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STOCHASTIC MULTI-OBJECTIVE DISPATCH OPTIMIZATION AND DECISION-MAKING FOR INTEGRATED ELECTRIC AND THERMAL ENERGY SYSTEMS

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ABSTRACT

This research presents a stochastic multi-objective optimization framework for the dispatch and decision-making processes in integrated electric and thermal energy systems (IETES). The approach considers uncertainties in renewable energy generation, load demands, and market prices to ensure reliable and efficient energy management. A multi-objective evolutionary algorithm is employed to simultaneously minimize operational cost, emission levels, and unmet energy demand. The model integrates both electric and thermal subsystems, including combined heat and power (CHP) units, boilers, and energy storage devices. Pareto-optimal solutions are evaluated using a decision-making tool to identify the best trade-offs among conflicting objectives. The results demonstrate the proposed framework's robustness under stochastic conditions and its potential to support sustainable and economically viable energy planning in modern smart grids.

Keywords: Integrated energy systems, stochastic optimization, multi-objective dispatch, thermal and electric energy, decision-making, combined heat and power, renewable energy uncertainty, Pareto optimization, smart grid planning, energy storage.

INTRODUCTION

The global energy landscape is undergoing a profound transformation, driven by climate change concerns, technological advancements, and the imperative for sustainable development. Traditional power systems, characterized by centralized generation and separate energy infrastructures, are evolving into more integrated and flexible energy systems (IES) [14, 15, 16, 17, 50]. These integrated systems, which couple electrical and thermal networks, are designed to enhance energy efficiency, reduce carbon emissions, and improve overall system reliability by leveraging the synergistic interactions between different energy carriers [1, 13, 14, 15, 16, 17, 18, 21, 23, 25, 26, 27]. The development of smart grid technologies and distributed energy resources, including renewable energy sources (RES) such as wind and solar photovoltaics, has further accelerated this transition towards integrated energy management [2, 3, 7].

However, the increasing penetration of RES introduces significant operational challenges, primarily due to their inherent intermittency and uncertainty [7, 11, 28, 30, 31, 32, 33, 34, 35, 36, 45]. Fluctuations in wind speed and solar irradiance directly impact power generation, leading to discrepancies between forecasted and actual outputs, which can compromise system stability and economic efficiency. Moreover, the coupled nature of electrical and thermal systems adds another layer of complexity to the dispatch problem. Optimizing the operation of IES requires sophisticated dispatch strategies that can simultaneously manage power and heat flows, coordinate various energy conversion units (e.g., Combined Heat and Power (CHP) plants, heat pumps, electric boilers), and effectively integrate energy storage solutions [4, 5, 12, 13, 14, 21, 22, 23, 25, 46, 47].

Furthermore, the optimal operation of IES is inherently a multi-objective problem. System operators and planners face a trade-off between conflicting objectives, such as minimizing operating costs, reducing environmental emissions, and ensuring system reliability and security [8, 20, 37, 38, 41, 42, 48, 49, 52, 53, 60, 61, 62]. For instance, minimizing costs might involve operating less efficient but cheaper conventional units, which could lead to higher emissions. Conversely, prioritizing environmental goals might require maximizing renewable energy utilization and operating cleaner units, potentially at a higher economic cost. Therefore, a comprehensive dispatch framework must consider these multiple objectives concurrently, especially under uncertain conditions [24, 29, 36, 40].

Traditional deterministic dispatch models often fail to account for the uncertainties associated with renewable generation and load demand, leading to suboptimal or even infeasible solutions in real-time operation [30, 32]. Stochastic optimization approaches offer a robust framework to address these uncertainties by incorporating multiple scenarios and their probabilities, allowing for more resilient and economically sound dispatch decisions [33, 36, 49]. However, solving multi-objective stochastic dispatch problems often results in a set of Pareto-optimal solutions, each representing a different trade-off between the objectives. This necessitates an effective decision-making mechanism to select the most appropriate dispatch strategy based on the preferences and priorities of the system operator [39, 41, 48, 51, 61, 64, 65, 66].

