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Adaptive Scheduling Strategies for Integrated Energy Systems under Renewable Energy Uncertainties#

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ABSTRACT

The efficient operation of Integrated Energy Systems (IES), which combine electricity, heat, and cooling, is challenged by the low predictability inherent in renewable energy sources like wind and solar power. Traditional scheduling methods, relying on day-ahead and intra-day forecasts, often fail to accommodate the deviations between forecasted and actual energy generation, leading to suboptimal performance and increased operational costs. This paper proposes an enhanced scheduling method that incorporates multiple scenarios outside the probabilistic prediction intervals to address forecast deviations. By calculating optimal scheduling schemes for these extra scenarios, the proposed method ensures that IES can adapt dynamically to real-time conditions, maintaining closer proximity to the optimal operating point. Simulation results using real power grid data from Belgium demonstrate that this method significantly reduces system costs compared to traditional scheduling approaches, effectively mitigating the economic impact of forecast inaccuracies. The study highlights the potential of scenario-based scheduling in improving the reliability and efficiency of IES under uncertainty.

Keywords: Integrated Energy Systems, Renewable Energy, Forecast Deviations, Scenario-based Scheduling, Stochastic Model Predictive Control, Operational Efficiency

NONMENCLATURE

Abbreviations	
IES	integrated energy system
SMPC	stochastic model predictive control
PV	photovoltaic
WT	wind turbine
MGT	micro gas turbine
BA	battery
ACH	absorption chiller
EB	electric boiler
EC	electric chiller
HP	heat pump
HT	heat tank
CT	cold tank
LD	load
Symbols	
t	time (h)
s	scenario
K	number of total scenarios
N	total time
C	cost
η	efficiency
P	probability

1. INTRODUCTION

The Integrated Energy System (IES) is a novel energy system that achieves efficient conversion and optimal utilization of energy by organically combining various energy forms such as electricity, heat, and cooling. Its core function relies on comprehensive scheduling and coordinated control to achieve the complementarity and synergy of multiple energy forms, thereby enhancing the overall system's operational efficiency and the ability to absorb renewable energy. However, renewable energy, particularly wind and solar power, exhibits significant randomness and intermittency. These characteristics pose substantial challenges to the stable operation of IESs [1][2].

Therefore, to maintain the stable and efficient operation of the IES, it is essential to develop an appropriate scheduling method that fully utilizes the characteristics of renewable energy, balances supply and demand, and ensures reliable operation under conditions of uncertainty.

Currently, the commonly used day-ahead and intra-day scheduling are based on forecast data to calculate

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the scheduling scheme. The scheduling layer issues operation instructions to each device based on the calculated optimal scheduling scheme, ensuring that the devices operate as closely as possible to the set scheduling instructions over the next period [3][4][5]. If the random variables in the system match the forecast, the scheme will be the optimal scheduling scheme in actual operation. However, due to the limitations of forecasting algorithms, there is often a deviation between the actual values and forecasted values of random variables in the IES. This deviation can cause the system to deviate from the optimal scheduling scheme during actual operation, leading to economic losses and potentially affecting system safety and stability.

Current forecasting algorithms are extensively studied and have high accuracy for large systems [6][7]. However, as the system's capacity decreases, forecasting becomes more challenging. Some IESs fall into this category of small-capacity systems. For example, predicting solar irradiance over a large area is relatively easier and more accurate, but for IESs at the household or industrial park level, which cover smaller areas, there is a greater need for highly accurate small-scale forecasting data. Achieving high-precision wind and solar forecasts for small areas remains a challenge because localized phenomena such as simultaneous sunshine and precipitation can occur, presenting significant difficulties for photovoltaic forecasting [8][9].

Even with a certain level of accuracy, forecast deviations have a much more significant impact on IESs compared to traditional large power grids. In large power grids, deviations in photovoltaic generation in some regions can be tolerated due to the grid's vast capacity. However, some IESs are located in remote areas and cannot connect to these large power grids. Even those IESs that are connected to large power grids face capacity constraints on their energy interactions due to economic considerations. Therefore, IESs have a weaker ability to resist random disturbances. Minor forecast errors can substantially impact the system because its limited capacity prevents it from tolerating these errors.

