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An innovative two-stage machine learning-based adaptive robust unit commitment strategy for addressing uncertainty in renewable energy systems

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ABSTRACT

Confronting the challenge of intermittent renewables, current unit commitment practices falter, urging the development of novel short-term generation scheduling techniques for enhanced microgrid stability. This study presents an adaptive robust unit commitment approach using machine learning techniques for renewable power systems, computing the Calinski-Harabasz index to identify prediction inaccuracies related to intermittent sources. The uncertainties are subsequently grouped together using the spatial clustering tool, and the average density of the K-means distribution is calculated. The clustering of points in space, considering noise, discrete uncertainty in renewable energy sources, and outliers within the comprehensive uncertainty set, is addressed via a nonparametric algorithm. The implementation of established methodologies and frameworks, in conjunction with density-based spatial clustering of applications with noise, introduces an innovative method for vulnerability clustering. This methodology guarantees that every cluster aligns with data pertaining to vulnerabilities of renewable energy sources. The performance of the suggested method is showcased by conducting experiments on modified IEEE 39-bus and 118-bus test systems that use intermittent wind power. The results demonstrate that the proposed framework may lower the cost of robustness by 8–48% compared to traditional robust optimization techniques. The results of stochastic programming showed that the optimized system with a stable economic organization would have 75 % faster calculations.

1. Introduction

Power system dependability and security can only be ensured by reserving enough dispatchable generating and transmission capabilities. Research is now being conducted to enhance the system's operational performance by optimizing schedules and taking unpredictability into account [1]. To achieve optimal operation, least-cost dispatching must reduce total operating costs while meeting electrical demand and other technical, environmental, and operational limitations. The Unit Commitment (UC) task in electrical power production is a large family of mathematical optimization problems where the production of a set of electrical generators is coordinated in order to achieve some common targets, usually either matching the energy demand at minimum cost or maximizing revenue from electricity production with a nonlinear solution space [2]. The intermittent nature of renewable energy sources poses new challenges to the classic UC [3,4]. One of the main issues is the unpredictability of these sources, which causes uncertainty in their fixed production capacity. Different models and programs are used to solve the uncertainty problem. These models help to ensure the stability of power systems to increase economic profit and reduce construction costs [5]. The uncertainty can be modeled by using Stochastic Programming (SP) [6]. Additionally, three main approaches to tackle uncertainty in the optimization of the UC problem when dealing with renewable energy generation uncertainty are incorporating modeling of failure and reliability, like Chance-Constrained Programming (CCP) [7], utilizing optimization techniques to handle uncertainty while

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optimizing for particular objective functions, and employing methods such as robust optimization [8]. The CCP method, on the other hand, allows for the inclusion of constraints and increases the probability value. In addition, single-stage and two-stage methods are used in energy system optimization. In [9], a two-stage Adaptive Robust Optimization (ARO) model has been used to demonstrate the Robust Unit Commitment (RUC), where the first stage is related to binary on/off decisions and integrating model scenarios [10]. The ARO method considers the economic basis in the minimum critical situation [11], and the solution is flexible [12] and based on the reliability of the system [13] in obtaining predictions and uncertainties [14]. The utilization of considerable data in conjunction with uncertainty in Renewable Energy Systems (RES) increases the stability and dependability of the optimized cycle [15]. In this manner, various possible distributions with innovative methods developed optimization chains of the RES uncertainty are more efficient than SP and CCP techniques in application and technical and economic calculations [16]. Box and budget uncertainty is a set of uncertainties that are used for RUC [17]. In [18], the Distributed Robust Optimization (DRO) method was developed. An intermediate combination of the SP method and the ARO method was used to solve a single committed optimization problem [19]. In addition, the prediction and uncertainty have hardened renewable energy sources modeling. [20]. Despite the models that operate in the form of RES forecasts, the Gaussian mixture models have a more significant geographical correlation [21]. Forecast error in renewable energy resources is usually complex and disjointed [22]. This data increases the prediction error and reduces the calculation speed and therefore a more general distribution and even Gaussian mixture prediction models are used due to the simplicity of their calculation [23]. An RUC model that uses input data prediction in discontinuous clustering creates a committed random unit and can significantly reduce the scheduling of energy forecasting systems and increase the commitment of power and flexibility systems [26]. Research related to the flexible scheduling of energy systems in the state of uncertainty of renewable energy sources has been reviewed in [27].

Machine learning (ML) techniques introduce a proportional ensemble for individual uncertainty applications rather than more comprehensive uncertainty clusters. This method may not be able to absorb the data of renewable energy sources in the uncertainty space with good flexibility and accuracy. Still, it can provide manual division of subsets. So far, no operational methods have been introduced to handle discrete Uncertainty Bulk Data (UBD) [24]. The solution to the design of the stable power operational optimizer system using ML is less conservative and provides an approach that has more capabilities than the conventional case of separation uncertainty in renewable energy power systems [25]. The use of ML in renewable energy mass disjoint data, especially wind energy, has uncertainty in planning the commitment of a sustainable unit in sub-clusters and worst-case scenario conditions and was not found in the research literature review. In contrast, the multistage ARO model-based clustering and vulnerability analysis method for ML clustering and robust optimization uses the inherent periodicity of renewable energy sources. It makes the model efficient and the solution easier and faster. To address this, there have been other approaches, such as kernel density estimation (KDE), the Gaussian approach to support vector domain description (SVDD), and support vector clustering (SVC), which are similar to previous conventional and established techniques. As discussed in the literature, the main problems of the traditional UC in the renewable power system are dealing with the intermittency and variability of renewable energy, uncertain forecasting, grid integration and stability, and economic dispatch challenges. To cope with these problems, researchers have developed some methods. The main drawbacks of those methods are high computational cost, technological complexity, integration challenges, scalability, and adaptability with large power systems.

To enhance the efficacy of UC results, this paper proposes an ML-based adaptive robust optimization method to solve the UC problem in the power system connected to wind power generation. The ML techniques are first used to calculate the Calinski-Harabasz index, leading to the separation of forecasting errors of intermittent renewable energy sources. Then, the uncertainties are grouped using the spatial clustering tool and the average density of the K-means distribution. The nonparametric algorithm for clustering points in space and incorporating noise, the discrete uncertainty in renewable energy sources, and the outliers in the comprehensive uncertainty set are taken into account accordingly. Improving and combining a few strategies and frameworks and utilizing Density-Based Spatial Clustering of Applications with Commotion (DBSCAN) presents an unused fashion of vulnerability clustering so that each cluster compares to the RES vulnerability information. A Principal Component Analysis (PCA) set uses these normal boxes as a nonparametric method of estimating Dirichlet density and analyzing different dimensions of large datasets. Finally, by implementing the proposed model in the widely used power system based on renewable energy sources, IEEE 39-bus and 118-bus systems, the solution process is changed, and the proposed technique is analyzed and compared, considering the uncertainty of the clusters in each subset of ML.

