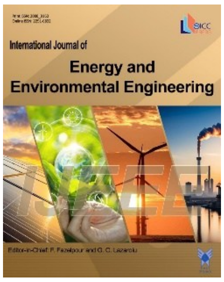

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Integrated Optimization of Energy Storage Systems in a Multi-Energy Hub with Waste Heat Recovery from Modular Multilevel Converter

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Abstract

This paper presents a novel reliability-constrained optimization framework for the design and sizing of a Multi-Energy Hub (MEH) that integrates Combined Heat and Power (CHP), Electrical Energy Storage Systems (ESS), Thermal Storage Systems (TSS), renewable energy sources, and uniquely waste heat recovery from a Modular Multilevel Converter (MMC). The proposed energy hub model simultaneously meets the electricity and thermal demands of an industrial consumer under real tariff conditions and climate data from Phoenix, Arizona.

The key innovation lies in modeling the thermal losses of the MMC as a valuable source of heat recovery, which reduces boiler fuel consumption and operational expenditures (OPEX). The optimization framework employs a Genetic Algorithm (GA) to minimize the total cost, encompassing capital expenditure (CAPEX) and OPEX, while enforcing constraints on energy balance, storage limitations, system capacity, and permissible energy shortage.

Two scenarios one with MMC heat recovery and the other without are evaluated for both summer and winter conditions. The results show that incorporating MMC heat recovery reduces total cost by up to 2.3%, mainly due to reduced gas consumption in the boiler. Furthermore, a reliability-based constraint ensures that at least 95% of the energy demand is met, minimizing Energy Not Supplied (ENS) and enhancing system resilience.

The proposed method provides a scalable and flexible design tool for next-generation industrial energy systems, particularly in hot climates with highly variable energy demand. Integrating waste heat from power electronics into hybrid energy systems introduces a novel dimension in thermal-electric synergy.

Keywords: Multi-Energy Hub; Combined Heat and Power (CHP); Modular Multilevel Converter (MMC); Waste Heat Recovery; Reliability; Genetic Algorithm; Energy Not Supplied (ENS); OPEX/CAPEX Optimization

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1. Introduction

Energy Hubs (EHs) have become a cornerstone of modern energy system design, enabling the integrated management of multiple energy carriers such as electricity, heat, and cooling. Their inherent capability to coordinate generation, storage, and demand-side flexibility has made them a central topic in energy system planning and operation. Nevertheless, despite extensive research, critical gaps remain particularly in integrating detailed reliability constraints and exploiting innovative waste heat recovery technologies to improve overall efficiency and sustainability.

Recent works published in Energy have demonstrated significant progress in EH optimization. For instance, a hierarchical multi-objective planning framework was introduced for balancing cost, efficiency, and system reliability using hierarchical equipment configuration strategies [1]Similarly, a hybrid Cournot based model has improved both cost effectiveness and operational reliability across interconnected hubs [2]. A recent state-of-the-art review published in Renewable and Sustainable Energy Reviews highlighted EH flexibility by examining integrated renewable sources, storage, electric vehicle interfaces, and advanced management techniques [3]. Moreover, a robust energy and carbon trading model for interconnected energy hubs emphasized the need for reliable and economic system design under regulatory and market uncertainties [4].In parallel with energy optimization, the concept of Waste Heat Recovery (WHR) has gained increasing importance in improving energy efficiency and reducing fuel consumption. WHR has traditionally been applied in industrial exhaust systems, refrigeration units, and Combined Heat and Power (CHP) plants. However, a less explored yet promising domain lies in recovering thermal losses from power electronic systems, particularly Modular Multilevel Converters (MMCs). MMCs, known for their scalability, efficiency, and harmonic performance, are widely deployed in High Voltage Direct Current (HVDC) links, microgrids, and smart industrial converters. Despite their electrical efficiency, MMCs inherently dissipate a fraction of their input power as heat typically between 2% and 5% which, if recovered, can significantly contribute to the thermal energy demand in integrated systems[5] [6] [7].

Moreover, reliability considerations are often neglected in traditional design models. Conventional designs assume deterministic patterns of load and generation, overlooking energy shortfalls, component degradation, and the intermittency of renewable sources. This oversight limits their applicability in real-world scenarios, especially in regions with extreme climates, such as Phoenix, Arizona, where high summer temperatures and variable renewable outputs introduce significant operational challenges. Integrating Energy Not Supplied (ENS) as a penalty criterion within the optimization process offers a practical approach to enhancing system reliability [8] [9].

