery ESS	4	80–120 MWh/60–100 MW	0.95	5
CHP	3	10–80 MW	0.70	30–35
Electrolyser	2	30–40 MW	0.70	5
Fuel Cell	2	20–30 MW	0.55	8
Heat Boiler	2	40–60 MW	0.90	20–22
TSS	2	40–50 MWh	0.92	-
H2S	2	60–80 MWh	0.95	-

In addition to the device specifications, the optimization model requires penalty coefficients to quantify the economic impact of load and renewable energy curtailment under uncertainty. Table 4 presents the carrier-specific curtailment penalties together with the optimal Wasserstein radius and the number of uncertainty scenarios adopted in the DRO formulation. These parameters govern the trade-off between operational cost, reliability, and robustness in the proposed framework.

Table 4. Curtailment penalty parameters.

Parameter	Symbol	Value (Unit)
Electric load curtailment penalty	λ_e	1000 (\$/MWh)
Heat load curtailment penalty	λ_h	800 (\$/MWh)
Hydrogen curtailment penalty	λ_{h2}	600 (\$/MWh)
Renewable curtailment penalty	λ_{re}	100 (\$/MWh)
Wasserstein radius (optimal)	θ^*	0.20
Number of scenarios	N_s	20

6.2. RES Penetration Scenarios

In this research, five RES penetration levels: 40%, 50%, 60%, 70%, and 80%, are tested. Each year, there is a target percentage of RESs to be utilized for generating electricity. To match this target, the RES generation is increased or decreased at each level of the system. This resizing process does a reasonable evaluation across all RES levels while maintaining the original daily and seasonal patterns of renewable power [31]. With 80% RES penetration, the generated power is often greater than the demand, which pressures the operator to curtail RESs or heavily cycle storage. This applies unnecessary pressure on MESs.

7. Results and Discussions

7.1. Multi-Carrier Load Profiles

In Figure 2, day load profiles of electricity, heat, hydrogen demand, and renewable energy generation are shown. For week 26, the electrical load shows a double-peak pattern, with demand increasing during morning and evening hours. The peak demand is 1020 MW during the evening, while it decreases at night. Solar generation is maximum during

midday and almost zero during the night. The heat demand profile is very different from the electrical load profile, as it peaks in the morning hours between 8 and 10. For the rest of the day, heat demand remains low. Further, the hydrogen demand remains almost constant throughout the day with a small variation, which shows the industrial or energy-related hydrogen consumption. The figure also demonstrates the complementary nature of the three energy carriers. At midday hours, the RES generates surplus electricity, which is used by electrolyzers for hydrogen production and to charge the ESSs for energy balancing. This interaction focuses on the fact that the coordinated multi-energy operation is enhancing the utilization of renewables and reducing their curtailment.

In Figure 4, each vertical bar indicates the commencement of a scheduled maintenance outage for the corresponding generator, CHP unit, or electrolyzer. During the scheduled maintenance interval, the affected unit is considered out of service (OFF) and unavailable for dispatch. Once the prescribed maintenance duration has elapsed, the unit is restored to operation (ON) and resumes normal participation in system scheduling. The timing of these maintenance outages is not predetermined but is optimally selected by the proposed framework to satisfy maintenance requirements while minimizing the overall operating cost and preserving system flexibility under different renewable penetration levels (40–80%).