Currently, commonly used scheduling schemes, such as day-ahead and intra-day scheduling, assume that random variables remain constant within each time interval until the next scheduling period. These scheduling periods are generally 1 hour or 15 minutes. However, in reality, random variables do not stay fixed within this time frame, leading to deviations in the generation of photovoltaic and wind power from expectations. Meanwhile, other equipment continues to operate according to the previous scheduling scheme. To maintain energy conservation, the IES must have devices to manage these discrepancies. For off-grid IESs, batteries, heat storage tanks, and cooling storage tanks can absorb these fluctuations. For grid-connected IESs, the grid can also be used for absorption. However, because the system's storage capacity is limited, large deviations can impact the system's safe and stable operation.

To address the issue of deviations caused by random disturbances in existing scheduling algorithms, which lead to the system operating away from the optimal operating point, this paper proposes a scheduling method that considers extra scenarios. First, the scheduling scheme is calculated based on the original probabilistic prediction interval. Then, multiple scenarios deviating from the original prediction interval are established outside this interval. Optimal scheduling schemes are calculated for each of these extra scenarios. During actual operation, if the random variables fall within the original probabilistic interval, the original scheduling scheme is used. However, if the random variables fall outside the probabilistic prediction interval due to forecast deviations, the pre-calculated scheduling values from the extra scenarios are used to replace the original scheme. This ensures that the system operates under the new scheduling scheme, thereby maximizing the likelihood of the system operating near the optimal operating point.

2. PROBLEM STATEMENT AND DATA ANALYSIS

2.1 Problem Statement

The IES combines multiple forms of energy, such as cooling, heating, and electricity into a unified large system. Currently, renewable energy accounts for a high proportion of these systems. The stable operation of the system depends on the accuracy of predicting random variables. If there are deviations in the predictions, the system will continue to operate according to the previous scheduling scheme, inevitably leading to increased operating costs and potentially compromising the safety of system operations.

Most of the existing literature focuses on algorithm development without addressing the issues encountered in actual operations. Even the most commonly used scheduling algorithms assume a predefined range for random variables, guaranteeing optimal performance only within this range. However, when random variables exceed the predicted probabilistic interval—a situation that does occur in actual operations—there is a lack of corresponding research in the literature. This is the focus of this study: how to ensure the safe, economical, and efficient operation of the system when random variables exceed the predicted interval.

2.2 Data Analysis

To substantiate the premise of this paper, it is essential to understand the prediction deviations produced by existing forecasting algorithms in actual systems. Elia has published photovoltaic (PV) power generation forecast data and actual data for Belgium [10]. By analyzing this data, we can determine the deviations between the forecasted values and the actual values. A histogram depicting these deviations over a year is presented in *Fig. 1*.

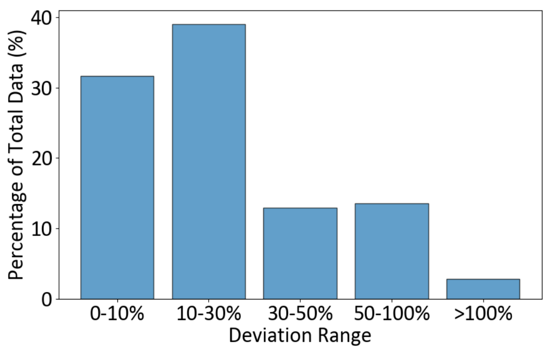

Fig. 1 Histogram of Deviations between PV Power Generation Forecasts and Actual Values

First, it is calculated that the average prediction deviation is 27.09%. The most frequent deviation range is 10%-30%, accounting for 39.04% of the data. Additionally, 31.68% of the prediction deviations fall within the 0-10% range, while deviations exceeding 50% account for 16.36%. These figures indicate that in actual power systems, deviations between forecasted and actual values are common due to the limitations of forecasting algorithms and data collection.