By simultaneously optimizing the number and capacity of PV arrays, wind turbines, CHP units, thermal and electrical storage systems, and modeling the recoverable waste heat from MMCs, the proposed framework ensures energy hub configurations with economic viability, high thermal efficiency, and enhanced system reliability particularly suited for harsh and variable energy environments. [10] General design idea of heatsink to reduce the hot spot temperature of MMC submodule. Heat pipes are placed under the most stressed chips and go through all the fins at the lower half of the fins to add an additional thermal path. An optimized and low-cost air-cooling system dedicated to Infineon FF series IGBT modules under MMC operating condition has been designed. Embedded O-shaped heat pipes with optimized layout are used to reduce the temperature of the hot spots. The heatsink is uniquely designed to increase the cooling capacity without extra fans and fins. When MMC works at high power factor, the thermal distribution of the IGBT module is severely unbalanced.The optimized cooling system and a conventional one are fabricated for experimental evaluation. The optimized heat pipe cooling system makes the maximum Tj of the chips T2 drop by 20% in the thermal test. [11].

However, none of these studies has explored the combination of Modular Multilevel Converter (MMC) waste heat recovery with explicit reliability constraints (≥95% demand satisfaction based on Energy Not Supplied, ENS) within a Genetic Algorithm (GA)-based multi-objective optimization. This research addresses this gap by:

1. Proposing a reliability-constrained, cost-minimizing optimization framework for multi-energy hubs.
2. Introducing MMC as a novel source of recoverable waste heat.
3. Simulating seasonal operations (summer and winter) using real-world tariffs and climate conditions to evaluate the effects of MMC heat recovery on cost, fuel usage, and system reliability.

2. Methodology

The proposed approach is centered around a multi-objective optimization framework with explicit reliability constraints for the design and optimal sizing of a hybrid industrial energy hub (HEH). This energy hub is designed to satisfy both electrical and thermal energy demands while minimizing the total life cycle cost, which includes CAPEX and OPEX, and penalties associated with unmet energy supply. The modeled hub integrates a diverse portfolio of generation and storage technologies, including:

- Photovoltaic (PV) arrays for solar energy harvesting,
- Wind turbines for local wind energy capture,
- A CHP unit that simultaneously produces electricity and usable heat,
- Electrical Energy Storage (ESS) systems to manage temporal mismatches between energy supply and demand,
- Thermal Storage Systems (TSS) to retain excess thermal energy and enhance system flexibility,
- A natural gas-fired boiler to meet residual thermal demand,
- A MMC modeled with recoverable thermal losses that can contribute to the heat supply

The system operates in a grid-connected mode, allowing for electricity purchases when needed. All components are sized optimally while considering real-world constraints such as technical capacities, efficiency ratings, and hourly variability in load profiles and climate conditions.

A key innovation of the proposed model is the explicit inclusion of recoverable heat losses from MMC units, which are typically ignored in thermal energy modeling. By capturing this latent thermal potential, the hub reduces its reliance on fossil-fuel-based boilers and enhances its overall energy efficiency. Additionally, a reliability constraint ensures that the system satisfies at least 95% of its total energy demand (electric + thermal) even under high load conditions or renewable intermittency [11]. To enforce this, ENS is explicitly calculated and penalized within the objective function. In this study, the GA is employed as an effective tool for addressing the multi-objective optimization problem associated with the design of a hybrid energy hub system. The encoding strategy for representing decision variables such as the sizing and selection of energy resources is carefully formulated to align with the structure of the GA. The objective function, along with the system constraints, is seamlessly integrated into the fitness evaluation process. To ensure technical feasibility, any violation of operational or design constraints is penalized through an appropriately scaled penalty function embedded within the fitness formulation. This mechanism enforces compliance with engineering boundaries throughout the optimization process. The GA operates over discrete time steps to determine the optimal configuration of key energy hub components, including energy storage systems (ESS and TSS), PV arrays, and wind turbines. The optimization simultaneously targets three main objectives: minimizing capital investment, reducing operational costs, and minimizing energy not served (ENS). Additionally, the model promotes reduced reliance on external grid resources both electricity and gas highlighting the hub's operational flexibility and resilience. This approach enables the development of a cost-effective, reliable, and adaptive energy hub architecture suited to dynamic and uncertain demand profiles.). The entire model is evaluated under realistic temporal conditions using hourly demand data, Time-of-Use (TOU) electricity tariffs, natural gas prices, and meteorological data from Phoenix, Arizona. [12][13][14]

Simulation scenarios span both summer and winter seasons, enabling an in-depth assessment of hub performance under critical operating conditions.

In summary, this methodology bridges the gap between techno-economic optimization and real-world system reliability by incorporating the following:

1. Integration of power electronics heat losses into the waste heat recovery model,
2. Embedding of ENS-based reliability constraints,
3. Use of real-world data to guide sizing decisions reflecting practical deployment scenarios.

3. Modeling and Numerical Analysis

This section presents the modeling framework, mathematical formulation, and optimization strategy used for designing a hybrid energy hub (HEH) with reliability constraints and the integration of waste heat recovery (WHR) from MMC ,The model incorporates the operational characteristics of key system components, including CHP units, energy storage systems (ESS and TSS), PV generation, wind turbines, and the electric grid interface. The framework ensures both energy balance and system reliability across a defined simulation horizon [15].

