Cross-Sectoral Reliability-Constrained Sizing of Thermal Storage in Multi-Energy Systems

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***Abstract*—The increasing electrification in district heating systems through electric heat pumps and the resulting coupling between electrical and heating systems presents challenges to network operators and planners, but it also offers high flexibility potential in distribution network operation. The flexibility offered by electric heat pumps and thermal storages can play a vital role in providing affordable energy storage and the potential for load shifting. However, this flexibility comes with uncertainty as it depends on changing weather conditions and customer behavior. Therefore, the correct sizing of the thermal storage capacities in the planning phase of multi-energy systems (MES) is essential for guaranteeing sufficient flexibility for electrical network operation. Moreover, existing reliability metrics do not capture the interactions between the electrical and thermal domains of MESs. In this paper, a novel methodology is presented for optimal sizing under the uncertainty of thermal storage capacities in a heating network coupled to an electrical network. Distributionally robust chance-constrained optimization (DRCC) is used to model the system to limit the probability of insecure operation due to uncertainty in heat demand forecasting. The proposed approach is demonstrated on a modified MES and the results are compared to those obtained from a conventional deterministic optimization model. A new reliability metric, Expected Heat Not Supplied (EHNS), is introduced to evaluate system reliability. The proposed methodology is designed to provide network planners and operators with the optimal storage capacities needed to balance robustness against existing uncertainties, costs, and system reliability.**

***Index Terms*—Distributionally robust chance-constrained optimization, flexibility, heat pump, multi-energy systems, reliability-informed optimization, uncertainty.**

I. INTRODUCTION

Decarbonizing energy systems is a critical goal to mitigate climate change, with heat pumps (HP) emerging as a central technology in the household heating sector by providing sustainable heating solutions [1]. However, integrating HP with electrical networks presents challenges, particularly in balancing supply and demand. This issue is further complicated by the uncertainties in heat demand driven by weather conditions [2]. To address these challenges, multi-energy systems (MES) combining electricity and heat networks have gained prominence for their potential to enhance operational flexibility and efficiency [3]. Therefore, integrated planning of MES is crucial, with thermal storage (TS) being one of the most important flexibility resources. In this paper, the optimal sizing of TS is determined to address these challenges.

TS plays a key role in providing the flexibility needed to accommodate fluctuations in heat demand, reducing peak loads, and minimizing infrastructure investments [4]. Optimal sizing of TS is critical for maximizing its economic and operational benefits. Traditional optimal TS sizing approaches, such as those based on iterative optimization frameworks [5], often ignore the uncertainties inherent in heat demand. Optimization methods that model this uncertainty, such as stochastic programming [6], robust optimization, and distributionally robust chance-constrained optimization (DRCC) [7], have emerged as powerful tools for addressing these uncertainties while ensuring cost-efficient system performance by incorporating probabilistic demand forecasts [8]. Additionally, integrating thermal and electrical planning through sector coupling can further improve system performance, reducing the need for expensive network reinforcements [9].

While significant progress has been made in storage sizing problems and MES expansion planning, existing methods often focus on either economic optimization, static designs, or deterministic models, neglecting the combined impact of uncertainty and infrastructure reliability. This shows the need to incorporate reliability considerations and uncertainty modelling into the planning of MES. Reliability analysis in power systems traditionally relies on metrics like Expected Energy Not Supplied (EENS), Loss of Load Probability (LOLP), System Average Interruption Frequency Index (SAIFI), and System Average Interruption Duration Index (SAIDI) to quantify the availability of electrical networks [10, 11]. These metrics calculated through *State Enumeration* (SE) [12] and *Sequential Monte Carlo* (SMC) Simulations [13], are well-suited for purely electrical systems but fail to address the unique interplay between electricity and heating networks in MES. In MES combining both heating and electrical power, heat supply reliability is as critical as electricity supply. The heating network is coupled with the electrical power network through HP, introducing an additional layer of complexity. Failures in these integrated systems, such as transformer outages, HP malfunctions, or storage limitations, impact not only electrical energy delivery but also the ability to provide

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sufficient heating to end users. This is particularly important in district heating networks, where TS can act as a buffer to mitigate the effects of such failures. However, existing reliability indices, e.g. EENS, fail to capture the reliability of heating services to consumers, leaving a critical gap in integrated MES planning and reliability analysis.