Large power grids can accommodate substantial deviations. However, for IESs, the absorption capacity is limited. A 10% forecast error can lead to a decline in system economic efficiency, and more severe forecast errors could even cause system failure. This underscores the significance of our research.

3. SYSTEM MODEL AND ALGORITHM CONSTRUCTION

3.1 System Model

The IES discussed in this paper comprises three major subsystems: electricity, heating, and cooling. The electric power system includes generation equipment, loads, and the grid, specifically photovoltaic panels, wind turbines, micro gas turbines, and batteries, all connected to the grid and electrical loads. The heating system consists of heat pumps, electric boilers, and heat loads. The cooling system includes electric chillers, absorption chillers, cold storage tanks, and cooling loads. Each device has its corresponding constraints, with their mathematical models described as follows:

3.1.1 Photovoltaic Panels

$$\begin{aligned} &PV_{P,E}(t,s)=\eta_{PV}\cdot Irr(t,s)\\ &PV_{P,E}(t,s)\le PV_{P,E,\max} \end{aligned} \tag{1}$$

3.1.2 Wind turbine

$$\begin{aligned} &WT_{P,E}(t,s)=\eta_{WT}\cdot Wind(t,s)\\ &WT_{P,E}(t,s)\le WT_{P,E,\max} \end{aligned} \tag{2}$$

3.1.3 Micro Gas Turbine

$$\begin{aligned} &MGT_{P,E}(t,s)=\eta_{MGT,E}\cdot H_{Fuel}\cdot Q_{m,Fuel}(t,s)\\ &MGT_{P,E,\min}\le MGT_{E}(t,s)\le MGT_{P,E,\max}\\ &MGT_{P,H}(t,s)\le \eta_{MGT,H}\cdot H_{Fuel}\cdot Q_{m,Fuel}(t,s) \end{aligned} \tag{3}$$

3.1.4 Battery

$$\begin{aligned} &BA_{Ca,E}(t,s)=BA_{Ca,E,ini}+\sum_{k=1}^{t-1}BA_{P,E}(k,s)\cdot T(k)\\ &BA_{SOC}(t,s)=\frac{BA_{Ca,E}(t,s)}{BA_{Ca,E,total}}\times 100\%\\ &-BA_{P,E,Discharge,\max}\le BA_{P,E}(t,s)\le BA_{P,E,Charge,\max}\\ &BA_{SOC,\min}\le BA_{SOC}(t,s)\le BA_{SOC,\max} \end{aligned} \tag{4}$$

3.1.5 Absorption Chiller

$$\begin{aligned} &AC_{P,E}(t,s)=\eta_{AC,E}\cdot AC_{P,H}(t,s)\\ &AC_{P,H}(t,s)\le AC_{P,H,\max}\\ &AC_{P,C}(t,s)\le \eta_{AC,C}\cdot AC_{P,H}(t,s) \end{aligned} \tag{5}$$

3.1.6 Electric Boiler and Chiller

$$\begin{aligned} &EB_{P,H}(t,s)=\eta_{EB,H}\cdot EB_{P,E}(t,s)\\ &EB_{P,E}(t,s)\le EB_{P,E,\max} \end{aligned} \tag{6}$$

$$\begin{aligned} &EC_{P,C}(t,s)=\eta_{EC,C}\cdot EC_{P,E}(t,s)\\ &EC_{P,E}(t,s)\le EC_{P,E,\max} \end{aligned} \tag{7}$$

3.1.7 Heat Pump

$$\begin{aligned} &HP_{P,H}(t,s)=COP_{H}\cdot HP_{P,E}(t,s)\\ &HP_{P,E}(t,s)\le HP_{P,E,\max} \end{aligned} \tag{8}$$

3.2 Algorithm Construction

The optimization objective of this paper is to minimize the system cost. This includes the start-up and shut-down costs, maintenance costs of each device, and fuel costs for the micro gas turbine. The IES is connected to the power grid, allowing for the purchase and sale of electricity, but with power limitations. We use the Stochastic Model Predictive Control (SMPC) algorithm to construct the loss function. The system's loss function is expressed in an expectation form, as shown in Equation (9).