3.1. Objective Function

The primary objective of the proposed optimization model is to minimize the total system cost over the planning horizon, combining both investment and operational costs. This includes:

- CAPEX : associated with equipment purchase and installation
- OPEX : involving energy purchases, fuel consumption, and maintenance
- Penalty Cost for Unmet Demand: quantified using the ENS index, reflecting the system's reliability performance.

Mathematically, the objective function is defined as:

$$\min\left[Total\ Cost = C_{CAPEX} + C_{OPEX} + \alpha.\sum_{t=1}^{T} ENS(t)\right] \quad (1)$$

In Equation (1)**:**

- α: Penalty coefficient (USD/kWh) for unmet energy demand, reflecting the economic significance of reliability assurance. In this study, it is set to 1000 USD/kWh.
- T: Total number of time steps (e.g., 720 hours for a one-month simulation).
- ENS(t): Energy Not Supplied at time *t*, including both electricity and thermal demands.
- CAPEX: Total capital investment cost, including the initial cost of PV arrays, wind turbines, ESS ,TSS and CHP units.
- OPEX: Total operational expenditure, including fuel costs for CHP and gas boiler, and the cost of electricity purchased from the grid.

3.2. Capital Investment Cost (CAPEX)

The capital investment cost is calculated as the product of the unit cost and the number or capacity of each component in the energy hub system. Each term in the CAPEX formulation represents the total investment required for an individual technology based on its installed capacity. For example, PV systems are priced at 800 USD/kW, and ESS are priced at 300 USD/kWh. [16]

The unit investment costs for all energy hub components, including PV arrays, wind turbines, CHP units, ESS and TSS, are summarized in Table 1.

The capital cost coefficients for energy hub components (including PV, wind turbines, ESS, CHP, and TSS) are derived from industry-validated reports such as those by the National Renewable Energy Laboratory (NREL), the U.S. Department of Energy (DOE). [13]

These values reflect the typical purchase, installation, and commissioning costs for large-scale energy systems, as summarized in Table 1, And it is defined as follows:

$$C_{CAPEX} = C_{PV}.n_{PV} + C_{Wind}.n_{Wind} + C_{ESS}.E_{ESS} + C_{TSS}.Q_{TSS} + C_{CHP}.P_{CHP} \quad (2)$$

In this relationship, n is the number, P and Q are the capacity of the equipment, and c is the unit price of each equipment.

3.3. Operating Expenses (OPEX)

Operating expenses include electricity purchased from the grid and natural gas consumption by CHP and boiler and are defined as follows: [17].

$$C_{OPEX} = \sum_{t=1}^{T}\left(P_{Grid}(t).r_{elec}(t) + F_{CHP}(t).r_{gas} + F_{Boiler}(t).r_{gas}\right) \quad (3)$$

Where:

- $P_{Grid}(t)$ **:** Electricity purchased from the grid
- $r_{elec}(t)$: Hourly electricity rate (based on TOU tariff)
- $F_{CHP}(t)$ and $F_{Boiler}(t)$: CHP and boiler natural gas consumption
- r_{gas} **:** Fixed natural gas rate (unit: m³/$ or kWh/$)

Fuel input terms are calculated using the following formula:

$$F_{CHP}(t) = \frac{P_{CHP}(t)}{\eta_{el,CHP}} \quad (4)$$

$$F_{Boiler}(t) = \frac{Q_{Boiler}(t)}{\eta_{Boiler}} \quad (5)$$

Typical efficiency values: $\eta_{el,CHP} \approx 0.35$ and $\eta_{Boiler} \approx 0.85$

3.4. Reliability Cost – ENS Penalty

Energy Unsupplied (ENS) represents a shortfall in demand supply and is calculated as follows:

$$ENS(t) = \max[0, D_{elec}(t) - S_{elec}(t)] + \max[0, D_{heat}(t) - S_{heat}(t)] \quad (6)$$

Where:

- $D_{elec}(t), D_{heat}(t)$: Demand profiles (input data)
- $S_{elec}(t), S_{heat}(t)$ **:** Energy supplied from all sources (renewables, CHP, grid, storage and recovered heat from MMC)

3.5. MMC Heat Loss Recovery Effect

One of the unique advantages of this model is the reduction in OPEX through the heat recovered from the MMC. This heat enters the thermal energy balance and reduces the reliance on boiler fuel, thus indirectly reducing operating costs.