The rest part of this paper is arranged as follows: the problem formulation is defined in Section II. Section III presents the proposed method. Test results and discussion are provided in Section IV. Finally, the work conclusions are described in Section V.

2. Problem formulation

The UC task involves solving diverse mathematical optimization problems. These problems revolve around the strategic coordination of multiple electrical generators to achieve common objectives. The primary goals typically involve meeting energy demand efficiently at the lowest possible cost or maximizing the revenue generated from electricity production considering the power losses. This intricate process entails navigating a solution space characterized by its nonlinear nature. This means that traditional linear optimization techniques may not suffice, and more sophisticated approaches are required to find the most effective strategies for deploying and operating the generators. The (1) shows the objective function for minimizing UC costs.

$$min\sum_{i\in I}\sum_{t\varepsilon T-\{t_0\}}(C_i^G x_{i.t}+C_i^S u_{i.t}+C_i^D v_{i.t})+max\left\{\min(\sum_{i\in I}\sum_{t\in T-\{t_0\}}C_i^D P_{i.t}+\sum_{t\in T-\{t_0\}}C^+q_t^+ +\sum_{t\in T-\{t_0\}}C^-q_t^- +\sum_{k\in K}\sum_{t\in T-\{t_0\}}(C_i^L q_{k.t}^L))\right\} \quad (1)$$

where i is the generator parameters index, t shows the time parameters, ${}_i^G x_{i.t}$ indicates the parameters for determining commitment status, C is the commitment parameter and the Calinski-Harabasz index, ${}_i^S u_{i.t}$ represents the current operational status of unit i at time t, represented in binary format, ${}_i^D v_{i.t}$ is the binary shutdown status of unit i during period t, ${}_i^D P_{i.t}$ shows the total power demand at time t, $P_{i.t}$ is the power generated by unit i at a given time t, C^+ indicates the penalty parameters are utilized to enforce compliance with energy balance constraints, q_t^+ represents the inclusion of slack variables in power balance constraints,

C^- shows the penalty parameters associated with the violation of energy balance constraints, q_t^- represents the inclusion of slack variables in power balance constraints, K is the index sets for transmission lines, and $C_i^L q_{k.t}^L$ represents the line losses in transmission line k at time t, where C_i^L is the penalty parameter associated with line losses for generator i, and $q_{k.t}^L$ is the slack variable for line losses in transmission line k at time t.

The goal of optimization using the two-step "min-max-min" method in this research is to minimize UC costs under the most severe conditions of fluctuating power generation. The two-step "min-max-min" has arisen due to sequential decision-making and the unpredictability of outputs from variable RES. In the first step, which consists of (2) to (6), 24 h before the realization of uncertainty, generators' UC for the day-ahead market consists of their "here-and-now" choices [28]. The first "min" in the "min-max-min" represents the UC cost, the goal of the initial decisions. Based on the generator commitment decisions obtained in the first stage, which reflect the Economic Dispatch (ED) process. In the second phase, which includes relation (7)-(16) and a "max-min" problem to minimize cost, which is shown in relation (17) [29]:

$$s \bullet t \bullet u_{i.t} - v_{i.t} = x_{i.t} - x_{i.t-1}; \{\forall i \in I.t \in T - \{t_0\}\} \tag{2}$$

$$u_{i.t} + v_{i.t} \leq 1; \{\forall i \in I.t \in T - \{t_0\}\} \tag{3}$$

$$\sum_{\tau=t-UT_i+1}^{t} u_{i.\tau} \leq x_{i.t}; \{\forall i \in I.t \geq UT_i\} \tag{4}$$

$$\sum_{\tau=t-\Psi_i+1}^{t} v_{i.\tau} \leq 1 - x_{i.t}; \{\forall i \in I.t \geq \Psi_i\} \tag{5}$$

$$x_{i.t}.u_{i.t}.v_{i.t} \in \{0.1\}; \{\forall i \in I.t \in T - t_0\} \tag{6}$$

where s shows the logical relationships among generators, $u_{i.t}$ indicates the current operational status of unit i during period t as a startup, $v_{i.t}$ represents the operational status of unit i during period t, specifically referring to its shutdown status, T is the time, τ shows the collection of time, UT_i is combined uncertainty sets of multiple basic uncertainty sets to determine the minimum uptime-downtime of generators, Ψ_i indicates logical relationships among generators:

$$P_{i.t} \geq P_i^{min} \bullet x_{i.t}; \{\forall i \in I.t \in T - t_0\} \tag{7}$$

$$P_{i.t} \leq P_i^{max} \bullet x_{i.t}; \{\forall i \in I.t \in T - t_0\} \tag{8}$$

$$P_{i.t-1} - P_{i.t} \leq R \bullet D_i \bullet x_{i.t} + S \bullet D_i.v_{i.t}; \{\forall i \in I.t \in T - t_0\} \tag{9}$$

$$P_{i.t} - P_{i.t-1} \leq R \bullet U_i \bullet x_{i.t-1} + S \bullet U_i.u_{i.t}; \{\forall i \in I.t \in T - t_0\} \tag{10}$$

$$\sum\nolimits_{i=I} P_{i.t} + \sum\nolimits_{b\in B} w_{b.t} + q_t^+ - q_t^- = \sum\nolimits_{b\in B} D_{b.t} + \sum_{k\in K} (C_i^L q_{k.t}^L); \{\forall i \in I.t \in T - t_0\} \tag{11}$$

$$\sum\nolimits_{b\in B} S \bullet F_{b.k} \left\{ \sum\nolimits_{i\in I} \varnothing_i^L \bullet p_{i.t} + \sum\nolimits_{j\in J} WF_{b.j} \bullet w_{j.t} - D_{b.t} \right\} + q_{k.t}^L \leq \delta_k; \{\forall k.t\} \tag{12}$$

$$\sum\nolimits_{b\in B} S \bullet F_{b.k} \left\{ \sum\nolimits_{i\in I} \varnothing_i^L \bullet p_{i.t} + \sum\nolimits_{j\in J} WF_{b.j} \bullet w_{j.t} - D_{b.t} \right\} - q_{k.t}^L \geq -CAP_k; \{\forall k.t\} \tag{13}$$

$$w_{j.t} \leq \omega_{j.t} + \omega_{j.t}; \{\forall j \in J.t \in T - t_0.\omega_{j.t} \in U\} \tag{14}$$