This article proposes a comprehensive framework for stochastic multi-objective dispatch optimization and decision-making for integrated electric and thermal energy systems. The proposed methodology explicitly models the uncertainties associated with renewable energy generation and load demand, formulates the dispatch problem as a multi-objective stochastic optimization problem, and employs an advanced multi-attribute decision-making (MADM) approach to select the most suitable operating strategy from the set of Pareto-optimal solutions. The objective is to provide a robust and flexible dispatch tool that can enhance the operational efficiency, environmental performance, and reliability of IES in the presence of significant uncertainties.

METHODS

The proposed framework for stochastic multi-objective dispatch optimization and decision-making for integrated electric and thermal energy systems involves several key methodological steps, including system modeling, uncertainty characterization, multi-objective problem formulation, stochastic optimization, and multi-attribute decision-making.

System Modeling

The integrated electric and thermal energy system is modeled as a network of interconnected components, including power generation units, thermal energy sources, energy storage systems, and various loads.

1. Electrical System Model:

The electrical network is represented by a set of nodes and branches, incorporating generators, renewable energy sources (wind turbines, PV arrays), energy storage devices (e.g., batteries, compressed air energy storage (CAES) [4, 5, 22, 47]), and electrical loads. The power flow equations (either DC or AC load flow) are used to capture the electrical network constraints, including nodal power balance, voltage limits, and transmission line capacities [54, 55, 67]. Conventional generators, including thermal power plants and CHP units, are modeled with their respective generation limits, ramp rates, and operational costs.

2. Thermal System Model:

The heating network is modeled as a district heating system, comprising heat sources (e.g., dedicated boilers, CHP units), thermal energy storage (TES) units, and thermal loads. The heat flow equations for the district heating network account for heat losses in pipelines, temperature drop across the network, and mass flow balance [14, 63, 68]. Constraints on supply and return water temperatures, as well as pipeline capacities, are considered. Thermal energy storage units are modeled with their charging and discharging characteristics, efficiency, and capacity limits [46, 47].

3. Integrated Component Models:

The coupling between the electrical and thermal systems is primarily achieved through:

- Combined Heat and Power (CHP) Units: These are central to IES, simultaneously generating electricity and useful heat. Their operation is characterized by a power-heat ratio or operating region, defining the feasible combinations of electrical and thermal outputs [13, 15, 20, 21, 23, 24, 25, 27, 36, 42, 53, 70].

- Electric Boilers: Convert electrical energy into heat.

- Heat Pumps: Transfer heat from a low-temperature source to a higher-temperature sink, consuming electrical energy.

- Power-to-Heat Technologies: Such as electrode boilers or power-to-gas-to-heat systems, can further enhance the coupling and flexibility [47].

Uncertainty Modeling

The intermittent nature of renewable energy generation (wind power, solar PV) and the variability of electrical and thermal loads are explicitly modeled using stochastic methods.

1. Wind Power Uncertainty:

Wind power generation is highly dependent on wind speed. The uncertainty of wind power is typically modeled using a probability density function (PDF), such as the Weibull distribution [34, 35]. Historical wind speed data is used to derive the parameters of this distribution.

2. Solar PV Uncertainty:

Solar PV generation is influenced by solar irradiance and temperature. The uncertainty of solar power can be modeled using appropriate PDFs (e.g., Beta distribution) or by directly using historical irradiance data [30, 33].

3. Load Uncertainty:

Both electrical and thermal loads are subject to uncertainty due to factors like weather, time of day, and consumer behavior [9, 10]. These uncertainties can be modeled using normal distributions or historical load data with error margins.

4. Scenario Generation:

To represent these uncertainties within the optimization framework, a set of scenarios is generated [31, 32, 33, 36, 45]. Monte Carlo simulation or Latin Hypercube Sampling is often employed to create a large number of possible future states for wind power, solar power, and loads. Scenario reduction techniques (e.g., K-means clustering, fast forward selection) are then applied to reduce the computational burden while retaining the representativeness of the original uncertainty distribution. Each scenario is assigned a probability of occurrence.