To address these gaps, this paper presents four key contributions to the field of MES planning under uncertainty, which are named as follows:

- *Integrated planning framework*: A new framework is proposed for the sizing problem of TS that integrates DRCC-based optimization with a cross-sectoral reliability metric for MES.
- *Extension of EENS to the thermal domain*: The *Expected Heat Not Supplied* (EHNS) metric is introduced, extending the concept of EENS to the thermal domain. EHNS quantifies the expected deficiency in heat delivery to end users, providing a cross-sectoral reliability metric for MES.
- *Modeling of thermal storage dynamics*: EHNS explicitly captures the system's ability to bridge temporary supply-demand mismatches caused by component failures by modeling the dynamics of TS, enhancing the reliability assessment of MES.
- *Unified optimization and reliability assessment framework*: The proposed approach combines DRCC optimization for robust TS sizing with reliability analysis based on EHNS, allowing for a balanced evaluation of the trade-offs between TS capacity, cost, and system reliability. The use of DRCC ensures resilience against heat demand uncertainty with an unknown probability distribution function, while EHNS quantifies the reliability benefits of different storage capacities under multiple contingency scenarios.

In Section II, the proposed DRCC optimization problem is formulated. Section III presents the reliability analysis and explains the EHNS metric. The solution methodology is explained in section IV. A case study is given in section V, and the results of the study are presented. In Section VI, the work is summarized, conclusions are drawn, and an outlook for the expansion of this model is discussed.

II. OPTIMIZATION PROBLEM FORMULATION

Consider a distribution network with a set of nodes $\mathcal{N} := 0, 1, ..., N$ denoted by index n and a set of lines $\mathcal{L} := 0, 1, ..., L$ denoted by index l. The optimization time frame is a week divided into 1 hour time steps represented by the set $\mathcal{T} := 0, 1, ..., T$ denoted by index t. The network has a central HP coupling the electrical network to a district heating network (DHN) containing a TS and feeding all the houses in the electrical network.

A. Objective Function: Cost Minimization

The objective function in (1a) is a cost minimization function of the weekly investment costs, operational costs, and the cost of heat not supplied (CHNS).

$$\min_{X} \underbrace{\left(C^{\mathrm{TS}} h^{\mathrm{TS}}\right)}_{\text{Investment Costs}} + \underbrace{\sum_{t\in\mathcal{T}} \Pi^{\mathrm{e}}_t \left(p^{\mathrm{HP}}_t + p^{\mathrm{Ext}}_t\right)}_{\text{Operational Costs}} + \mathrm{CHNS}, \quad (1a)$$

where h^{TS} is the capacity of the TS and C^{TS} is the weekly annualized investment cost assuming an initial investment per energy unit $C^{\mathrm{TS,tot}}$ and weekly interest rate r^{w} and a lifetime of n^{w} and presented in (1b). The weekly operational costs consist of the cost of importing and exporting electricity to and from the upstream network p^{Ext} and the HP dispatch costs resulting from a price of electricity Π^{e}_t and the HP power p^{HP}.

$$C^{\mathrm{TS}} = C^{\mathrm{TS,tot}} \cdot \frac{r^{\mathrm{w}}(1+r^{\mathrm{w}})^{n^{\mathrm{w}}}}{(1+r^{\mathrm{w}})^{n^{\mathrm{w}}}-1}, \quad (1b)$$

where the weekly interest rate r^{w} is calculated in eq. (1c) from the annual interest rate r and the total number of weeks n^{w} in a year.

$$r^{\mathrm{w}} = (1+r)^{1/n^{\mathrm{w}}} - 1 \quad (1c)$$

CHNS results from the price of heat not supplied Π^{HNS}_t as shown in (1d). The price of heat not supplied is assumed to be significantly higher than any other prices and is used to restrict shortages in heating supply only to cases where any other solution is infeasible. The heating power not supplied $\dot{q}^{\mathrm{HNS}}_t$ is the amount of heating power in timestep t not supplied to the end consumers.

$$\mathrm{CHNS} = \sum_{t\in\mathcal{T}} \Pi^{\mathrm{HNS}} \dot{q}^{\mathrm{HNS}}_t \quad (1d)$$

B. Constraints: Thermal System Modeling

The thermal system consists of a district heating network supplied by an HP and a TS.