$$P_{i.t=t_0} = \mu_i; \{\forall i \in I.t \in T - t_0\} \tag{15}$$

$$x_{i.t=t_0} = \sigma_i; \{\forall i \in I.t \in T - t_0\} \tag{16}$$

where P_i^{min} represents the minimum power output of generator i, P_i^{max} is the Maximum power output of generator i, R shows the rates at which generator i increases or decreases its power output, D_i and U_i are the rates at which generator i is shut down or started up, $u_{i.t}$ indicates the binary decision variable represents the startup status of unit i during period t, $b \in B$ represents the variation between clusters (inter-cluster), $D_{b.t}$ shows the load demand for bus b at time t refers to the amount of power or energy required by bus b at a specific point in time, $w_{b.t}$ indicates the power generated by wind farm j at a given time t, q_t^+ and q_t^- are inclusion of slack variables in power balance constraints is a common practice in power systems analysis, $F_{b.k}$ represents the power transfer distribution factor refers to a metric used in power systems analysis to determine the distribution of power flow among different transmission lines or branches, $\varnothing_i^L$ shows the indicator for the presence of line losses for generator i, $q_{k.t}^L$ is the slack variable for line losses in transmission line k at time t, CAP_k is the transmission line k's capacity refers to its ability to carry and transmit electrical power or signals efficiently and effectively,$P_{i.t=t_0}$ shows the continuous decision variable represents the power output from unit i at a specific time t, μ_i and σ_i are the initial power output and online status of generator i, $x_{i.t=t_0}$ represents the current level of dedication or loyalty exhibited by unit i during period t. Examples of second-stage "wait and see" decisions include generator output, wind farm power dispatch, and slack variables for balancing constraints. The "min" in the "max-min" denotes the choice to reduce costs in the worst-case scenario. However, in the second stage of the "max-min" dilemma, "max" represents the worst-case scenario since it represents the realization of uncertainty that might result in the highest UC cost. As a result, the second-stage ED choices are made with the uncertainty of intermittent renewable power outputs in mind.

As a result, "here and now" and "wait and see" judgments can't be optimized since the uncertainty realization information isn't accessible when the first-stage decisions are being made. The logical relationships between generators are shown in (2) and (3). The on or off times of the generators are controlled by (4) and (5), respectively. Limits on a device's power output are shown in (7) and (8). Rate ramping restrictions are (9) and (10). As shown in (11), the system's energy balance is maintained, while the transmission line capacity limits are shown in (12) and (13). The (14) restricts wind farms' renewable power outputs to the greater of (a) the projected wind power outputs or (b) the sum of the predicted wind power outputs and their standard deviations. It's essential to keep in mind that (14) is valid for all imaginable realizations of the UC, guaranteeing the stability of the solutions and the viability of the system's operations. The model's major components are in line with previous studies [30–33], the disjunctive structures and uncertainty set in renewable power projections have been taken into consideration, and the (14) has been adjusted accordingly. Initial information on generator commitment status and power outputs is presented in (15) and (16). To clarify, (6) implies that the "here and now" choice variables are binary, whereas the "wait and see" variables are non-negative. Wind power output uncertainties are shown in (14), and these variations have a direct bearing on both the objective, which is shown in relation (1) and the (11) and (13). The variable U in (14) stands for the machine-learning-generated DDU sets based on data. Evidence-based approaches, including K-means, Dirichlet Process Mixture Model (DPMM), PCA, KDE, and SVC are used to generate uncertainty sets.

3. Proposed method

The functioning of sustainable and reliable power systems may depend on identifying and managing the uncertainties of renewable energy. This paper proposes a two-stage ARO system with Data-Driven Techniques (DDT) and Disjunctive Data Uncertainty (DDU) for renewable energy UC with uncertain forecast errors. Fig. 1 depicts the proposed framework's realistic implementation process.

The Calinski-Harabasz index is utilized to determine an appropriate

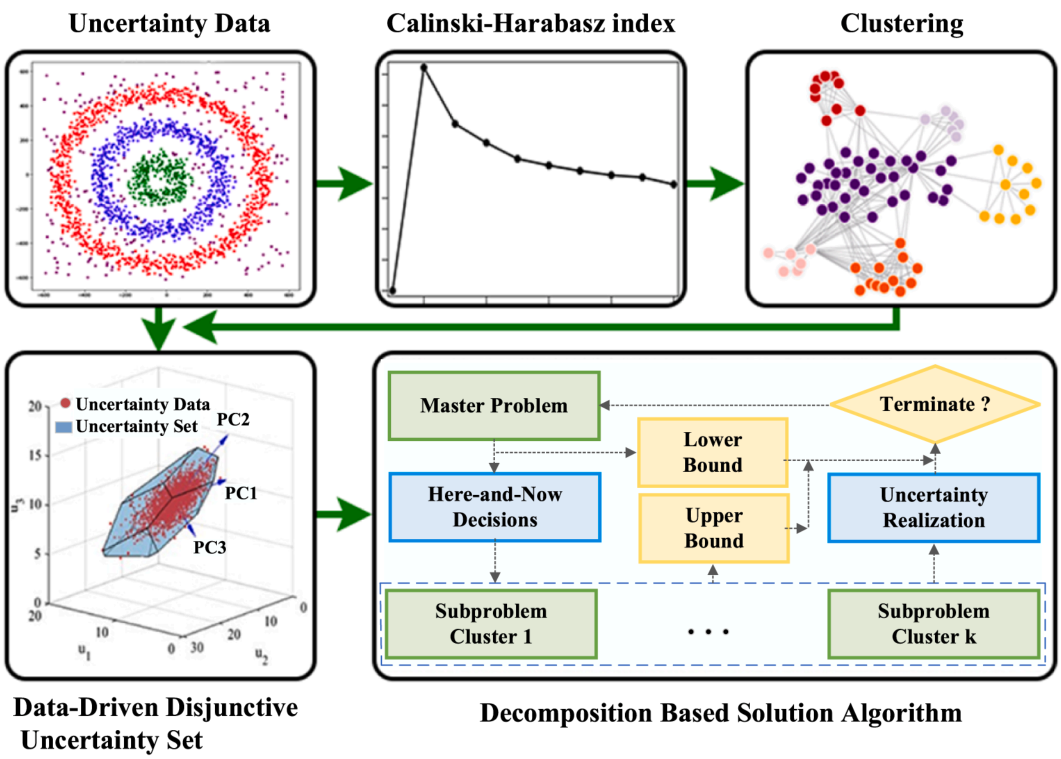

Fig. 1. Proposed method with separate uncertainty sets.

cluster size for data affected by uncertainty stemming from renewable energy sources. Using ML methods, the error data from renewable energy sources are grouped into the most appropriate number of categories. When ML is applied to uncertainty data and clustering results, it produces DDU sets. The associated ARO issue might be solved repeatedly using a targeted DBSCAN technique. The math behind the adaptive robust unit commitment (ARUC) model for running sustainable power grids while dealing with unpredictability in renewable energy sources is laid out here. In traditional ARUC, a single UC set is built to represent the whole UC space. However, several different basic UC sets make up the disjunctive uncertainty sets. The disjunctive UC space is equivalent to the union of the fundamental UC sets, as shown as follows:

$$U = \bigcup_{l} U_l; \{\forall l \in L - t_0\} \tag{18}$$

where, U represents the proposed DDT set built using ML techniques and $L - t_0$ are time dependents of U. Fig. 1′s first column is a visual depiction of the "one-size-fits-all" uncertainty sets, while the second and third columns are visual representations of the proposed disjunctive UC. Clustering techniques, when used in conjunction with data-driven uncertainty set construction, all while lowering the risk of mistakes in wind power predictions. ML techniques are used to group DDU samples, and disjunctive UC is derived from the union of several basic UC sets generated by more conventional or data-driven techniques.