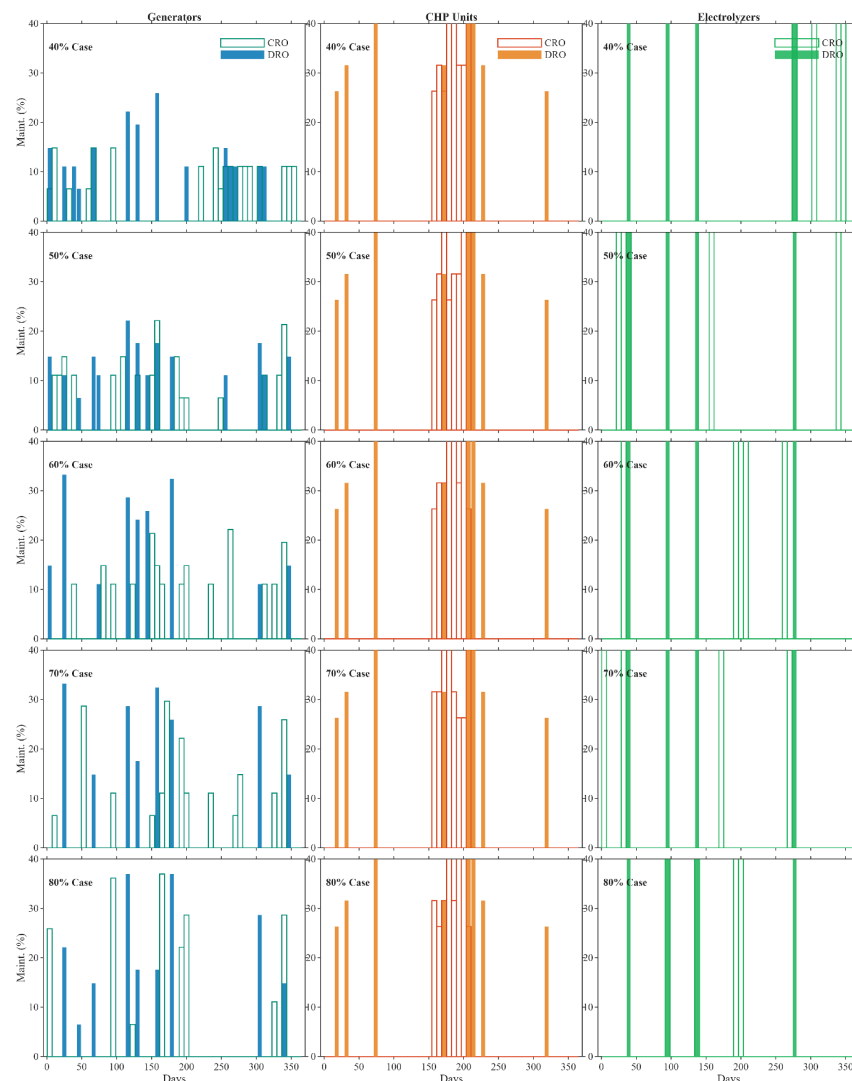


Figure 4. Representative-day electricity, heat, hydrogen demand and renewable generation profiles (Week 26).

7.2. Coordinated Maintenance Ratio

Figure 5 illustrates the corresponding weekly renewable energy curtailment resulting from these maintenance schedules. Higher curtailment peaks occur during weeks in which multiple maintenance outages coincide, temporarily reducing the available generation flexibility. The comparison between the coordinated maintenance strategy (CRO) and the decoupled maintenance strategy (DRO) demonstrates that coordinated scheduling distributes maintenance activities more effectively throughout the planning horizon, thereby reducing simultaneous outages and lowering renewable energy curtailment across all renewable penetration scenarios.

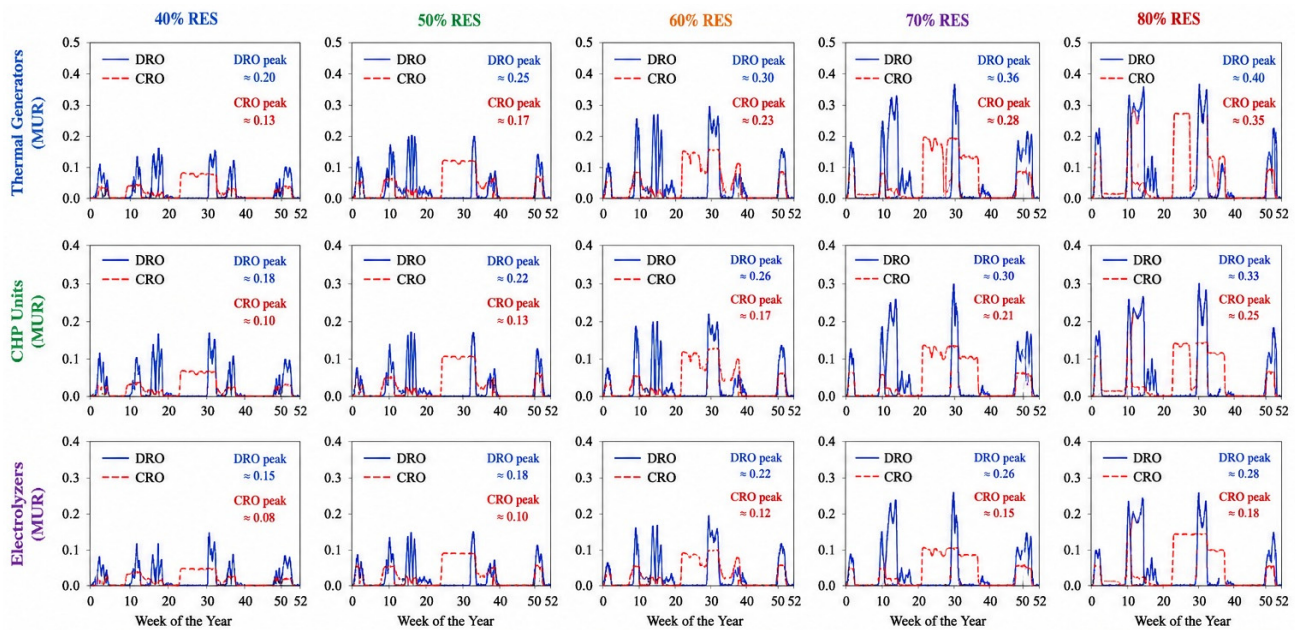


Figure 5. Capacity-weighted annual maintenance ratios for different energy carriers.