$$C = \sum_{i=1}^{K}\sum_{t=1}^{N} P_t^i \cdot (C_{\text{Start-stop},t}^i + C_{\text{Maintenance},t}^i + C_{MGT-Fuel,t}^i + C_{EG,t}^i) \quad (9)$$

In addition, it is necessary to construct extra scenarios. For instance, considering photovoltaic (PV) power generation, the forecast interval for PV generation has upper and lower limits. Traditional SMPC algorithms only calculate the optimal scheduling values within this interval. In this paper, we divide the range from the forecast lower limit to zero into multiple intervals. Similarly, the range from the forecast upper limit to the maximum possible PV generation is divided into multiple intervals. During scheduling, it is assumed that the PV generation lies within each of these intervals, and the scheduling schemes for the different intervals are calculated separately.

In actual operation, if the PV generation lies within the forecast interval, the equipment is scheduled according to the initial scheduling scheme. If the PV generation exceeds the forecast interval, the corresponding scheduling scheme is chosen based on the interval in which the actual PV generation falls. This approach is shown in *Fig*. 2.

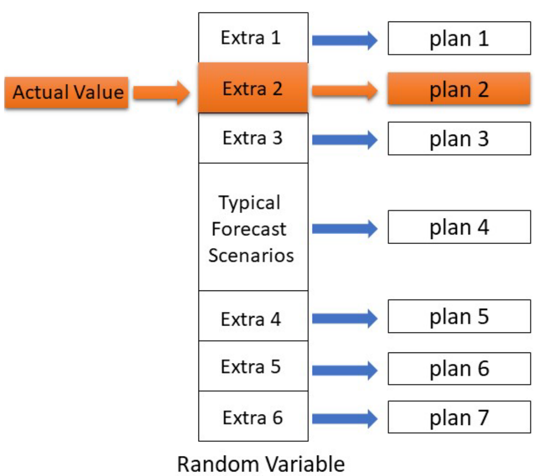

Fig. 2 Scheduling Scheme Considering Extra Scenarios

By incorporating these extra scenarios into the SMPC algorithm, the system can dynamically adjust its operation based on real-time conditions, ensuring that it remains close to the optimal operating point and enhancing its ability to handle prediction deviations. This method provides a more robust and flexible scheduling approach, accommodating the inherent uncertainties in renewable energy generation.

4. SIMULATION RESULTS AND DISCUSSION

The data used in this study is the real power grid data provided by Elia for Belgium. Since Elia's raw data represents the total power generation, it needs to be normalized and then multiplied by the rated power of the corresponding equipment in our system. In this simulation case, the power data for a specific day in Belgium was selected. On this day, there was a significant deviation between the forecasted and actual PV values, as shown in Fig.3. The data has been normalized.

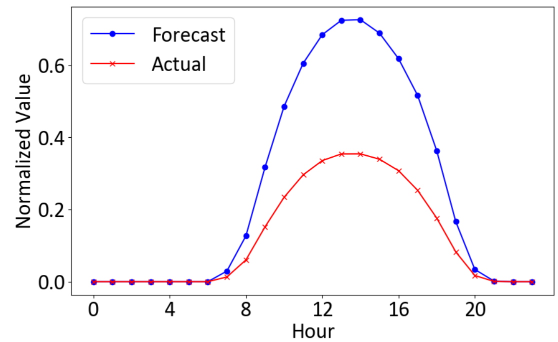

Fig. 3 Comparison of Normalized Forecasted and Actual PV Values for a Specific Day

It is noteworthy that the power interaction between the IES and the grid is constrained, with a maximum interaction power of 10 kW, reflecting real-world conditions. In the electric subsystem, the grid is used to absorb fluctuations in renewable energy. In the thermal subsystem, thermal storage tanks are used to absorb fluctuations. In the cooling subsystem, cold storage tanks are used to absorb fluctuations.

In *Fig.* 4, the scheduling situation of the IES is compared under the ideal condition, the traditional method, and the proposed method. The ideal condition is the case when PV generation matches the predicted value, meaning no prediction bias occurs. The traditional method refers to the case when PV generation differs from the predicted value, indicating a prediction bias. In the traditional method, a single scheduling plan generated by the SMPC algorithm is directly applied to system scheduling.