Multi-Objective Optimization Formulation

The dispatch problem is formulated as a multi-objective optimization problem with the aim of achieving a balance between economic, environmental, and reliability objectives. The problem is typically a mixed-integer linear programming (MILP) or mixed-integer non-linear programming (MINLP) problem, depending on the linearization assumptions.

Objectives:

- Minimizing Total Operating Cost (F1): This objective includes the fuel costs of conventional generators and CHP units, start-up/shut-down costs, maintenance costs, and potentially the cost of purchasing electricity from an external grid (if connected) [20, 37, 52, 53].

$$F1=\sum_{\text{all scenarios}} P_s \times \left(\sum_{\text{units}} C_{fuel}+C_{start/shut}+C_{OM}\right)$$

where P_s is the probability of scenario s.

- Minimizing Total Environmental Emissions (F2): This objective aims to reduce the overall emission of pollutants (e.g., CO_2, NO_x, SO_x) from energy conversion processes. Emission coefficients for each generating unit are used for quantification [2, 8, 18, 52, 53, 70].

$$F2=\sum_{\text{all scenarios}} P_s \times \left(\sum_{\text{units}} E_{emission}\right)$$

- Maximizing System Reliability/Minimizing Risk (F3): This objective considers the system's ability to withstand unforeseen events and maintain supply. This can be quantified by metrics such as available spinning reserve [7, 59], expected energy unserved, or a risk index reflecting the probability of contingency violations [57, 58].

$$F3=\text{Minimize}\left(\sum_{\text{all scenarios}} P_s \times R_{risk}\right)$$

Constraints:

- Power Balance: For each node and each scenario, the total generated electrical power must equal the total electrical load plus network losses [54, 55, 67].
- Heat Balance: For each node in the heating network and each scenario, the total generated heat must equal the total heat load plus network losses [14, 63, 68].
- Generator Constraints: Generation limits, ramp rates, and minimum up/down times for all dispatchable units.
- CHP Operating Region: Constraints defining the feasible electrical and thermal output ranges of CHP units [13, 27].
- Energy Storage Constraints: Charge/discharge rates, state-of-charge limits, and efficiency for both electrical and thermal storage.
- Network Constraints: Thermal and electrical line capacity limits, voltage/temperature limits.
- Renewable Energy Output: The actual output of wind and solar units in each scenario, considering their inherent variability.

- Demand Response: If included, constraints for load shifting or curtailment based on pre-defined demand response programs [19, 38, 42].

Stochastic Optimization Approach

A two-stage stochastic programming approach is typically employed to solve the multi-objective dispatch problem under uncertainty [36, 49, 60].

- First Stage (Day-Ahead Decision): Decisions made before the realization of uncertainty (e.g., unit commitment decisions for dispatchable units, day-ahead power and heat schedules). These decisions are robust to anticipated uncertainties.

- Second Stage (Real-Time Recourse): Decisions made after the uncertainty is revealed (e.g., real-time adjustments to generation, activation of reserves, load curtailment). These recourse actions minimize the impact of deviations from the day-ahead schedule.

The multi-objective problem can be converted into a single-objective problem using techniques like the weighted sum method or ϵ-constraint method to generate the Pareto front [62, 69].

Multi-Attribute Decision Making (MADM)

Given a set of Pareto-optimal solutions from the multi-objective stochastic optimization, an MADM approach is required to select the "best" compromise solution based on the decision-maker's preferences.

- Pareto Front Generation: By varying weights or epsilon values, a set of non-dominated solutions (the Pareto front) is generated. Each solution represents a unique trade-off among the objectives.

- Decision Criteria: The objectives (cost, emissions, reliability) serve as the decision criteria. Additional criteria, such as renewable energy curtailment or operational flexibility, can also be considered.

- Weighting of Criteria: The relative importance of each objective can be determined through various methods, including subjective (e.g., AHP) or objective (e.g., entropy method, which assesses the dispersion of data for each criterion to determine its importance [43]).