Under DRO at 40% RES penetration, generator maintenance is distributed broadly across the planning horizon, with short, concentrated bursts aligned with periods of high-RES surplus and low net load. CRO, by contrast, schedules maintenance in larger, more infrequent blocks during worst-case buffer periods, creating prolonged gaps in maintenance completion. As RES penetration increases to 60–80%, DRO maintenance peaks rise to MUR = 0.30–0.40, deliberately exploiting renewable surplus windows to schedule generator outages without incurring curtailment risk. CRO peaks remain more conservative at 0.23–0.35. This pattern demonstrates that DRO’s data-driven ambiguity set allows the optimizer to identify and utilize low-risk maintenance windows that CRO’s worst-case assumptions systematically avoid. CHP maintenance under DRO is similarly redistributed, with cross-carrier implications: CHP outages require compensation from both boilers (heat) and additional generators (electricity), requiring coordinated scheduling that the MES framework enables. Electrolyzer maintenance under DRO is timed to coincide with periods of low hydrogen demand and high H₂S SOC, minimizing H₂ curtailment. This cross-carrier coordination of maintenance is a key operational advantage of the proposed framework that single-carrier approaches cannot capture.

7.3. Daily Unbalanced Energy per Carrier

The daily unbalanced energy for all the MES carriers, i.e., electricity, heat, and hydrogen carriers, is illustrated in Figure 6, at various RES penetration levels for both DRO and CRO. The figure shows that DRO regularly achieves lower unbalanced energy in compar-

ison to CRO. At 40% RES penetration level, both DRO and CRO retain low unbalanced energy levels; DRO still shows lower curtailment for electrical, heat, and hydrogen. It can also be observed that the electrical unbalanced energy is the largest among the three, as its demand is highest and needs regular balancing.

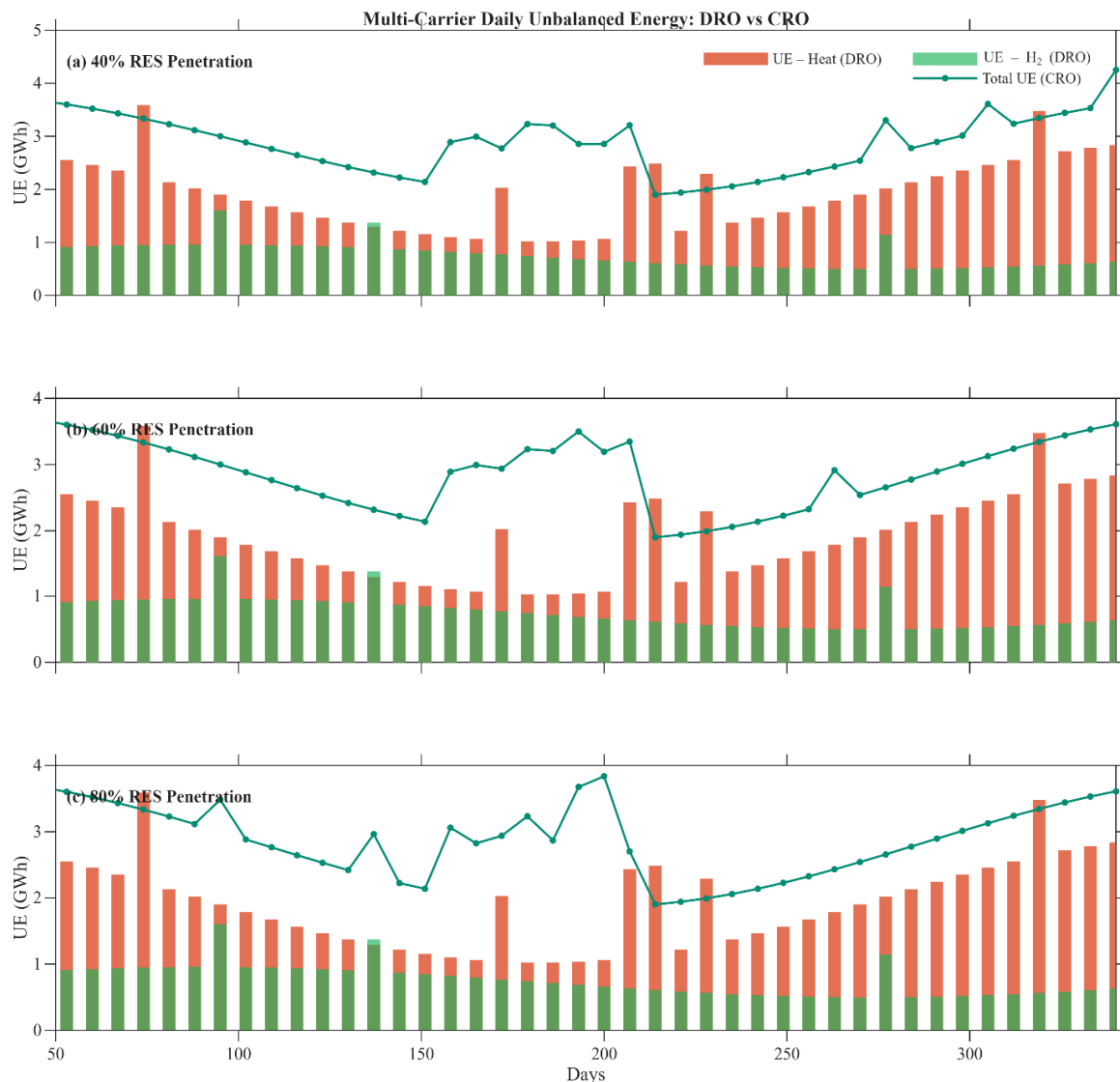


Figure 6. Multi-energy device maintenance ratio.