1) Thermal storage model: The TS is modeled using a discrete-time equation [14]. This gives the stored heat h_t of the TS at time t as:

$$h_{t+1} = h_t + \eta^{\mathrm{TS}} \dot{q}^{\mathrm{in}}_t - \frac{\dot{q}^{\mathrm{out}}_t}{\eta^{\mathrm{TS}}} - \alpha h_t \left(T^{\mathrm{s}}_t - T^{\mathrm{amb}}_t\right), \quad (2a)$$

where η^{TS} is the efficiency of the TS, α is the heat loss coefficient, T^{s}_t is the suppy temperature of the DHN, and T^{amb}_t is the ambient temperature. $\dot{q}^{\mathrm{in}}_t$ and $\dot{q}^{\mathrm{out}}_t$ are the thermal power inflows and outflows of the TS at time step t. The storage inflow $\dot{q}^{\mathrm{in}}_t$ is constrained by the heating power $\dot{q}^{\mathrm{HP}}$ of the heat pump in (2b) and the outflow $\dot{q}^{\mathrm{out}}_t$ is constrained to the maximum value $\dot{Q}^{\mathrm{max}}_t$ in (2c).

$$\dot{q}^{\mathrm{in}}_t \leq x^{TS,in}_t . \dot{q}^{\mathrm{HP}}_t, \quad \forall t \in \mathcal{T} \quad (2b)$$

$$\dot{q}^{\mathrm{out}}_t \leq x^{TS,out}_t . \dot{Q}^{\mathrm{max}}_t, \quad \forall t \in \mathcal{T} \quad (2c)$$

$$x^{TS,in}_t + x^{TS,out}_t \leq 1, \quad \forall t \in \mathcal{T} \quad (2d)$$

Equation (2d) defines the operation mode of the TS by introducing two binary variables, $x^{TS,in}_t$ and $x^{TS,out}_t$. This constraint ensures that the simultaneous occurrence of thermal power inflow and outflow is prevented. In (2e) the stored heat h_t is constrained to be a positive value less than its maximum designed capacity h^{TS}.

$$0 \leq h_t \leq h^{\mathrm{TS}} \quad (2e)$$

2) Heat pump model: The thermal power of the HP is calculated from its electrical power p^{HP} and the coefficient of performance (COP) in (3a) and is constrained to a maximum value of $\dot{Q}^{\mathrm{HP,max}}$ (3b).

$$\dot{q}_t^{\mathrm{HP}} = \mathrm{COP} \cdot p_t^{\mathrm{HP}}, \quad \forall t \in \mathcal{T} \tag{3a}$$

$$\dot{q}_t^{\mathrm{HP}} \leq \dot{Q}^{\mathrm{HP,max}}, \quad \forall t \in \mathcal{T} \tag{3b}$$

The COP of the HP is calculated in (3c) as follows [15]:

$$\mathrm{COP}_t = \eta^{\mathrm{C0}} \eta^{\mathrm{PL}} \frac{T_t^{\mathrm{s}} + \Delta T}{T_t^{\mathrm{s}} - T_t^{\mathrm{amb}} + 2\Delta T}, \quad \forall t \in \mathcal{T} \tag{3c}$$

assuming the constant ΔT describes the temperature difference between T_t^{s} and the condenser temperature, and T^{amb} and the evaporator temperature. η^{C0} and η^{PL} are the Carnot efficiency and part load degradation coefficient factors, respectively. The Carnot efficiency factor η^{C0} is assumed to be constant. The part load degradation coefficient η^{PL} is given by:

$$\eta_{\mathrm{PL}} = 1 - \psi \left(1 - \frac{\dot{q}_t^{\mathrm{HP}}}{\dot{Q}^{\mathrm{HP,max}}}\right), \quad \forall t \in \mathcal{T} \tag{3d}$$

with $\psi \in (0, 1)$ being a constant factor [16].

3) Heat balance: The heat balance can be expressed as follows:

$$\dot{q}_t^{\mathrm{HP}} + \dot{q}_t^{\mathrm{out}} - \dot{q}_t^{\mathrm{in}} = \frac{\dot{Q}_t^{\mathrm{dem}} - \dot{q}_t^{\mathrm{HNS}}}{\eta^{\mathrm{DHN}}}, \quad \forall t \in \mathcal{T} \tag{4}$$

where η^{DHN} is the efficiency of the district heating network.