In the ideal condition, the scheduling scheme tends to use the micro gas turbine (MGT) to provide the system's electricity. This is because the MGT's power generation cost is lower than that of the grid, and it can simultaneously produce electricity and heat, reducing the consumption of heat-generating equipment.

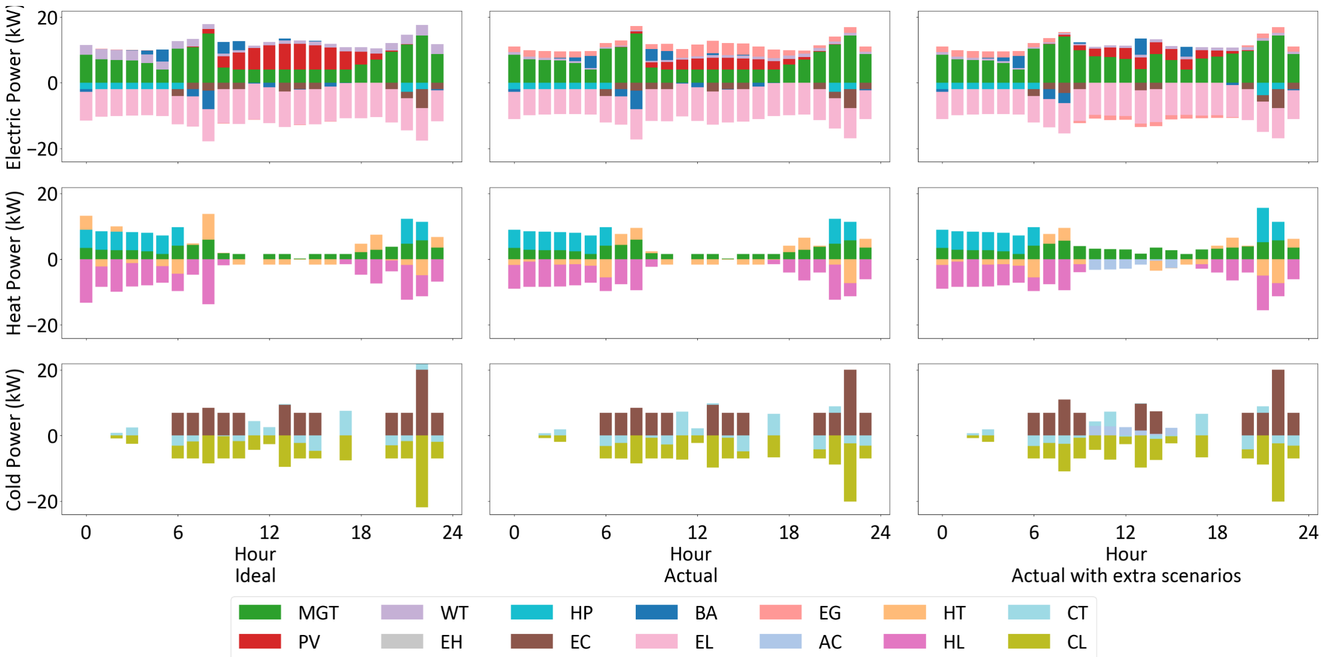

Fig. 4 Power Stack Histogram of IES Under Different Methods Over One Day

Therefore, in the ideal condition, purchasing electricity from the grid is minimized due to its higher cost and the need for additional equipment to provide heat.

The actual situation is different. If the system is scheduled according to the ideal condition values, given that the PV generation is less than the ideal value and the MGT operates at the pre-set power, the power shortfall will be supplemented by purchasing from the grid. It can be observed that the power purchase from the grid increases significantly, leading to higher system costs.

When using the proposed method that considers extra scenarios, if the PV generation exceeds the forecast interval, the system switches to the pre-calculated extra scenarios. As shown in the figure, between 8:00 and 18:00, the power generation of the MGT increases significantly, indicating that the system has switched to a new scheduling scheme. This reduces the demand for power purchase from the grid. With the increase in MGT power generation, the heat production also increases, causing a decrease in the power consumption of the heat pump.