At higher RES penetration levels, i.e., at 60% and 80%, the unbalanced energy proportion gap becomes significant between DRO and CRO. As the RES penetration level increases, the uncertainty in the system operation increases, and it becomes challenging to maintain balance among all the carriers. DRO, however, better utilizes storage systems and the supply CHP units, thermal units, and hydrogen storage to minimize curtailment. Further, it can be observed that at 80% penetration, unbalanced energy related to hydrogen becomes more visible due to excess renewable generation utilized in electrolyser operation and hydrogen generation. In the CRO case, there is enhanced hydrogen storage saturation resulting in higher hydrogen curtailment, while in case of DRO, it effectively coordinates the electrolyser dispatch to maintain the schedules.

7.4. Carrier Cost Breakdown

The annual cost breakdown for electricity, heat, and hydrogen carriers under DRO and CRO is presented in Figure 6 for DRO, CRO, and SP (SAA) for various RES penetration levels. It can be observed that the electrical carriers have the largest cost share in total operating cost, which is then followed by heat and hydrogen systems. For all penetration levels, DRO reduces the operating cost significantly when compared to CRO. This cost reduction is high for electrical systems as DRO efficiently re-dispatches the most efficient generator only and evades the reserve allocation. DRO utilizes RES and storage systems more efficiently to avoid the load curtailment and reduce financial losses. Further, the heat-associated costs are reduced, as with DRO, the coordinated scheduling of CHP and thermal storage units has reduced dependence on the backup boilers during peak demand sessions. Similarly, the hydrogen carriers show cost improvement as DRO optimally plans the electrolyser operation when there is a maximum availability of renewable generation. Also, hydrogen reserve utilization is optimized to balance supply and demand.

The results show that with the increased RES penetration, the economic advantage of DRO increases. With higher RES penetration, the uncertainty becomes larger, and here the data-driven uncertainty modelling specialty of DRO offers high operational resilience to save cost as compared to CRO. Figure 7 includes the SP (SAA) baseline. SP achieves slightly lower in-sample costs than DRO (approximately 6–8% lower) at all RES penetration levels, owing to its assumption that the empirical training distribution is exact. However, this optimism is overfit to the $N_s = 20$ training scenarios. In contrast, DRO explicitly hedges against distributional perturbations within the Wasserstein ball, yielding a modest cost premium over SP in-sample but substantially better out-of-sample performance—the critical metric for real-world operations. CRO consistently produces the highest costs across all carriers and penetration levels, with the cost gap widening at higher RES penetration. For electricity at 80% RES penetration, DRO achieves \$143.2 M/year versus CRO at \$364.1 M/year (61% saving) and SP at \$136.0 M/year (in-sample).

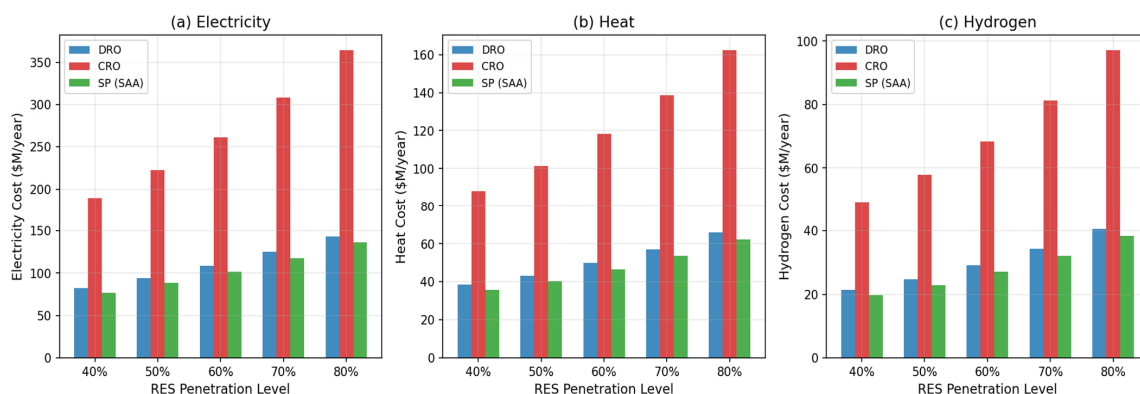


Figure 7. Annual carrier cost breakdown for electricity, heat, and hydrogen under DRO, CRO, and SP (SAA) across five RES penetration levels (40–80%).