4) non-negativity constraints: These constraints ensure that the inflow and outflow of TS, as well as unsupplied heat values, remain non-negative.

$$\dot{q}_t^{\mathrm{in}} \geq 0, \quad \dot{q}_t^{\mathrm{out}} \geq 0, \quad \dot{q}_t^{\mathrm{HNS}} \geq 0, \quad \forall t \in \mathcal{T} \tag{5}$$

C. Constraints: Electrical System Modeling

The DC power flow equation defines the power $p_{i,t}$ at bus i and time t based on the voltage angle θ differences between the connected buses, divided by the line reactance X_{ij} connecting the two busses.

$$p_{i,t} = \sum_{j:(ij) \in \mathcal{L}} \frac{\theta_{i,t} - \theta_{j,t}}{X_{ij}}, \quad \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \tag{6}$$

D. Uncertainty Modelling

The distributionally robust chance constraint probabilistic formulation in (7) ensures that the probability of the power flow staying within its limits holds. In other words, this equation ensures that for all possible probability distribution functions D within the ambiguity set $\mathcal{D}$, $(D \in \mathcal{D})$, the probability that the power flow $|p_{ij,t}|$ between buses i and j at time t remains within the allowable limit $p_{ij}^{\max}$ is at least $1 - \varepsilon$, even in the worst-case scenario.

$$\inf_{D \in \mathcal{D}} \mathbb{P}\left[|p_{ij,t}| \leq p_{ij}^{\max}\right] \geq 1 - \varepsilon, \quad \forall (ij) \in \mathcal{L}, \forall t \in \mathcal{T} \tag{7}$$

The original DRCC probabilistic constraint needs to be reformulated into a deterministic equivalent. By *Chebyshev's inequality*, for the variable power $p_{ij,t}$ with expected value $\mathbb{E}\left[p_{ij,t}\right]$ and variance $\mathrm{Var}\left[p_{ij,t}\right]$, the probability lying within k standard deviations of its mean is:

$$\mathbb{P}\left(p_{ij,t} - \mathbb{E}\left[p_{ij,t}\right]\right) \leq k \cdot \sqrt{\mathrm{Var}\left[\mathrm{p_{ij,t}}\right]} \geq 1 - \frac{1}{k^2} \tag{8a}$$

thus the deterministic reformulation of the DRCC becomes:

$$\mathbb{E}\left[p_{ij,t}\right] + k_\varepsilon \cdot \sqrt{\mathrm{Var}\left[p_{ij,t}\right]} \leq p_{ij,t}^{\max}, \quad \forall (ij) \in \mathcal{L}, \forall t \in \mathcal{T} \tag{8b}$$

where expected power flow is calculated as:

$$\mathbb{E}\left[p_{ij,t}\right] = \frac{\mathbb{E}\left[\theta_{i,t}\right] - \mathbb{E}\left[\theta_{j,t}\right]}{X_{ij}}, \quad \forall (ij) \in \mathcal{L}, \forall t \in \mathcal{T} \tag{8c}$$

and the variance of power flow $p_{ij,t}$ is derived as:

$$\mathrm{Var}\left[p_{ij,t}\right] = \frac{\mathrm{Var}\left[\theta_{i,t}\right] + \mathrm{Var}\left[\theta_{j,t}\right] - 2 \cdot \mathrm{Cov}\left[\theta_{i,t} . \theta_{j,t}\right]}{X_{ij}} \tag{8d}$$

here $\mathrm{Var}\left[\theta\right]$ is the variance of the voltage angles and $\mathrm{Cov}\left[\theta_i . \theta_j\right]$ is the covariance between θ_i and θ_j. The safety margin, k_ε is defined in (8e). This term quantifies the scaling of power flow variability based on the desired confidence level $(1 - \varepsilon)$. Parameter k_ε ensures robustness by accounting for uncertainties, with higher confidence levels leading to larger safety margins, e.g., for $\varepsilon = 0.05$, $k_\varepsilon \approx 4.36$.

$$k_\varepsilon = \sqrt{\frac{1 - \varepsilon}{\varepsilon}} \tag{8e}$$

III. CROSS-SECTORAL RELIABILITY ANALYSIS

The reliability of the heat supply is determined through a reliability analysis using SMC scenario generation, which accounts for the stochastic nature of component failures and repair times. The reliability analysis evaluates the system's overall reliability based on the reliability of its individual components by using component failure rate (λ), and their mean time to repair (MTTR).