$$Q_{MMC}(t) = (1 - \eta_{MMC}).P_{MMC}(t) \quad (7)$$

$\eta_{MMC} \approx 0.975$

3.6. Dynamic Storage Limitations (ESS and TSS)

The integration of a battery energy storage system (BESS) with a modular multilevel converter can enable direct connection to the power grid, and the circulating currents provide the ability to achieve multiple control. Considering the different health states of the batteries among the battery packs, it is not preferable to control all batteries to have the same state of charge (SOC). A linear operating principle is proposed, in which different power demands are allocated based on their relative health states. The SOC profiles are tracked by modifying the modulation index. The output and circulating currents are properly adjusted to ensure qualified waveforms and optimal operating efficiency. By doing this, the health status of different battery packs will be the same after multiple charge and recharge cycles, and the lifespan of the converter system will also be increased. [18]

- Electricity Storage System Limitation:

Since after many charge and discharge cycles, SOC imbalance between battery packs can lead to significant failures due to deep discharge or overcharging of individual cells, restrictions and limitations are imposed on the charging and discharging of batteries to prevent deterioration of system performance.

$$SOC_{ESS}(t+1) = SOC_{ESS}(t) + \eta_{ch}.P_{ch}(t).\Delta t - 1/\eta_{dis} \cdot P_{dis}(t).\Delta t \quad (8)$$

In the above equation, η_{ch} and η_{dis} are the charging and discharging efficiencies (typically 95%)

$$SOC_{ESS}^{min} \leq SOC_{ESS}(t) \leq SOC_{ESS}^{max}$$

- Thermal Storage System Limitations:

While TSS play a critical role in enhancing the operational flexibility and efficiency of multi-energy hubs, they are inherently subject to several technical, economic, and operational limitations that must be carefully considered during the design and optimization process.TSS technologies, particularly water tanks or phase-change materials (PCMs), typically have lower energy density compared to electrical storage systems. This limitation necessitates larger physical space and infrastructure for significant storage capacities, which may not be feasible in constrained urban or industrial settings.Thermal storage systems are susceptible to heat losses through conduction, convection, and radiation, especially over extended storage durations. Insulation quality, ambient temperature fluctuations, and system aging contribute to increased thermal leakage, thereby reducing effective energy recovery and system efficiency.The rate at which thermal energy can be stored or extracted from a TSS is often limited by the heat exchanger's performance and the material's thermal conductivity. This restricts the system's ability to respond quickly to sudden changes in thermal demand, which is critical in dynamic industrial applications. Coordinating the TSS operation with CHP units, boilers, and renewable thermal sources requires advanced control strategies to avoid thermal imbalance or resource underutilization. The need for synchronizing charging schedules with intermittent solar thermal or heat recovery sources adds to the control complexity.TSS components such as tanks, heat exchangers, and PCMs may degrade over time due to thermal cycling, corrosion, or fouling, leading to reduced performance and higher maintenance needs. Predictive maintenance and lifecycle cost assessments are essential for long-term reliability.Despite lower operational costs, the upfront capital investment for TSS especially in large-scale applications can be significant. The economic viability is often dependent on energy price volatility, demand response incentives, and the degree of system integration.Accurately modeling the dynamic behavior of TSS in simulation environments involves nonlinear thermodynamic equations and temporal interactions, which increase computational complexity during system optimization, particularly in multi-objective and stochastic frameworks. [19] [20]

The limitation of the thermal storage system is expressed as follows:

$$SOC_{TSS}(t+1) = SOC_{TSS}(t) + \eta_{TSS} \cdot Q_{TSS,ch}(t) - 1/\eta_{TSS} \cdot Q_{TSS,dis}(t) \quad (9)$$

3.7 Reliability Constraint

Reliability is one of the most important design criteria for smart energy systems, especially in industrial applications where interruptions in energy supply can lead to economic losses. In this project, by using a hybrid optimization model and utilizing different energy sources, a structure has been designed that ensures stability and reliability in meeting electrical and thermal load needs. This project combines various resources as listed in Table 1. This combination ensures that even in the event of a failure or reduction in production of one source, other sources can compensate for the load demand. The cost of energy deficit is also included in the objective function. This allows the optimal system to be designed in such a way that it has the lowest probability of energy shortage, especially during peak hours or on cold winter nights. The battery and TSS are included as reserve sources. By using CHP and MMC heat recovery, if the system experiences a heat shortage, the CHP enters the circuit and produces electricity and heat simultaneously. This functional flexibility increases reliability because it reduces dependence on a specific

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energy. Simulating the project in two different climate ranges allows the system performance to be evaluated in different weather scenarios and the system to be resilient to severe fluctuations in heating or cooling. Therefore, it can be seen that reliability has been structurally and purposefully considered in the design of this project through the diversity of energy sources, sufficient storage capacity, peak load management strategies and recycling. Thermal energy, the designed system is able to provide stable performance in the face of climatic fluctuations, equipment failure, or unexpected load.