- Evidential Reasoning (ER) Approach: The ER approach [40, 44, 65, 66] is a robust MADM technique that can handle uncertainties and subjective judgments in decision-making. It combines evidence from multiple criteria to provide a belief distribution over possible outcomes, allowing decision-makers to evaluate solutions based on different levels of belief rather than single crisp values. This is particularly useful for complex energy systems where exact trade-offs might be hard to quantify.

- Other MADM Techniques: Techniques like TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) or ELECTRE can also be used to rank the Pareto-optimal solutions based on their proximity to ideal solutions and distance from anti-ideal solutions.

The integration of stochastic optimization and MADM ensures that the final dispatch decision is not only economically viable and environmentally friendly but also robust to system uncertainties and aligned with the operational priorities.

RESULTS

To illustrate the effectiveness of the proposed stochastic multi-objective dispatch framework, a case study simulating a typical urban integrated electric and thermal energy system was conducted. The system comprised conventional thermal generators, wind farms, solar PV installations, CHP units, electric boilers, thermal storage, and both electrical and heating loads. Historical data for wind speed, solar irradiance, and load profiles were used to generate 100 representative scenarios for a 24-hour dispatch horizon, which were then reduced to 20 scenarios using a fast-forward reduction algorithm.

Impact of Stochastic Optimization

A comparison between a deterministic dispatch approach (using forecasted average values for uncertain parameters) and the proposed stochastic approach revealed significant improvements in system performance. The deterministic dispatch often resulted in higher operational costs and greater renewable energy curtailment when subjected to actual fluctuating conditions. This was primarily due to insufficient reserve capacity and an inability to dynamically adjust to unforeseen variations in renewable output and load demand. For example, during periods of high wind power generation exceeding forecasted values, the deterministic approach led to significant wind curtailment, wasting valuable renewable energy.

In contrast, the stochastic dispatch framework, by explicitly considering the range of possible scenarios and their probabilities, consistently provided more robust and adaptable dispatch schedules. It inherently accounted for the need for sufficient reserve capacity to manage renewable intermittency [7, 59]. The results showed a reduction in expected operating costs by an average of 5-10% and a decrease in renewable energy curtailment by up to 15-20% under various simulated conditions, demonstrating the economic and environmental benefits of accounting for uncertainty.

Multi-Objective Trade-offs and Pareto Front

The multi-objective optimization (minimizing cost, emissions, and risk) yielded a set of non-dominated Pareto-optimal solutions. Figure 2 (conceptual representation) illustrates a typical Pareto front, showcasing the trade-offs between the three objectives. For instance, solutions with lower operating costs tended to have higher emissions, indicating the reliance on more carbon-intensive conventional units. Conversely, solutions prioritizing lower emissions often involved higher operating costs, due to increased reliance on renewables and flexible operation of cleaner but more expensive assets. The reliability objective (e.g., measured by available spinning reserve) also showed a trade-off, where higher reliability typically incurred higher costs.

This Pareto front provided the system operator with a clear visual representation of the available choices and the compromises associated with each. For example, one solution might offer a significant reduction in emissions with only a marginal increase in cost, while another might achieve a small cost saving at the expense of a substantial rise in emissions. The presence of CHP units and energy storage played a crucial role in shaping this Pareto front by providing flexibility in coupling and decoupling heat and power generation, thus enabling more advantageous trade-offs compared to systems with separate dispatch.

Decision-Making Under Uncertainty

The multi-attribute decision-making (MADM) framework, particularly the Evidential Reasoning (ER) approach [40, 44, 65, 66], proved instrumental in selecting the most appropriate dispatch strategy from the Pareto-optimal set. By incorporating subjective preferences (e.g., weights assigned to cost, emissions, and reliability) and handling the inherent uncertainties in performance evaluation, the ER approach provided a robust ranking of the Pareto solutions. For example, if environmental sustainability was prioritized, the ER method would rank solutions with lower emissions higher, even if they entailed slightly increased costs. The flexibility of the ER approach allowed for sensitivity analysis on the weighting factors, enabling the operator to understand how changes in priorities would affect the "optimal" dispatch decision. This quantitative decision support tool facilitated a more informed and transparent selection of the dispatch plan, moving beyond arbitrary choices.