In our model, the heat supply can be interrupted or derated by failures in either the transformer, the HP, or the TS. For each generated scenario, the reliability state of the system is simulated, followed by solving an optimal power flow (OPF) problem. The proposed OPF calculation shown in (9a) can be considered as a simplified deterministic version of the DRCC optimization problem described in Section II, without including the annualized investment cost. The objective function minimizes the operational costs and CHNS, while TS capacity is considered a fixed parameter in the reliability analysis.

$$\min_X \sum_{t \in \mathcal{T}} \Pi_t^{\mathrm{e}} \left(p_t^{\mathrm{HP}} + p_t^{\mathrm{Ext}}\right) + \mathrm{CHNS} \tag{9a}$$

The EHNS is then calculated as the expected value of HNS, expressed in eq. (9b) over all simulated scenarios for a given TS capacity, providing a measure of the system's reliability, and the CHNS provides an economic equivalent to EHNS.

$$\mathrm{HNS} = \sum_{t \in \mathcal{T}} \dot{q}_t^{\mathrm{HNS}} \tag{9b}$$

IV. Proposed Integrated Planning Framework

In this section, the proposed integrated planning methodology for finding the optimal TS capacity is presented. The proposed framework is shown in fig. 1.

The methodology is centered around the DRCC optimization, formulated in section II, which integrated demand forecast uncertainty in the system modeling to ensure robust system performance. The DRCC optimization requires the network model, household electrical load profiles, weather data, and forecasted heat demand. The solution of the DRCC optimization is then validated through an out-of-sample analysis. This process is repeated for different confidence levels or chance of constraint violation ε, which represents different levels of conservativeness in dealing with forecast uncertainty.

The resulting TS capacity is assessed under various system reliability states generated through SMC scenario generation using the failure rates (λ) of components and their MTTR. The OPF model described in section III is solved for each scenario and the results are used to compute HNS for each scenario and subsequently the EHNS for each TS capacity, which serves as the main reliability metric for the system.

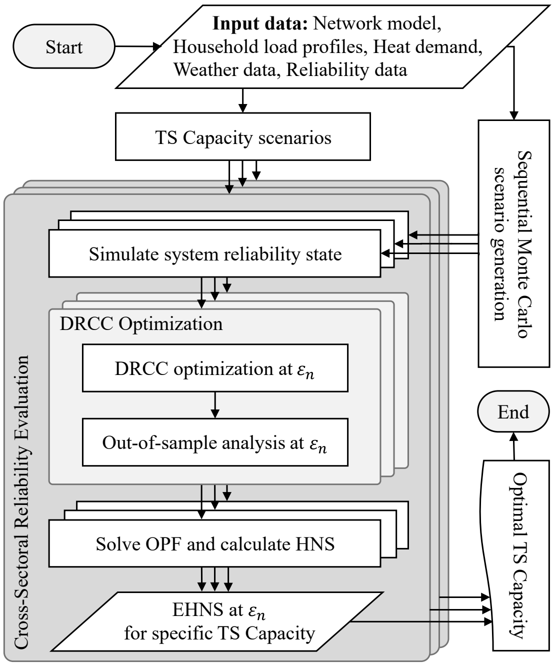

Fig. 1. Proposed cross-sectoral reliability-constrained integrated planning framework of MES

V. Case Study

A. Case study setup

In order to demonstrate the effectiveness of the proposed method, a case study is developed based on the *Simbench benchmark radial LV suburban network* with 3 feeders presented in [17]. The benchmark network is modified to include only household loads and the deterministic electrical household load profiles are generated based on the WPuQ dataset [18]. All houses are connected to a heating network fed by an electric HP and TS as shown in fig. 2. The HP is connected to a separate feeder, which was upgraded from the standard single NAYY 4x150SE to double NAYY 4x300SE to handle the higher HP current.

The optimization parameters are given in table I. The study was conducted for an exemplary winter week in 1-hour timesteps. The electricity price and ambient temperature data are based on the data for the first week of January 2022 from the WPuQ-dataset. All other parameters are unchanged from the benchmark network.