The K-means and DBSCAN are used for uncertainty data related to errors in renewable energy projections and are clustered using ML techniques. Clustering data using a centroid is called k-means [34]. Each data sample is then independently aligned with the cluster center with the shortest Euclidean distance and is carried out iteratively throughout the process. In other words, the procedure terminates when no more data samples switch clusters or when there is no longer any movement of the centroids between iterations. It has been introduced as an advantage in research from DBSCAN [35]. Each data sample must be located inside a neighborhood with more data samples than the minimum required by this approach. The main difference between DBSCAN and K-means is that the former can identify outliers while the latter is susceptible to noise. To determine the optimal number of clusters the Calinski-Harabasz indices are utilized. Therefore, the proposed issues have three basic parameters: multi-level structure, semi-infinite constraints, and non-convex objective functions. The maximizing over the whole DDU set U can only be accomplished on the extrema of basic UC and DDU sets. This optimization strategy, known as decomposition, involves repeatedly solving the main problem and smaller problems over a period of time. The optimality of UC choices is maximized by solving the master problem under a variety of optimality cuts that correspond to the extremes of the basic UC, some of which are partially enumerated [37]. Therefore, the two-stage ARO takes advantage of discrete uncertainty by respecting the main optimization objective and considering a lower bound for minimization. After the implementation of the model, when the basic optimization solution is found, the economic dispatch scenario is applied, and the sub-problems of the first stage are decided, and appropriate scenarios are obtained. Since each Ul in the basic UC set represents a unique subproblem, we construct a set of subproblems for the DDU sets. A possible simplification of the ARO's "min-max-min" structure is a "max-min" structure in the subproblem. The basic problem is being solved in a package while the subproblem is rewritten and immediately evaluated by off-the-shelf solvers as well, and the big −M extended is used. The accuracy of the calculations and the lengthening of the calculation process is an issue that is involved based on the scenario of the ARO problem, which is involved in the goal of optimizing the larger component and introduced in the entire set of uncertainty "sets l.", together with a schedule is applicable under the specified first-stage judgments for the worst-case scenario after the collection of subproblems has been solved. The master issue is then reworked based on what was learned from the realization of uncertainty in the worst-case scenario, and the process repeats. Finally, the number of iterations is limited when the relative optimal gap is smaller than the value introduced as the tolerance threshold. Further, the suggested technique reduces the need to recreate the whole master and subproblems by building them just once while updating a subset of the variables, hence improving computing efficiency. The enhancements in computational

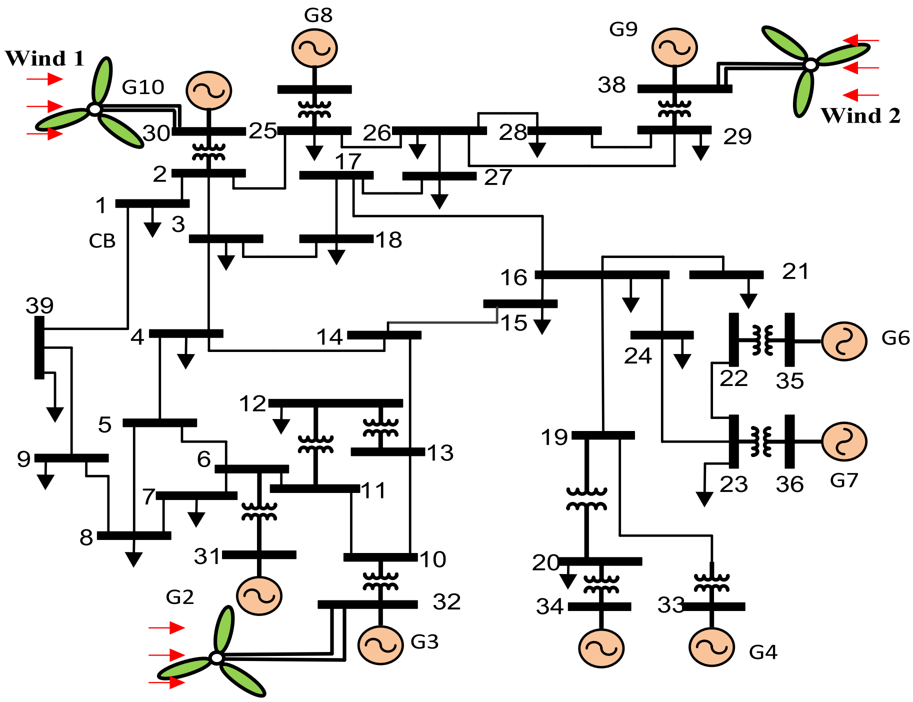

Fig. 2. IEEE 39-bus test system.

efficacy are highlighted through the use of case studies. In summary, the algorithm performs a partial enumeration over the extrema of DDU sets; more specifically, the extrema of all UBC, and new extrema may be established through every iterative process. The developed technique is certain to lead to the optimum solution due to the presence of finite extrema in disjunctive uncertainty sets.

4. Test results and discussion

A modified IEEE-39 bus system with wind power generation is investigated in depth. Fig. 2 shows the IEEE-39 bus tested system that there are a total of 46 lines, ten generators, and 39 buses in the system. You may find details on the 39-bus network in [38]. In this research, our primary objective is to optimize the computation time of the model. We focus on applying the Calinski-Harabasz index using machine learning techniques to identify prediction inaccuracies originating from intermittent sources. Each wind farm with a wind penetration (%) of 10 % generates 252 MW, 162 MW, and 209 MW of power, respectively. If wind penetration hits 24 %, wind farms will provide an average of 485 MW of electricity. The synchronous generators on buses 30, 32, and 38 will be replaced with wind turbines with the same capacity as the original machines, accounting for 40.4 % of the total power. The Gaussian mixture model is utilized to generate 800 samples of uncertainty data for wind forecast error [39], and the renewable energy prediction data are downscaled based on previous research [40]. Python and Pyomo were used to create the code for the two-stage RUC challenge, which was run on a last-generation PC with an Intel processor and more than 32 GB of RAM. Gurobi 9.1 software solves complex relationships with high capability and limited error and completes the technology development strategy. The solved problems will finally be displayed in the latest version of the Windows operating system.