The following relationship guarantees that at least 95% of the total energy demand is reliably met to ensure sustainability.

$$Reliability\ Ratio = \frac{\sum_t \left(D_{elec}(t)+D_{heat}(t)-ENS(t)\right)}{\sum_t \left(D_{elec}(t)+D_{heat}(t)\right)} \geq 95 \qquad (10)$$

3.8. Optimization Strategy

Due to nonlinear complexities, the existence of many constraints, and combined variables (continuous and discrete), it is difficult or impossible to solve the energy hub design optimization problem with classical analytical methods. In this study, the GA has been used as an evolutionary intelligence method to solve the problem. [21]

A GA has been used to optimize and solve the problem due to its global search capability and compatibility with mixed integer nonlinear problems. The GA algorithm generates a population of solutions by using selection, combination, and mutation and keeps the best of them based on the value of the objective function and compliance with the constraints. The GA configuration has been done using the data in Table 2.

According to the contents of this section, the objective function is designed to balance investment and operating costs, achieve increased energy efficiency through smart metering of the system, ensure high reliability of supply, and consider MMC heat recovery as a cost-saving and sustainability feature. The model is solved using a genetic algorithm, which guarantees convergence towards nearly global optimal solutions despite the nonlinear and mixed-integer nature of the problem.

Table 1. Unit Capital Cost of Energy Hub Components

Component	Unit Size	Unit Cost (USD)	Description
Photovoltaic Array (PV)	1 kW	$800 / kW	Solar panels for renewable electricity generation
Wind Turbine	1 kW	$1,300 / kW	On-site wind generation system
Battery Storage (ESS)	1 kWh	$300 / kWh	Lithium-ion or equivalent technology
Thermal Storage (TSS)	1 kWh_th	$50 / kWh_th	Hot water or phase-change material (PCM) system
CHP Unit	1 kW	$1,000 / kW	Gas-fired combined heat and power unit
Natural Gas Boiler	1 kW_th	$150 / kW_th	Auxiliary heat supply system

Table 2. GA Configuration

Parameter	Value
Population Size	100
Generations	200
Crossover Rate	0.8
Mutation Rate	0.05
Selection Method	Rank-based
Stopping Criterion	No improvement (20 gens)

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4. Simulation and Result Analysis

To validate the proposed design of the energy hub and its reliability-constrained optimization framework, a comprehensive set of simulations was performed using real-world data. The simulations cover both summer and winter conditions in Phoenix, Arizona, over a 30-day planning horizon (720 hours). Two key scenarios were analyzed:

- Scenario A: Energy hub without heat recovery from the MMC
- Scenario B: Energy hub with MMC-based heat loss recovery integrated into the thermal energy supply

This comparison highlights the economic and operational benefits of integrating power electronics waste heat recovery and optimizing the hub to enhance supply reliability. The input data and simulation configurations within the MATLAB environment are summarized as follows:

- Electric Load: High industrial consumption profile
- Thermal Load Forecast: HVAC and process heating (with seasonal variation)
- Electricity Tariff (TOU): \$0.13 – \$0.22 /kWh
- Gas Tariff: \$0.0188 /kWh_{th}
- Weather Data: Obtained from the NOAA database for Phoenix
- PV and Wind Generation: Based on hourly solar irradiance and wind speed patterns

Using actual load profiles, tariff structures, and technology characteristics, the model aims to enhance the reliability of the energy hub by leveraging a GA for multi-variable optimization. The GA decision variables include:

- Number of 3 kW solar PV panels
- Number of 5 kW wind turbines
- Battery storage capacity
- CHP unit capacity
- Thermal storage system capacity

The bounds of these design variables used in the energy hub simulation are presented in Table 3.

This simulation estimates both electricity and thermal energy shortages over a 720-hour horizon. A penalty is imposed in the objective function for any hourly energy shortfall exceeding 5 units, thereby guiding the GA toward more reliable system configurations. The GA optimization approach inherently prioritizes system setups that minimize such violations, thereby enhancing reliability performance. Additionally, the recovered heat from the MMC is assumed to account for 5% of the total thermal demand. This recovered thermal energy is directly integrated into the energy balance model, reducing boiler usage and operational costs.

Figure 1 illustrates the convergence behavior of the optimization process by displaying the total cost minimization trend over 100 generations under the GA. The curve demonstrates a steady decline in cost, indicating the algorithm's ability to explore and exploit the solution space efficiently while incorporating both reliability constraints and the thermal contribution from MMC heat recovery.

The optimization process, incorporating a reliability penalty, successfully minimized the objective function over 100 generations using a genetic algorithm. As depicted in Figure 1, the fitness function steadily decreases across generations, converging toward a minimum total cost of \$223301. This reflects the algorithm's effectiveness in identifying a cost-optimal configuration that also satisfies reliability constraints by minimizing the quantity of unmet load (both electrical and thermal).