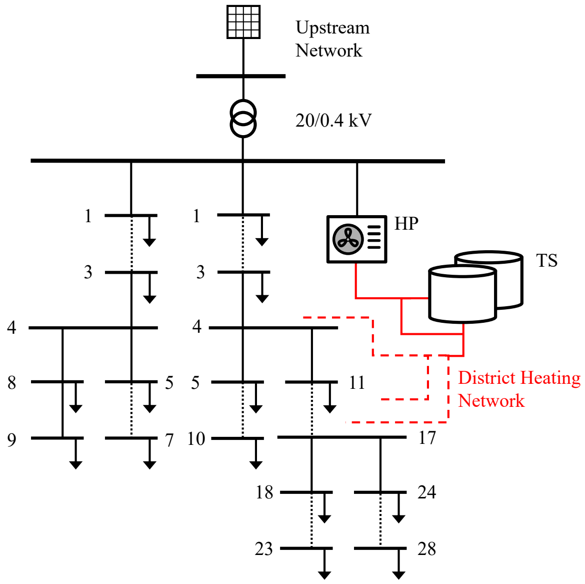

Fig. 2. Network model for the case study based on [17]

B. Results of DRCC optimization

In this subsection, the optimization results for the TS capacity sizing problem are presented. The optimization problem was solved with Gurobi optimization solver [23] in Python. The problem was solved initially, as a deterministic optimization problem, where uncertainty was not modeled, to represent a benchmark case. The problem was subsequently solved as a DRCC optimization problem and the enforced chance constraint violation probability was gradually reduced from 15% to 5%.

The resulting TS capacity for each optimization run is shown in fig. 3. The plot demonstrates how the conserva-

TABLE I
Optimization parameters

Heat Pump			District Heating Network		Thermal Storage				
ψ	η_{C0}	ΔT	T^{s}	η_{DHN}	α	η^{TS}	$C^{\mathrm{TS,tot}}$	r	n
0.13 [19]	0.6 [16]	2.1966°C [20]	75°C [15]	95% [21]	1×10^{-4}	90% [22]	8000 €/MWh [22]	5%	20 Years

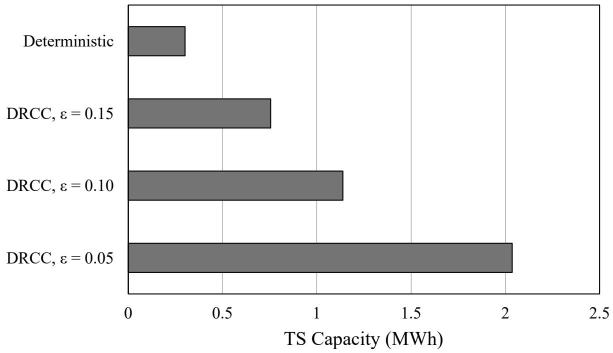

Fig. 3. TS capacity across various conservativeness levels

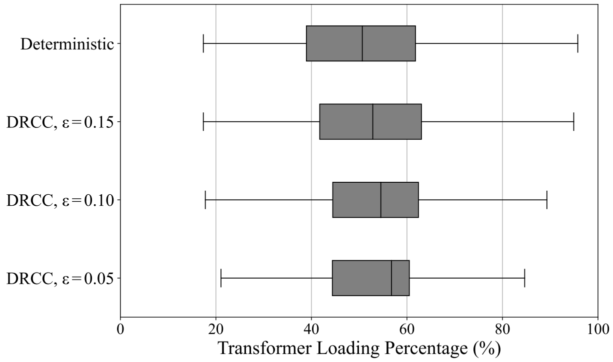

Fig. 4. Boxplots of the transformer loading percentage across various conservativeness levels.

tiveness of the DRCC optimization influences the sizing of the TS capacity. Lower chances of constraint violations (ε) correspond to higher levels of conservativeness in handling uncertainty, resulting in larger TS capacity needed for load shifting and reducing the line and transformer loading. In contrast, the deterministic approach, which doesn't model demand uncertainty, results in the smallest capacity requirement.

These results were validated through an out-of-sample analysis using 1000 SMC-generated scenarios. Figure 4 highlights the effect of demand uncertainty on the transformer loading. Each boxplot shows the minimum, the first quartile, the median, the third quartile, and the maximum values. As it can be seen in fig. 4, although the median value for transformer loading is effectively reduced by increasing the conservativeness level, the variance—and consequently the associated risk—is increased.