To compare the number of optimal clusters in research article development, some well-known techniques are employed, as shown in Fig. 3. These methods have proven to be reliable in determining the ideal number of clusters by considering the within-cluster variance and inter-cluster separation. Additionally, the Calinski-Harabasz index is utilized as a criterion to assess the clustering performance. The elbow method, DBI, and Calinski-Harabasz index serve as valuable tools in determining

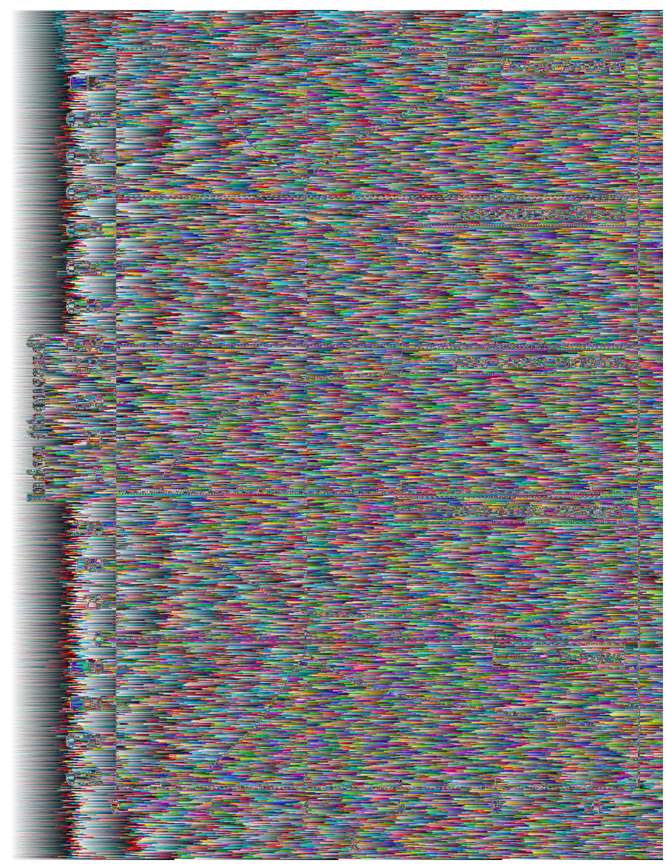

Fig. 3. Calculation of the optimal number of clusters using various methods.

the optimal number of clusters for organizing research findings. The findings elbow method and Davies Bouldin Index, which perform the confirmed clustering, criteria values have been used to evaluate the number of optimal clusters (Calinski-Harabasz index). Then, the

DBSCAN is used for optimizing the number of clusters algorithm in reducing the number of outliers in the nonparametric set of Density-Based (DB) clustering using the Calinski-Harabasz index.

In the data clustering phase, two methods can be utilized: K-means for clustering all objects and DBSCAN for filtering objects based on noise, density, and outliers. K-means has limitations with spherical clusters, while DBSCAN does not follow Euclidean density tradition. The uncertainty of the clustering set can produce accurate results in modeling research. Decision-makers can balance risk and robustness by selecting DDT and DDU sets with the same level of conservatism, which is 90 % in this investigation. The disjunctive uncertainty sets proposed here may be more effective than standard methods in capturing varying uncertainty spaces between data samples. Combinatorial optimization operation using a decomposition-solution algorithm improves the handling of more than 700 integer variables, 7000 continuous variables, and 13,000 constraints in the main problems. Subproblems allow a maximum of 6514 integer variables, 7581 continuous variables, and 26,921 constraints.

Fig. 4 shows a particular convergence with variable uncertainties with horizontal dashed lines and the upper and lower Bound (UB and LB) of the convergence points. Upper band and lower band optimization are done with the Gurobi library under Python programming language in the range of 6–10. Therefore, it can be confirmed that the relative error for convergence points and other points in Fig. 4 is equal to and less than 0.0001 %.

For a problem involving DDU sets, the solution technique using DBSCAN and DPMM entails a total of five iterations. The values outside the dashed horizontal lines indicate a positive deviation from the values. Depending on the specifics of the case study, the approach may converge in as little as eight iterations using the supplied framework. ARO, DDU unit commitment (DDARUC), and the standard "one-size-fits-all" approach (CA) are all acronyms for the same thing. Data-driven uncertainty sets produced using principal component analysis and K are referred to as principal component analysis and K-means (PCA & KDE) and K-means with principal component analysis and principal component analysis (DBSCAN), respectively. The acronyms in Fig. 4 are split into two portions to indicate the different kinds of problems and UBD. There will be tests of both traditional ARUC and data driven ARUC (DDARUC). Suggestions for DDU sets using K-means and DBSCAN are denoted by KM and DB, whereas basic uncertainty set types are represented.

The optimal target values are the lowest possible operating costs for all possible realizations of RES included in the UBD. More stringent solutions are indicated by larger values. With no unknowns, the deterministic scenario has a minimum cost of 426,443 USD. The price of robustness measures the extent to which robust optimization scenarios

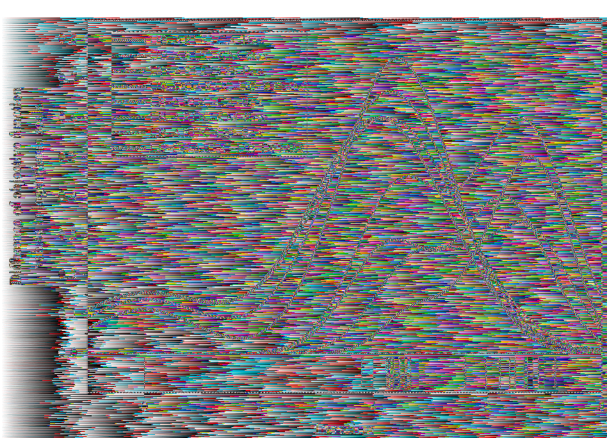

Fig. 4. The optimization method based on decomposition converges when applied to situations including a mix of disjoint and traditional uncertainty factors.