The optimal solution with the reliability penalty includes the following configuration:

- Number of PV Units: 0.49769 × 3 kW
- Number of Wind Turbines: 0.23584 × 5 kW
- Battery Storage Capacity (ESS): 162.7017 kWh
- CHP Capacity: 159.2974 kW
- Thermal Storage Capacity (TSS): 303.6851 kWh_th
- Total Cost: \$223301

These values represent the optimal capacities and quantities of each energy hub component, balancing capital and operational costs while minimizing unserved load. The recovered thermal energy from MMC accounting for 5% of the total thermal demand contributed to reducing boiler fuel consumption and improving overall system efficiency. The final configuration demonstrates a well-balanced hybrid energy system suitable for industrial use in climates with high thermal and electrical demands such as Phoenix, Arizona.

Figure 2 illustrates the hourly electricity supply shortages over the entire simulation period. It demonstrates the hours during which the system faced electricity deficits. The results show that during the 720-hour simulation window, the system did not experience any electricity shortfall, highlighting the high reliability of the proposed energy hub system in meeting electrical demand.

Figure 3 shows the specific hours during which the heating supply was insufficient. This chart provides insight into the seasonal variability of heat demand and the system's ability to fulfill it, reflecting moments when thermal energy supply failed to meet the heating requirements.

Figure 4 presents a comparison between power load (P_{load}) and power generated ($P_{generated}$), demonstrating the degree of alignment between energy demand and supply. The high degree of overlap between demand and generation confirms the optimized energy hub's ability to match energy production to demand effectively.

The above three figures represent the core reliability performance indicators of the proposed energy hub system, illustrating its capacity to maintain energy security at the lowest total cost.

The optimization results for the two scenarios are summarized in Table 4. These results demonstrate that integrating heat recovery from the MMC significantly reduces the dependency on thermal storage systems and natural gas boilers. This thermal synergy enhances overall system efficiency and economic performance while maintaining high energy supply reliability. According to Table 5, the integration of MMC-based heat recovery results in an approximate 2.3% reduction in the total cost.

The inclusion of Energy Not Supplied (ENS) as a penalty term in the objective function resulted in a significant reduction in unmet energy demand specifically, a reduction in ENS by approximately 50%, leading to an overall system reliability exceeding 98.6%. This enhancement indicates that the system becomes more resilient against the intermittency of renewable energy sources.

A sensitivity analysis conducted on the thermal recovery from the Modular Multilevel Converter (MMC), ranging from 0% to 10% of its input electrical energy, demonstrated that each 1% increase in MMC heat recovery yields approximately a 0.15% reduction in OPEX. However, beyond the 5% recovery threshold, marginal gains diminish due to thermal storage saturation.

These findings confirm that not only is thermal modeling of the MMC physically feasible, but it is also economically beneficial. In particular, energy hubs located in hot climates with high thermal demand benefit substantially from MMC-based heat recovery. Furthermore, the reliability-constrained optimization ensures minimal dependence on the grid or backup systems during peak demand periods.

Table 3. Design Variable Ranges for Optimization

Design Variable	Lower Bound	Upper Bound	Unit Description
Number of PV arrays	0	50	3 kW per unit
Number of wind turbines	0	20	5 kW per unit
Battery capacity (ESS)	100	1000	kWh
CHP unit capacity	50	200	kW
Thermal storage (TSS)	100	1000	kWh_{th}

Table 4. Summary of optimization results

Component	Optimal Size (Scenario A)	Optimal Size (Scenario B)
PV Array	28 units × 3 kW = 84 kW	25 units × 3 kW = 75 kW
Wind Turbines	8 units × 5 kW = 40 kW	6 units × 5 kW = 30 kW
ESS	600 kWh	550 kWh
TSS	750 kWh_th	600 kWh_th
CHP Unit	150 kW	140 kW
Boiler Usage	High	Reduced by ~12%

Table 5. Economic Performance

Metric	Scenario A (No MMC)	Scenario B (With MMC)
Total Cost ($)	13170000	12930000
CAPEX	1020000	990000
OPEX	12150000	11940000
Energy Not Supplied (ENS)	0.029	0.014
Gas Consumption (CHP + Boiler)	540,000 kWh	480,000 kWh