According to the scheduling scheme, the costs for each device on the specified day are shown in *Fig. 5*. The blue bars represent the ideal costs, calculated based on the optimal scheduling scheme derived from forecast data. If there were no deviation between the actual values and forecasted values, this scheme would minimize the total system cost. The orange bars represent the actual costs incurred when scheduling according to the ideal data for that day. The green bars

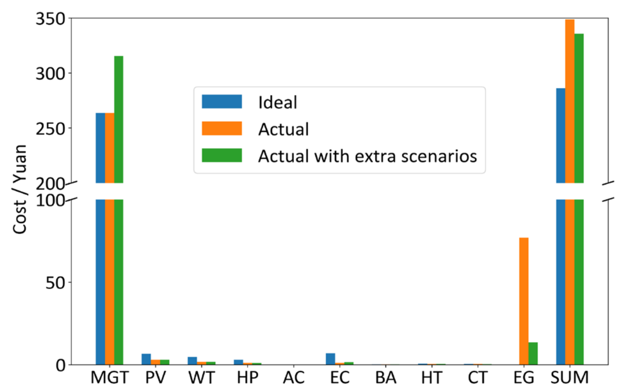

Fig. 5 Comparison of Costs for Each Device and Total Costs Under Different Methods

show the costs when using the proposed scheduling method.

The actual costs for each device align with our previous analysis. Under ideal conditions, the grid incurs almost no purchase costs, with the main power source being the micro gas turbine (MGT). In the real scenario, if the traditional algorithm is used, where device power is determined by pre-calculated schemes, the cost for the MGT remains the same, but the grid purchase cost rises sharply from 0.13 CNY to 76.92 CNY. This increase is due to the need to compensate for the reduced PV generation by purchasing more power from the grid.

When using the proposed method that considers extra scenarios, the cost of the MGT increases from 263.72 CNY to 315.31 CNY, an increase of 51.59 CNY. However, the grid purchase cost significantly decreases from 76.92 CNY to 13.51 CNY. Correspondingly, the operating cost of the heat pump also decreases.

Under ideal conditions, the total system cost is 286.04 CNY. This cost assumes that the system's random variables exactly match the forecast values, which is practically impossible. In the simulation, the actual PV generation was significantly lower than the forecasted generation, leading to an increase in the actual operating cost of the system. Following the original scheduling scheme, the actual system cost is 348.70 CNY, an increase of 62.66 CNY or 21.91% compared to the ideal cost.

Using the proposed scheduling method that considers extra scenarios, the actual system cost is 335.67 CNY, a reduction of 13.03 CNY compared to the original scheduling scheme. Compared to the 62.66 CNY increase in cost under the original scheduling method, our proposed method results in a cost increase of only 49.63 CNY, a reduction of 20.80%. Therefore, scheduling using the proposed method that considers extra scenarios brings the system cost closer to the ideal optimal cost.

This comparison demonstrates that the proposed method not only adapts to real-time fluctuations more effectively but also significantly reduces the overall system costs, making it a more efficient and economically viable approach for IES management.

5. CONCLUSION

This paper addresses the issue of deviations in actual operation from the optimal scheduling values in IESs caused by random variables deviating from their predicted values. To resolve this, we propose a scheduling method that expands the scenarios considered. Beyond the original prediction interval, our method selects extra data points outside the prediction interval for calculation. The results provide multiple scheduling schemes for different ranges of random variables. During actual operation, the appropriate scheduling scheme is selected from the pre-calculated options based on the actual values of the random variables. This approach prevents the increase in system costs that occurs when using traditional methods in the face of large discrepancies between predicted and actual values. Simulations demonstrate that the proposed method results in costs closer to the ideal optimal scenario, reducing the deviation from the ideal cost by 20.80% compared to traditional methods.

However, the proposed method has its limitations. In the simulation case, we only considered a single random variable. In real-world scenarios, multiple random variables may exceed the probabilistic interval, complicating the construction of extra scenarios.

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