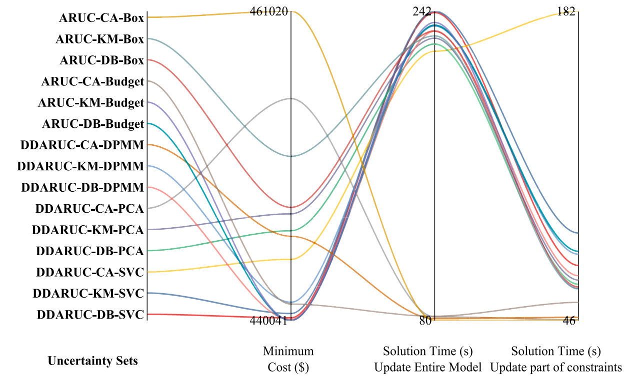

Fig. 5. The time required to find a solution when updating the complete model versus utilizing a other disscussed approaches.

incur more expense than deterministic ones [59] and is therefore used to evaluate the effectiveness of the strategy. The use of the proposed DDU sets decreases the price of robust optimization by 28–38 % for issues involving box, budget, DPMM, PCA coupled with KDE, and SVC uncertainty sets, and by 21–22 % for problems using SVC UBD. This will save significantly on the cost of uncertainty based on disagreeing data and increase optimization convergence. It also enhances DBSCAN and K-MEANS-based optimization by controlling the distinct points and noise of uncertainty data. The time required to find a solution is shown in Fig. 5 for both the traditional approach of developed the whole model and the recommended technique. In this work, instead of updating the whole model during iterative solution, certain constraints of a previously created model are updated depending on new input parameters using bespoke Python methods. As a result, each of the proposed DDU sets has a significantly reduced solution time of roughly 70 % to the proposed method. Using the proposed method, the time required to solve a problem involving the proposed disjunctive uncertainty sets is between 60 and 85 s, while the same time using a standard uncertainty set without clustering is between 46 and 182 s. Unclustering-free standard SVC-based uncertainty sets make issue solving substantially more time-consuming compared with more traditional uncertainty set kinds. The optimization of the proposed method can cover a greater range of uncertainty while reducing computational and operational costs and considering more vectors, which will be more efficient than conventional uncertainty sets.

The optimum and sustainable operations of the challenges involving uncertainty are shown in Fig. 6 via the commitment choices made by each of the ten generators. The optimal on/off settings for G6 and G8 when using ARUC depend on the nature of the problems being solved. For ARUC problems involving either conventional or DDU sets, the optimum on–off options are the same. This suggests that variations in their optimum costs are a direct result of variations in ED choices. Under the ideal solutions for the disjunctive Dirichlet Process Mixture Model (DPMM), the G4 would be online for 7–8 h. In contrast, generator G5 would be online at the same time under the best solution for the conventional DPMM. These times represent the best possible outcomes for DDARUC under the DPMM uncertainty conditions. Similarly, the best on–off choices for certain DDARUC issues with DDU or traditional SVC and the optimal operations schedules for the same problems when employing PCA paired with KDE vary. Table 1 displays the stochastic programming variables for at least three optimization scenarios, ordered by costs for stable operation within the uncertainty range. This table shows the economic effects of each economic activity in the power system with the RES assuming the worst case scenario. It is an optimal method that can include the lowest cost is less than 1 % of the total costs. In most cases, the fixed operating expenses will account for around 15 % of the total cost of the system. The discrepancies between the initial investment and the continuing fixed expenditures are directly related to

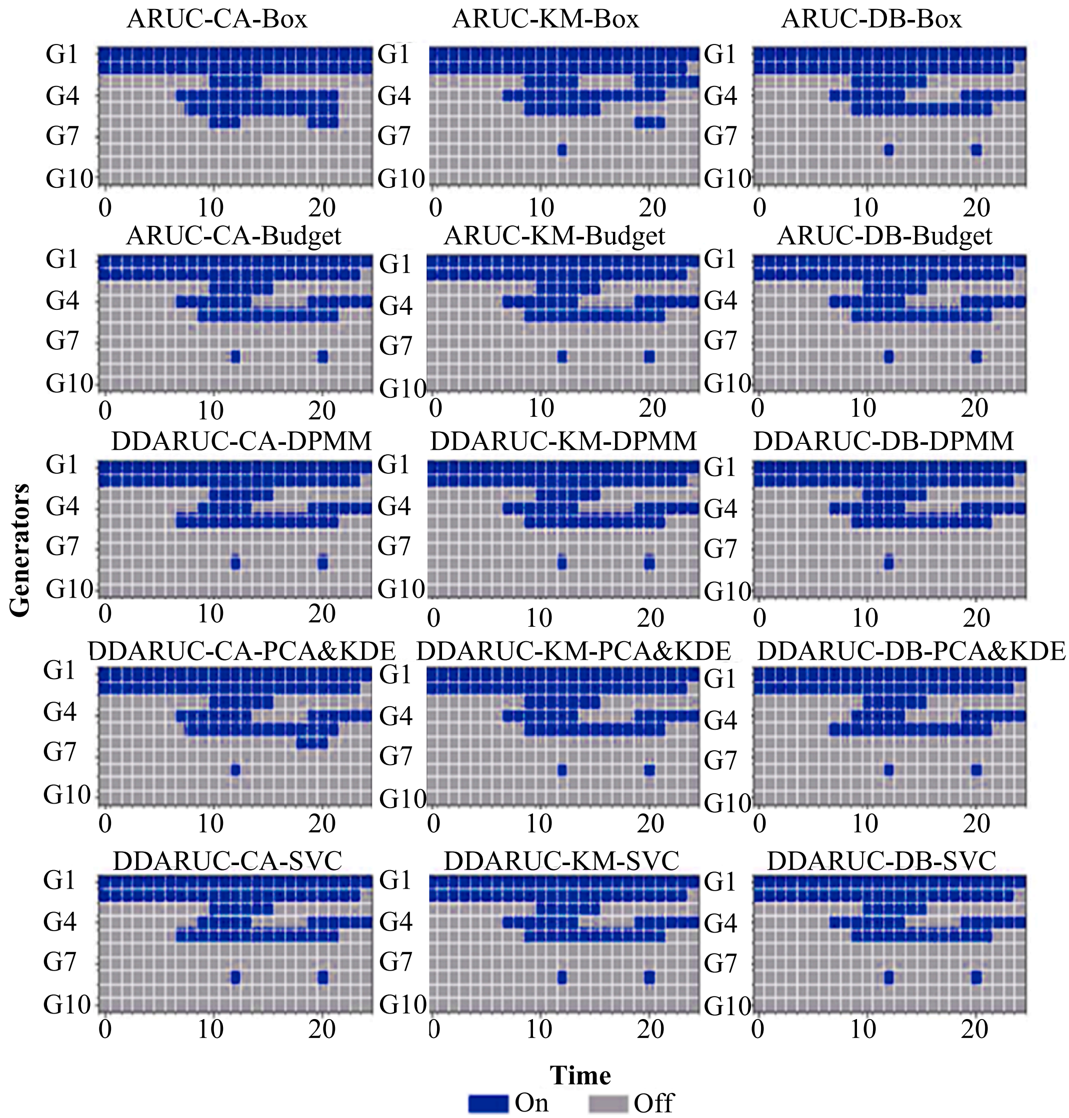

Fig. 6. The best on/off choices made by the generators by the proposed method.

Table 1
Specifics of the revised model of optimization for solving SP issues include a variety of various numbers of scenarios.

Variable	800 scenarios	100 scenarios	30 scenarios
Constraints	2,622,509	328,609	99,219
Variables	1,182,331	148,431	45,041
Continuous Variable	1,181,601	147,701	44,311
Integer Variable	730	730	730

the optimum operational schedules. Moreover, variable operating costs are greater than the startup and fixed operating costs of generators, and the bulk of changes in total costs as shown in Fig. 6 are due to operating costs for solutions that correspond to DDU.