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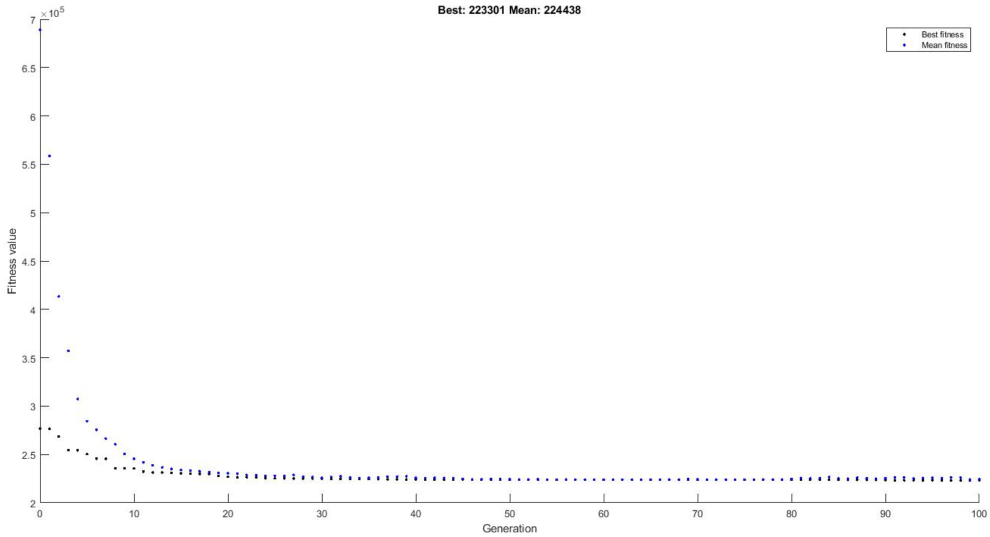