C. Results of cross-sectoral reliability analysis

The reliability analysis was conducted using probabilistic modeling and SMC scenario generation. Failure rates (λ) for the HP (0.1 failures/week), TS (0.005 failures/week), and transformer (0.0054 failures/week) [24] and their respective MTTR of 24 hrs, 48 hrs, and 10 hrs were used to simulate system behavior under failures. For each TS capacity (h^{TS}) calculated from the DRCC optimization, the EHNS, representing the heating energy interruption during component failures, was calculated. The CHNS, combined with operational costs, define the total cost used to evaluate the economic performance of the system.

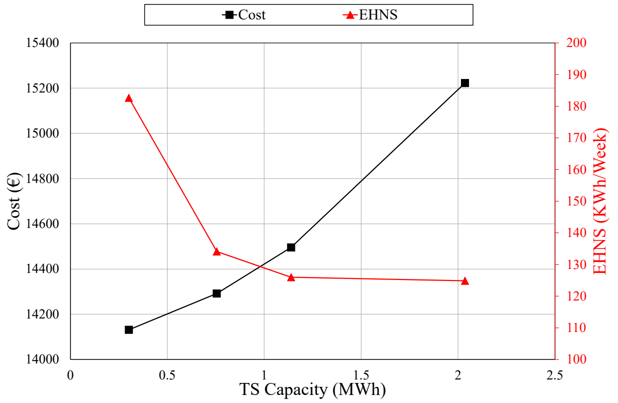

Fig. 5. Impacts of thermal storage capacity on weekly operational costs and total costs (left y-axis), and Expected Heat Not Supplied (right y-axis).

TABLE II
COMPARISON BETWEEN THE RESULTS OF VARIOUS CONSERVATIVENESS LEVELS.

Optimization Case	h^{TS} (MWh)	Cost (€)	EHNS (KWh)
Deterministic	0.3017	14130.93	182.659
DRCC, $\varepsilon = 0.15$	0.755	14291.48	134.130
DRCC, $\varepsilon = 0.10$	1.139	14495.39	125.983
DRCC, $\varepsilon = 0.05$	2.036	15222.98	124.844

The results, presented in table II and fig. 5, show that the optimal TS capacity (h^{TS}) lies between 0.5 MWh and 1 MWh. In this range, the EHNS decreases significantly, due to improved reliability, while the total costs remain low. Beyond 1 MWh, the reduction in EHNS becomes negligible, as the storage size is sufficient to cover most failure times, and longer repair times are less probable. On the other hand, for TS capacities higher than 1 MWh, the operational costs increase significantly, leading to a sharp rise in total costs. This behavior is depicted in fig. 5, where the total cost curve initially decreases with storage capacity due to reduced CHNS, but rises steeply beyond 1 MWh due to increasing operational costs. This highlights the diminishing returns of larger storage sizes and suggests an optimal range for a good balance between cost, security against uncertainty, and reliability.

VI. CONCLUSIONS

In this work, a probabilistic planning framework is presented that integrates electricity and heating networks, addressing critical challenges in the design of multi-energy systems (MES). By combining distributionally robust chance-constrained (DRCC) optimization for thermal storage sizing with the novel cross-sectoral reliability metric Expected Heat Not Supplied (EHNS), we bridge the gap between operational flexibility and system reliability under uncertainty. This dual focus not only advances the state of thermal storage planning, but also introduces a more comprehensive approach to reliability analysis, capturing the unique dynamics of interconnected energy networks.

The results show that the proposed framework effectively balances costs, robustness against uncertainty, and reliability. It offers a useful tool for energy system operators and planners dealing with the complexities of sector coupling. The introduction of EHNS as a reliability metric enables quantifying the reliability of MES, addressing shortcomings of traditional reliability metrics by explicitly modeling the role of flexibility through sector coupling in covering interruptions due to component failures. EHNS highlights the trade-offs between operation and investment costs and system reliability.

In future works, this approach will be extended by adding additional sources of uncertainty, such as renewable generation, and incorporating more flexibility and sector coupling technologies, such as electric vehicles. Furthermore, more comprehensive case studies based on different network topologies will be conducted to provide a holistic integrated planning approach for MES.

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