To compare the efficiency of different models, we simulate the operational costs of RES under the optimum solutions obtained from ARO models and the more traditional two-stage stochastic UC models. Because it relies on probabilistic assumptions, the CCP is not employed as a benchmark in the suggested data-driven robust optimization strategy. This is done so that the suggested method may be compared to the optimum solutions found. Solving SP-30 and SP-100 problems, for example, uses 342 and 1194 CPUs, respectively, and takes over three times as long as solving the problem, as shown in Fig. 7. This is because

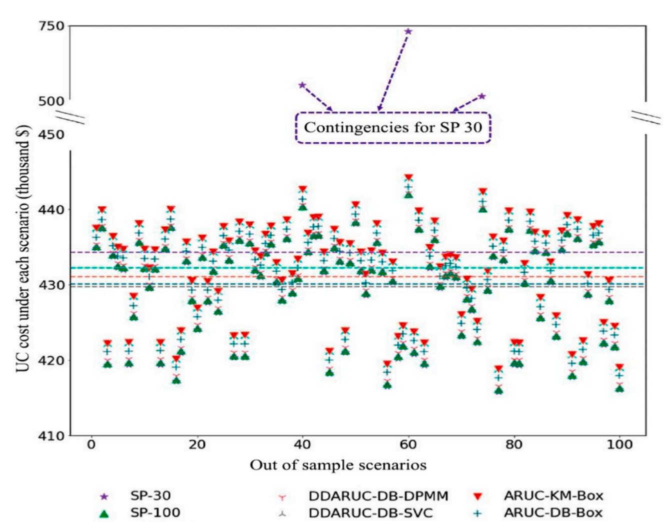

Fig. 7. UC cost with the proposed method.

SP problems typically have a higher level of computational difficulty.

A compromise may be reached between computing economy and solution quality or accuracy by scenario reduction [35,36,37,41]. It follows that this method has the potential to drastically reduce the time required to resolve a stochastic UC issue [42]. Scenario reduction isn't employed since it lowers the quality of the results achieved by using SP-based scheduling, which is why it isn't used in this case study. The solution's precision was deemed crucial for evaluating it against alternatives. Hence, this choice was selected. Additionally, the solver cannot offer lower and upper bounds of $427,677 and $429,768 after one hour, based on the DDU. Sustainable operating costs are shown in Fig. 7, which is based on simulation results using optimum solutions in ARO and SP in 100 out-of-sample scenarios. As a result, the out-of-sample results in ARO and SP are consistent with the cost simulations, suggesting that the former may be more suited to practical applications. The graph shows that the SP-30 technique is unsuccessful for dealing with system contingencies in two situations when the UC costs more than $500,000. UC costs for the SP-30 solution are generally similar to those of the SP-100, therefore the SP-30 solution's particularly high costs under system contingencies cause its average simulated cost to be higher. The average cost of the solution to the ARO problem in Fig. 7 is less than that of the SP-30 solution because of the standard box uncertainty set's superior ability to hedge against the uncertainties. While both solutions, ARUC-CA-Box and the one equivalent to the K-means-based DDU box sets are conservative, the former has a much lower average simulated cost. By comparison, the proposed method in solutions for UCs that are both resilient and accurate to within 0.001 % of the SP-100 solution. Importantly, the proposed ARO approach uses DDT sets, which take just a fraction of the time to compute as the SP-100 solution. Further, for all scenarios obtained from uncertainty data, scheduling costs are modeled. It is possible to compare the operation costs in different scenarios. The operation scenario of the SP-30 solution cannot adequately plan and develop the unforeseen conditions of the SP-100 solution scenario. The average cost simulated with the horizontal guidelines shown and the SP-30 is 0.1 % more than the costs of the SP-100 solution and SP-30 solution. The vertical column of Fig. 7 is partially broken, because the SP-30 solution is located far away from the averages in some places and requires convergence.

The highest simulated cost in all scenarios is 46 % higher than the cost in the SP-100 solution. Fig. 7 uses abbreviations to show the development of solutions and Unit Commitment data. SP-30 refers to a stochastic UC with 30 random situations; SP-100 refers to a stochastic generation unit with 100 random scenarios; ARUC refers to an adaptive robust UC; DDARUC refers to a DDT and RUC; UC renewable energy data could be clustered using DPMM.

A huge case scenario is also considered and tested using the IEEE 118-bus system. The system is comprised of 91 loads, 54 thermal units, 118 buses, and 186 lines. There are ten wind farms in the areas served by bus lines 4, 6, 8, 10, 12, 15, 18, 36, 69, and 77. The master problems may include as many as 20,267 constraints, 3942 integer variables, and 8372 continuous variables, so you can get a notion of how extensive the reformed concerns are. There are a total of 49,153 constraints and 7926 integer variables among the subproblems, in addition to 8485 continuous variables. The optimal cost of the traditional "one-set-fits-all" with DPMM is $779,414, according to the results of large-scale optimization, but it drops to $751,116 when using the presented the DDU sets constructed with DBSCAN and DPMM. The price tag for using deterministic planning is $720,122. In light of this, it becomes clear that this method leads to a 48 % more substantial decrease in the PoR than the conventional approach. It takes 965 CPUs to solve the large-scale resilience optimization issue using the proposed method. Between rounds, this approach revises some of the variables and constraints governing the master and subproblems. The optimally sustainable activities planned to use deterministic planning and the proposed framework are shown in Fig. 8.