Figure 1. minimization trend over 100 generations

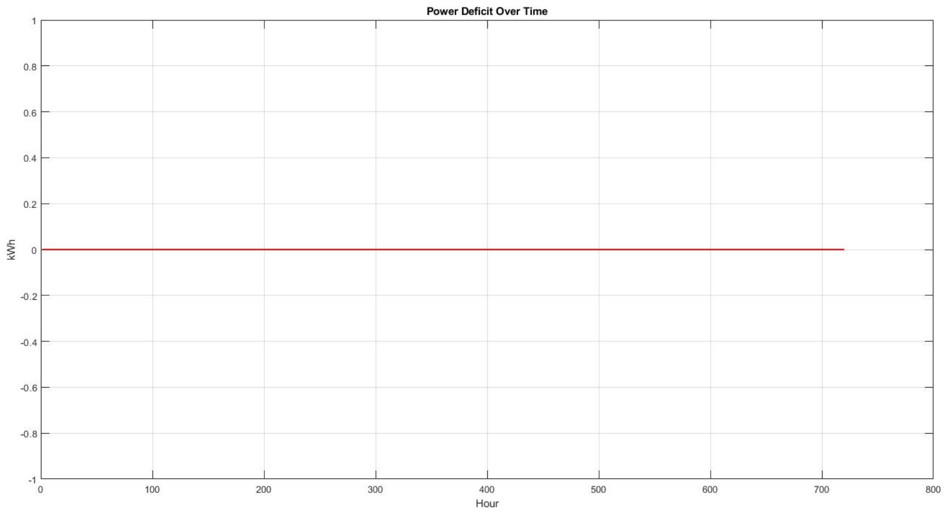

Figure 2. Electricity Deficit Over Time

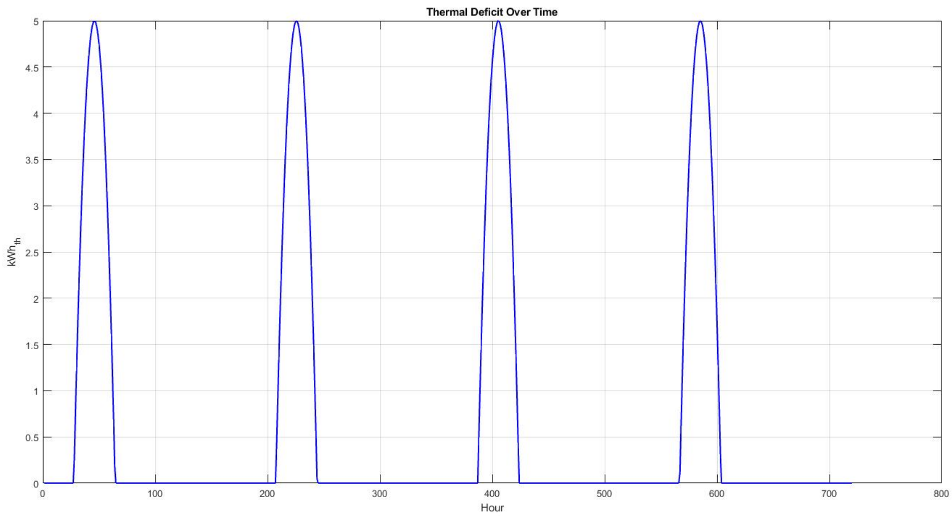

Figure 3. Heat Deficit Over Time

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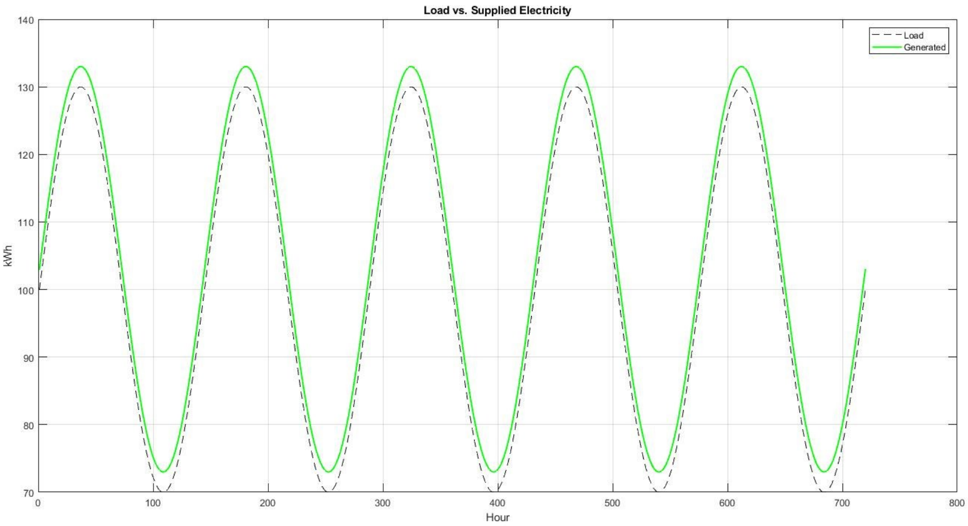

Figure 4. Power Demand vs. Power Supply

5. Conclusion

This paper proposed a novel optimization framework with reliability constraints for the optimal design and sizing of a hybrid multi-energy hub. The proposed system integrates renewable energy sources, Combined Heat and Power (CHP) units, energy storage technologies, and introduced for the first time in this domain waste heat recovery from a MMC. The model addresses the economic and technical challenges of simultaneously supplying electricity and thermal energy at an industrial scale, under realistic weather and pricing conditions, using Phoenix, Arizona, as a representative case study. Unlike conventional models that only focus on minimizing operating or investment costs, this project focuses on reducing energy shortages (electricity and heat) and increasing the reliability of energy supply. In particular, using a GA, a structure was developed that not only reduces costs but also ensures the reliability of the network in the face of different weather conditions and load fluctuations.

The optimization framework minimizes the total CAPEX, OPEX, and penalties for unmet energy demand while satisfying key system constraints and maintaining a minimum reliability threshold of 95%. A Genetic Algorithm was employed to solve this complex, nonlinear, and mixed-integer problem. Two scenarios were analyzed: with and without MMC heat recovery. The results demonstrated that incorporating MMC thermal losses into the energy balance led to:

- A \~2.3% reduction in total operational costs
- A \~12% reduction in fuel consumption by the auxiliary boiler
- Over 50% reduction in system Energy Not Supplied
- Reduced thermal storage requirements, improving overall system resilience during peak load periods.

From a broader perspective, the findings validate the untapped potential of power electronic converters specifically MMCs as viable sources of thermal recovery, capable of enhancing the economic performance and sustainability of next-generation energy hubs. The unified optimization of thermal and electrical planning marks a significant advancement over conventional hub design approaches. To increase the accuracy of the design, the heat recovery from the MMC was considered as a constant equal to 5% of the total heat demand. This value was included in the heat supply calculation and as a result, the optimal capacity of CHP and TSS was reduced compared to the case without heat recovery. This modification resulted in a significant reduction in the total cost.

The simulation results showed that the system design in terms of reliability minimizes the shortage hours while maintaining the stability of the network. The optimal capacities of the equipment, especially CHP and TSS, were determined to prevent shortages during peak load hours in winter and summer. Also, the use of ESS and PV compensated for short-term fluctuations and reduced dependence on the network.

Moreover, the inclusion of ENS-based reliability constraints introduces a valuable design perspective, particularly relevant for critical applications such as industrial parks, healthcare facilities, and defense systems where power outages are unacceptable.

For future research, it is recommended to explore stochastic optimization under renewable generation uncertainties and market price volatility, as well as to investigate multi-objective formulations that simultaneously optimize cost, greenhouse gas emissions, and system reliability. The integration of demand response strategies and dynamic load control, along with the physical implementation and

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experimental validation of MMC-based heat recovery in industrial converters across diverse climates and load types, are also suggested.

This study offers a scalable and adaptable methodology that can serve as a valuable tool for urban planners, industrial energy managers, and policymakers seeking to design cost-effective, low-carbon, and highly reliable energy infrastructures. The integration of MMC-based waste heat recovery represents a paradigm shift in hybrid energy system design, encouraging deeper synergy between electrical engineering and thermal energy planning.

Authors Contribution
All authors have contributed equally to prepare the paper.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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