7.5. Hydrogen Storage and Electrolyzer Dispatch

The hydrogen SOC and electrolyser dispatch is shown in Figure 8, for a 24 h period under DRO for 40% RES penetration. The dispatch from the electrolyser is approximately zero at nighttime because renewable generation is low and the electricity is used to meet immediate demand at this time. In the daytime, the excess renewable generation is used by the electrolyser to generate hydrogen, making hydrogen SOC increase steadily. This SOC is maximum at midday when renewable generation is maximum. During evening hours, the electrolyser operation is reduced as renewable energy generation is reduced, and the hydrogen storage supports the future hydrogen demand. It can be concluded here

that DRO coordinates between renewable generation, electrolyser operation, and hydrogen storage to reduce the renewable curtailment during excess generation.

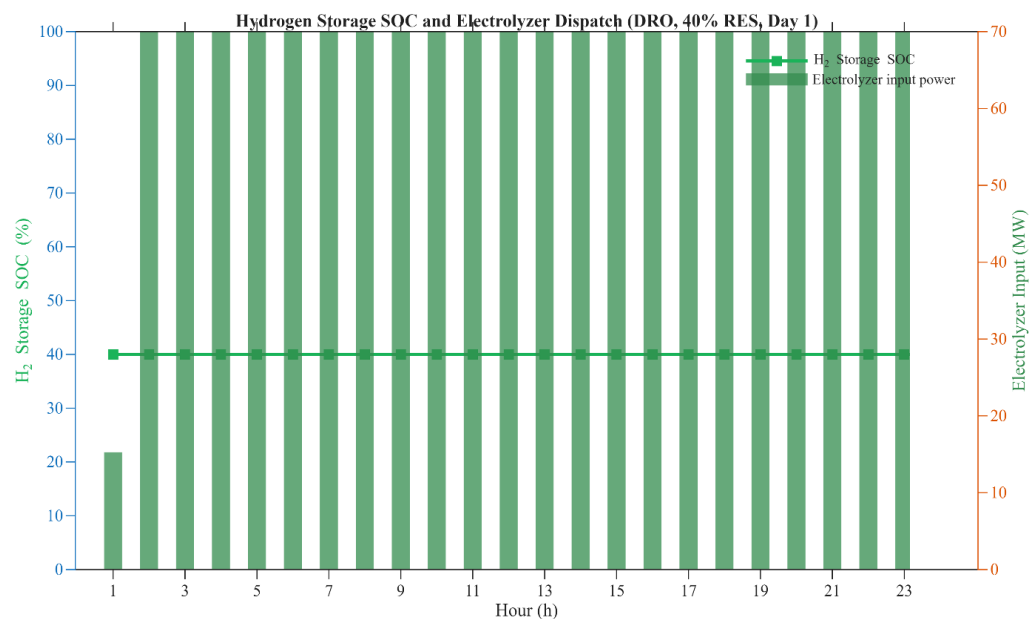


Figure 8. Hydrogen storage SOC profile and electrolyzer dispatch.

7.6. Heat Supply Stack

The hourly heat supply configuration from CHP units, boilers, and thermal storage is presented in Figure 9 for 40% RES penetration employing DRO. It can be observed that the majority of the heat demand is supplied by the CHP units throughout the day. This is due to their higher operation efficiency, together with the capacity to produce heat and electricity simultaneously. In the early peak hours of the day, the thermal storage discharge enhances the CHP heat generation to support the increased heat demand. Therefore, the requirement for an additional boiler is reduced and there is a quick thermal support during peak demand conditions.