It is worth noting that the ARO scenario and the deterministic

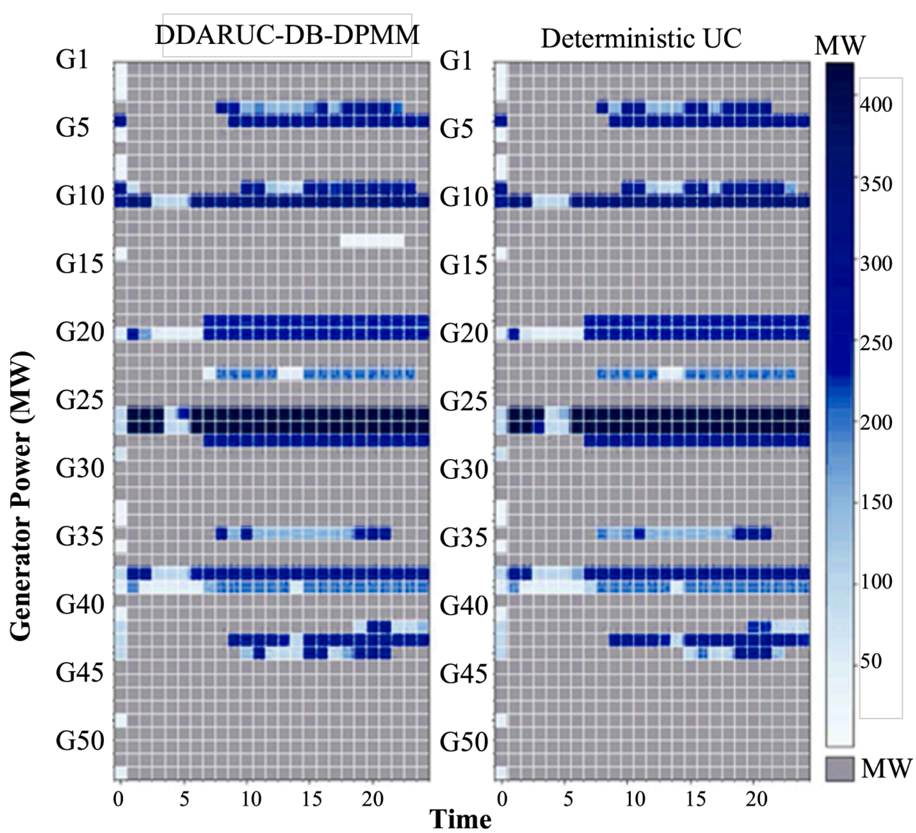

Fig. 8. The power outputs of the generators for both the deterministic planning scenario and the proposed robust optimization case.

planning scenario have a lot of similarities in terms of the elements that make up their respective optimal commitment schedules. Generators G4, G14, and G43 are run for a longer period of time in the evening if the ARO solution is implemented. As opposed to the ideal choices that would be created by deterministic planning, this is what happens. In contrast, the recommended framework's optimal solution would have the morning's most of the power coming from generators G24, G36, and G45. The ARO scenario necessitates more generators to be running in the morning and evening due to inaccurate wind power forecasts. This is mainly because of the potential for lower wind power outputs, which would need for a bigger number of capabilities from thermal units to make up for the shortfall. More thermal units need to come online to make up for the uncertainty in the wind output forecast. Therefore, in the ARO example, boosting the outputs of active units is a direct solution to the possible energy supply deficit caused by inaccuracies in wind power predictions during these hours. Power generators are controlled by different models through data-driven disjunctive uncertainty. The outcomes of this simulation are shown in Fig. 9. The average simulated costs of the given method were much lower than those obtained using the more conventional ARO and SP methods. Scheduling choices based on SP-30 and SP-100 approaches have very high costs related to systems contingencies, reaching over 1,000,000 USD in out-of-sample situations, while optimum judgments using the suggested framework are able to successfully buffer against the systems contingencies. Investigating random scenarios with additional commitment, for example, for SP-30 = stochastic UC with 30 random scenarios, and the same amount has been used to upgrade the scenarios, then SP-100 = stochastic UC in accordance with 100 scenarios.

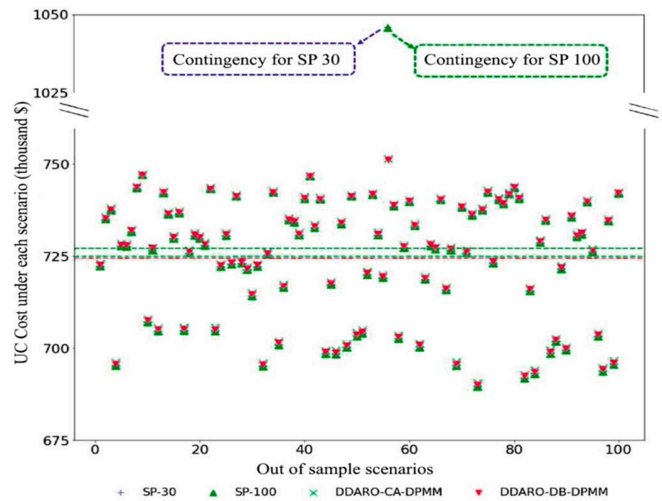

Fig. 9. UC cost with the proposed method for IEEE 118 bus test system.

5. Conclusions

This paper aimed to provide a robust UC solution considering renewable energy generation uncertainties within a novel ML-based two-stage ARO framework. This framework includes DDT and DDU sets to manage RES generation penetration, aiming to mitigate uncertainties arising during the operation of sustainable and reliable power systems due to the proliferation of RES. To this end, an ML strategy with a two-stage adaptive and resilient UC model was proposed to represent the uncertainty region of disjunctive structures in wind power prediction errors, enhancing flexibility and accuracy. This model proved to be both flexible and reliable. Subsequently, the number of clusters was determined using a valid index, and uncertainty data clustering was performed using two well-known criteria: K-means and DBSCAN. Lastly, a DDU set was utilized to streamline computational operations and address base uncertainties. These fundamental uncertainty sets encompass recognized Box and Budget UBD sets alongside DDU sets created using DPMM, PCA combined with KDE, and SVC.

The proposed utility-based framework was demonstrated through two case studies, illustrating its effectiveness in achieving sustainability amid uncertainties posed by renewable energy. The modified IEEE 39-bus and IEEE 118-bus systems served as the foundations for these case studies. Comparison with the standard 'one-size-fits-all' adaptive robust UC strategy revealed that the suggested framework reduces the cost of robustness by 8–48 %, signifying significant economic benefits. For robust UC, we adopted a 'one-size-fits-all' strategy. In terms of economic performance for renewable electricity system operations, the proposed framework can yield equivalent or superior results to SP, all while reducing computation time by around 75 %. Some certain limitations still exist within the proposed method. While the primary focus of this research was on ensuring reliable energy system operations using renewable energy sources, the suggested approach holds the potential for exploring various forms of energy system uncertainties in the future. Uncertainties often abound in power grids with renewable and non-renewable energy sources, stemming from factors like fuel availability, grid and equipment failures, and unforeseen repairs and demands. The proposed framework exhibits high adaptability, accommodating various clustering techniques. In this study, we employed the K-means and DBSCAN clustering algorithms. Researchers can use these algorithms or other models, adapting the research methodology to different clustering scenarios, hierarchical clustering, conservative clustering, or alternative uncertainty sets to construct networks grounded in renewable and clean energy.

CRediT authorship contribution statement

Mostafa Esmaeili Shayan: Writing – original draft, Writing – review & editing, Conceptualization, Data curation, Formal analysis, Investigation, Validation, Visualization, Resources. **Mario Petrollese:** Supervision, Data curation, Writing – original draft, Writing – review & editing, Conceptualization, Formal analysis, Investigation, Validation, Visualization, Resources. **Seyed Hossein Rouhani:** Investigation, Resources, Validation, Formal analysis, Visualization, Writing – review & editing. **Saleh Mobayen:** Visualization, Writing – review & editing, Validation. **Anton Zhilenkov:** Writing – review & editing, Validation. **Chun Lien Su:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of competing interest

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.

Data availability

The authors do not have permission to share data.

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