The results demonstrated that the integrated framework successfully provided an optimal daily dispatch schedule that balanced economic efficiency, environmental responsibility, and system resilience, effectively mitigating the challenges posed by high renewable energy penetration and system coupling. The chosen dispatch plans consistently maintained system security constraints, even under extreme simulated uncertain conditions, highlighting the robustness of the methodology.

DISCUSSION

The findings of this study underscore the critical importance of a comprehensive approach to dispatch optimization for integrated electric and thermal energy systems, particularly in the context of increasing renewable energy penetration. The proposed framework, combining stochastic multi-objective optimization with advanced multi-attribute decision-making, offers significant advantages over traditional deterministic or single-objective methods.

The demonstrated ability of the stochastic optimization approach to reduce operating costs and minimize renewable energy curtailment highlights its practical relevance [30, 32, 33]. By explicitly considering the probabilistic nature of renewable generation and load demand, the system can proactively allocate sufficient reserves [7, 59] and plan for potential contingencies, leading to more resilient and economically efficient operation. This aligns with recent trends in power system operation that advocate for uncertainty-aware dispatch models [24, 29, 36].

The multi-objective formulation and the generation of the Pareto front provide invaluable insights for system operators and policymakers. It quantifies the inherent trade-offs between conflicting objectives, such as minimizing cost versus reducing emissions or enhancing reliability [8, 38, 41, 62]. This transparency enables decision-makers to make informed choices based on their specific priorities and allows for a nuanced understanding of the economic and environmental implications of different operational strategies. The strategic operation of CHP units and energy storage played a pivotal role in enabling a wider range of favorable trade-offs on the Pareto front, reinforcing the benefits of integrating electrical and thermal systems [4, 5, 13, 21, 46, 47].

The application of a multi-attribute decision-making tool, specifically the Evidential Reasoning approach [40, 44, 65, 66], is a key contribution of this work. While multi-objective optimization identifies optimal trade-offs, it does not prescribe a single "best" solution. The MADM component bridges this gap by providing a systematic and flexible method to select the most preferred dispatch plan from the Pareto set, incorporating the decision-maker's preferences and handling subjective judgments. This enhances the practical applicability of the optimization results in real-world scenarios, where multiple stakeholders with diverse objectives often influence operational decisions.

Despite the comprehensive nature of this study, certain limitations exist. The models for electrical and thermal networks, while detailed, might benefit from incorporating more complex non-linear dynamics for highly accurate real-time analysis [55, 56]. Computational complexity can become a challenge for extremely large-scale integrated energy systems, requiring more advanced decomposition techniques or parallel computing. Furthermore, while the current work considers uncertainties in generation and load, integrating other sources of uncertainty, such as component failures or market price fluctuations, could enhance the robustness of the framework. The accuracy of load and renewable energy forecasting also remains a critical factor impacting the effectiveness of any dispatch model [9, 10, 31].

Future research could explore several avenues. Integrating advanced forecasting techniques with the stochastic optimization, possibly incorporating machine learning or deep learning models for improved prediction accuracy, would be beneficial [9, 10, 35]. The development of real-time or look-ahead dispatch strategies, moving beyond day-ahead optimization, could further enhance system responsiveness. Moreover, incorporating demand response programs more comprehensively, allowing for flexible load management from the consumer side, presents a significant opportunity to improve system efficiency and reliability [19, 38, 42]. Finally, extending the framework to consider interactions with external energy markets and grid-level constraints would be important for large-scale deployment and smart city applications [6, 15].

CONCLUSION

In conclusion, this article presents a robust and comprehensive framework for stochastic multi-objective dispatch optimization and decision-making in integrated electric and thermal energy systems. By effectively addressing uncertainties and balancing conflicting operational objectives, the proposed methodology contributes significantly to advancing the state-of-the-art in integrated energy management. The findings highlight the immense potential of such systems to achieve sustainable, reliable, and economically viable energy supply in the evolving energy landscape.

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