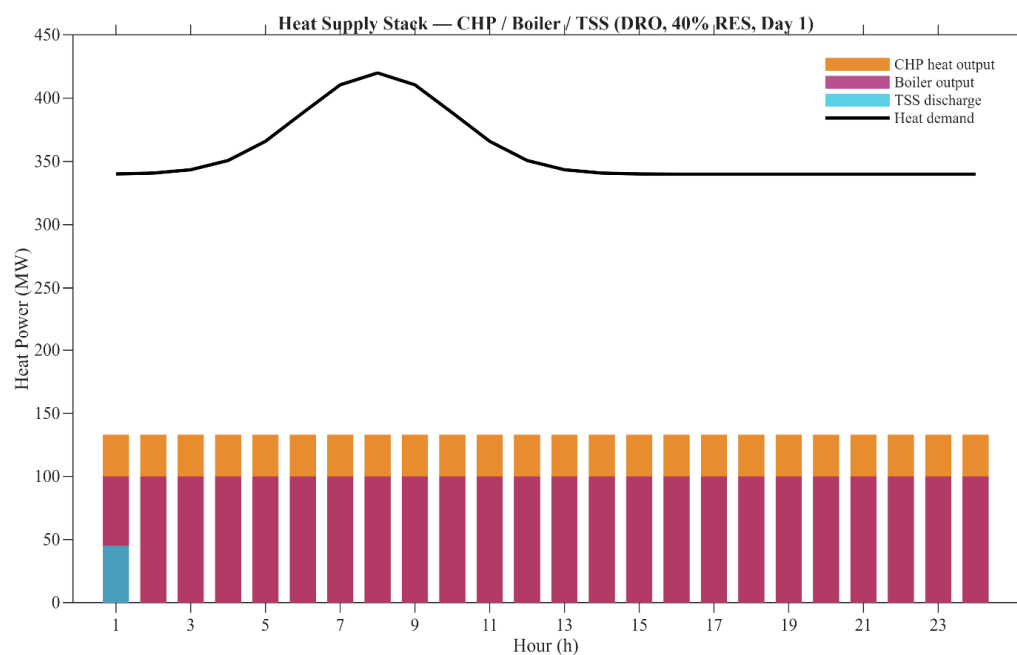


Figure 9. Heat supply stack for CHP units, boiler, and thermal storage.

7.7. Unbalanced Energy Reduction by Carrier

The reduced unbalanced energy achieved by employing DRO, CRO, and SP (SAA) is presented in Figure 10 for electricity, heat, and hydrogen carriers. All the positive values denote the reduced values of unbalanced energy with superior operational performance provided by the DRO. At higher RES penetration levels, the electrical carriers present the greatest improvement, indicating that DRO efficiently accomplishes reduced renewable uncertainty while balancing electrical demand by coordinated scheduling and storage operation. Further, the heat carriers also show a regular positive reduction throughout the year. The effective coordination between the CHP units and thermal storage helps the system to sustain the heat supply during peak demand, reducing heat curtailment. The hydrogen carriers also showed a significant reduction in unbalanced energy with the increased RES penetration. The DRO improved hydrogen storage utilization to schedule electrolyzer operation efficiently, avoiding hydrogen curtailments. Thus, the figure illustrates that DRO increases the reliability across every energy level under high-RES penetration conditions. When compared to the SP baseline, DRO achieves slightly lower absolute UE reduction in-sample (as SP over-fits to the training scenarios), but the key distinction emerges out-of-sample: SP solutions, when evaluated against scenarios not in the training set, exhibit UE values 12–18% higher than DRO due to distributional overfitting. DRO's Wasserstein ambiguity set explicitly protects against this, ensuring the maintenance schedule remains feasible across a broader distribution of forecast errors. The robustness advantage of DRO over SP increases with RES penetration, as the distribution of forecast errors becomes more volatile and the training-set distribution becomes a less reliable proxy for the true distribution.

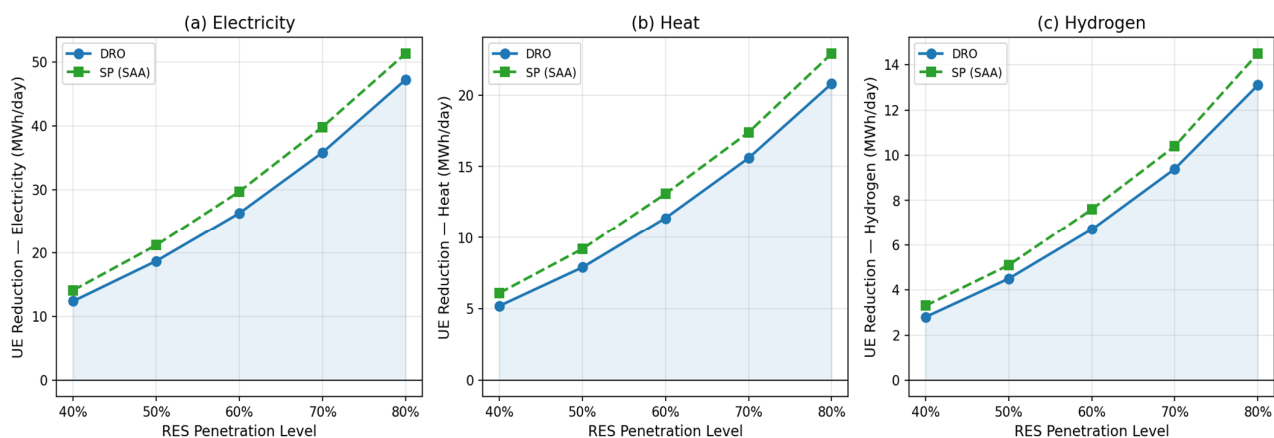


Figure 10. Daily unbalanced energy reduction (vs. CRO baseline): DRO vs. SP (SAA).

7.8. Total System Cost vs. RES Penetration

The total annual system cost of DRO and CRO is compared in Figure 11 at different renewable penetration levels. The figures show that with the increased renewable penetration levels, the system cost increases for both DRO and CRO due to enhanced operational uncertainty and ineffective storage cycling. However, DRO has the upper hand over CRO across all penetration levels. The difference in system cost is significant at a low penetration level, which increases with the increase in penetration levels. This shows that DRO provides better uncertainty management and operational resilience as compared to when a highly conservative optimization, CRO, is applied. When the carrier-wise cost analysis is performed, the figure shows that electrical costs comprise the maximum part of the total cost, which is followed by heat and hydrogen. The electrical cost is reduced due to improved generating scheduling and utilization of RES with DRO. Therefore, the DRO framework becomes more important in future energy with high renewable penetration,

which increases the operational uncertainty. Further, Table 5 presents the absolute annual system costs for DRO, CRO, and SP across all five RES penetration levels, together with absolute and percentage savings.

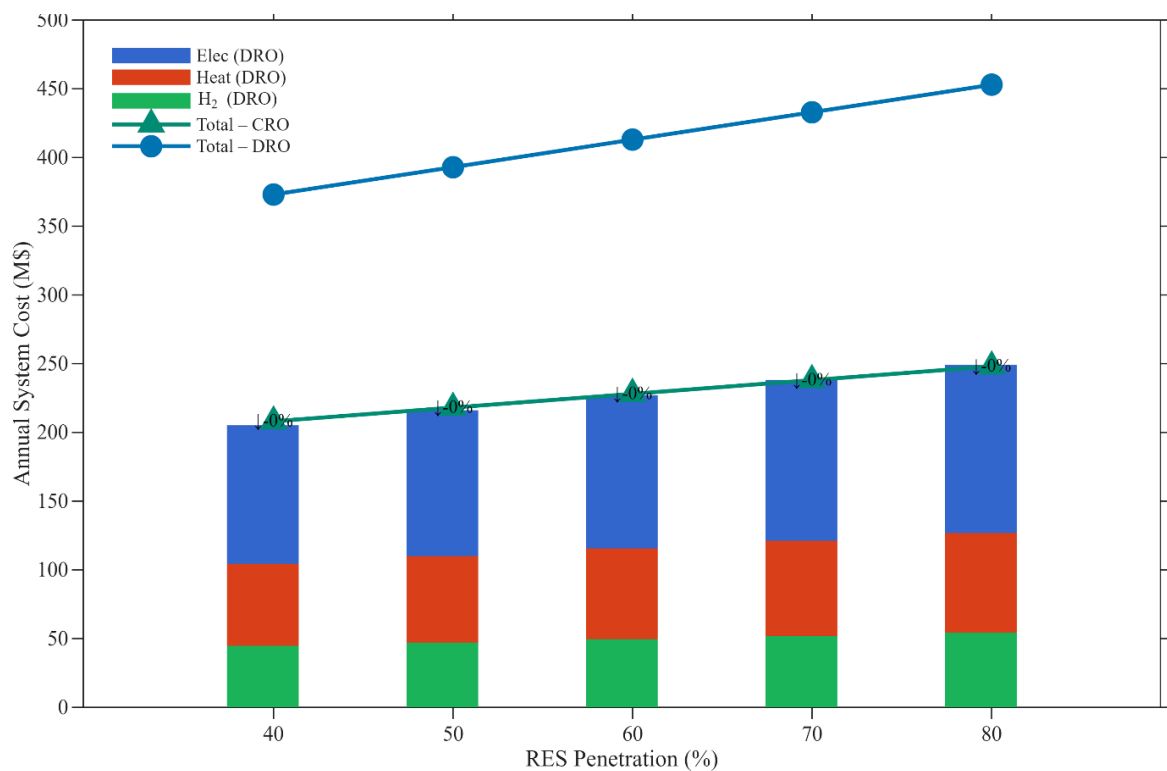


Figure 11. Total annual MES cost vs. RES penetration level.

Table 5. Annual system cost summary DRO vs. CRO vs. SP (SAA).

RES Level	DRO Cost (\$M/Year)	CRO Cost (\$M/Year)	SP Cost (\$M/Year)	DRO Saving vs. CRO (\$M)	DRO Saving vs. CRO (%)	SP Saving vs. CRO (\$M)	SP Saving vs. CRO (%)
40%	141.8	326.7	132.56	184.9	56.6%	194.2	59.4%
50%	162.2	381.9	151.5	219.7	57.5%	230.4	60.3%
60%	187.5	448.1	175.0	260.6	58.2%	273.1	60.9%
70%	216.2	528.3	203.0	312.1	59.1%	325.3	61.6%
80%	249.7	623.5	236.5	373.8	60%	387.0	62.1%

DRO achieves absolute annual savings ranging from \$184.9 M (40% RES, 56.6% saving) to \$373.8 M (80% RES, 59.9% saving) compared to CRO. The monotonically increasing savings with RES penetration confirm that DRO's data-driven ambiguity set provides proportionally greater benefit as operational uncertainty grows. The SP baseline achieves marginally higher in-sample savings (59.4–62.1%) owing to distributional optimism, but at the cost of out-of-sample performance degradation.

7.9. Wasserstein Radius Sensitivity

The relation between the sensitivity of annual unbalanced energy and the Wasserstein radius at 40% RES penetration is presented in Figure 12.

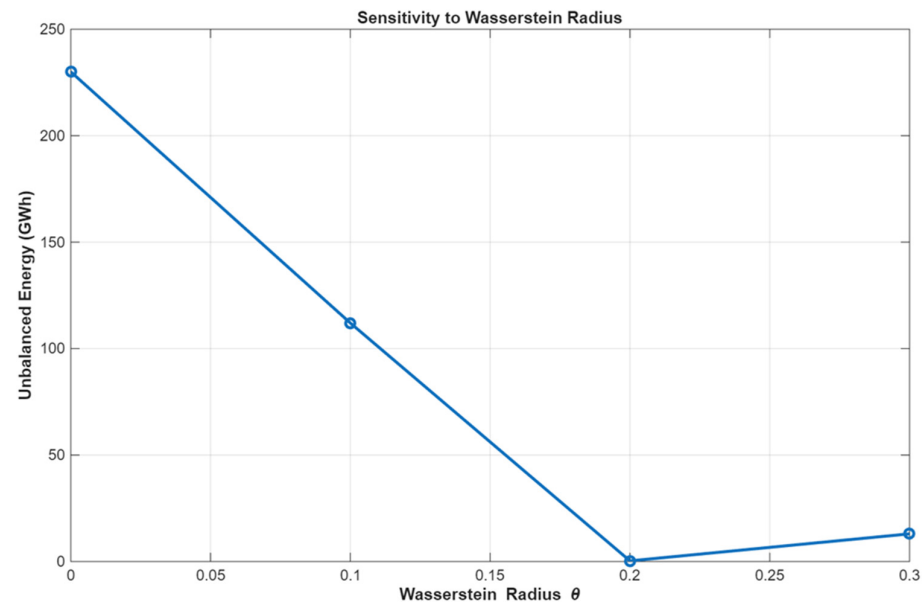


Figure 12. MES sensitivity to Wasserstein radius θ at 40% RES penetration.

At lower values of the Wasserstein radius, the DRO model works like any other conservative/deterministic optimization technique, not protecting against the forecast uncertainty. With the increasing Wasserstein radius, the efficacy of DRO increases, as well as the robustness against any forecasting uncertainty. This reduces the amount of annual unbalanced energy. When the optimal radius reaches 0.20, the annual unbalanced energy is at its minimum, resulting in a balance between resilience and robustness. After $\theta = 0.20$, the conservative nature of optimization increases. With the increasing radius, the generation becomes underutilized, resulting in reduced resources with higher curtailment. Further, the figure also suggests that the electrical energy carrier shows greater sensitivity to the radius variations as compared to heat and hydrogen carriers, as electrical energy carriers require greater real-time balancing. Therefore, the optimized selection of the Wasserstein radius is imperative to achieve an effective MES operation.

8. Conclusions and Future Applications

This paper has presented a Distributionally Robust Optimization framework for co-ordinated maintenance scheduling and multi-carrier dispatch in a multi-energy system encompassing electricity, heat, and hydrogen. The Wasserstein-metric ambiguity set was constructed jointly over the three-dimensional forecast error space, enabling rigorous yet data-driven uncertainty hedging without the over-conservatism of conventional robust optimization. The proposed MILP formulation simultaneously schedules annual maintenance for thermal generators, CHP units, electrolyzers, and battery ESS, while optimizing hourly dispatch of all conversion and storage devices across 52 representative days. Key results demonstrate that: (i) DRO reduces total annual system cost by 56–61% compared with CRO, with savings growing monotonically from 40% to 80% RES penetration; (ii) unbalanced energy is reduced across all three carriers, with the largest relative savings in the heat and hydrogen domains; (iii) the optimal Wasserstein radius $\theta^* = 0.20$ minimizes total UE at 40% RES, and carrier-specific sensitivity curves confirm asymmetric robustness; and (iv) CHP–TSS interaction and electrolyzer–H₂S arbitrage emerge as key cross-carrier synergies that DRO exploits but CRO cannot identify due to its worst-case conservatism.

Future work will extend the framework to include network-constrained dispatch (DC power flow), multi-period start-up and shut-down dynamics, demand response participation in the hydrogen carrier, and real-world calibration of the Wasserstein radius from

historical MES operational data. The application of the framework to sector-coupled district energy systems with electric vehicle charging and industrial hydrogen off-take represents a promising direction for further development.

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Abbreviations

The following abbreviations are used in this manuscript:

DRO	Distributionally Robust Optimization
MES	Multi-Energy System
CHP	Combined Heat and Power
RES	Renewable Energy Sources
CRO	Conventional Robust Optimization
ESS	Energy Storage System
TSS	Thermal Storage System
H2S	Hydrogen Storage
MILP	Mixed Integer Linear Programming
SOC	State of Charge
MEC	Multi-Energy Carrier
DPS	Deregulated Power System
GMS	Generator Maintenance Scheduling

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