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Unit Commitment with High Renewable Penetration: Formulations, Optimization, and Machine Learning Approaches – A Review

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ABSTRACT: Unit commitment (UC) remains a central short-term scheduling problem, but high penetration of renewable energy sources (RES) has increased its uncertainty, flexibility, and security requirements. This review synthesizes UC formulations and solution methods for renewable-rich power systems, emphasizing the relationship between formulation complexity, operational requirements, and solution-method suitability. It first organizes deterministic, network-constrained, security-constrained, stochastic, robust, clustered, storage-integrated, and multi-energy UC models, highlighting how forecast errors, net-load ramps, reserve needs, curtailment, low inertia, electric-vehicle flexibility, and network congestion shape commitment decisions. It then critically assesses classical mathematical programming, decomposition, and metaheuristic methods in terms of scalability, feasibility guarantees, optimality evidence, reproducibility, and applicability to RES-integrated UC. In addition, the review classifies machine learning applications according to their primary role in the UC workflow: input and uncertainty learning, learning-assisted optimization, and assurance, validation, and deployment. Recent directions such as renewable scenario generation, surrogate modeling, warm-starting, constraint screening, graph-based learning, reinforcement learning, and decision support are examined to clarify how ML can support, rather than replace, optimization-based scheduling. The review also discusses barriers to practical deployment, including generalization to unseen operating conditions, feasibility violations, interpretability, operator trust, and lack of standardized benchmarks. Finally, it identifies hybrid ML–optimization frameworks, benchmark-driven evaluation, and validation-oriented deployment as key research needs for reliable, scalable, and secure UC in low-carbon power systems.

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1- Introduction

Power systems constitute a critical national infrastructure, as the electricity they supply is indispensable for modern life. In contemporary societies, the availability and cost of electricity are central to economic activity and social welfare. Planning and operating power systems require solving several optimization problems. Among these, the unit commitment (UC) problem is a key challenge in short-term operation. [1]competition, and selection. In the subject algorithm an overall UC schedule is coded as a string of symbols and viewed as a candidate for reproduction. Initial populations of such candidates are randomly produced to form the basis of subsequent generations. The practical implementation of this procedure yielded satisfactory results when the EP-based algorithm was tested on a reported UC problem previously addressed by some existing techniques such as Lagrange relaxation (LR. It entails scheduling the operation of generating units within a day or a week, with the objectives of minimizing total production cost and emissions produced by the generation plants, increasing the reliability and security of the power system, and reducing power losses to meet fluctuating demand for electricity while adhering to a set of constraints. In general, the UC can be formulated as a large-scale, mixed-integer combinatorial optimization problem characterized by nonlinearity and the presence of both binary and continuous variables. [2]. The integration of RES has introduced complexities into the operation of electrical power systems, especially for the UC, necessitating the resolution of optimization challenges due to the inherent uncertainties of RES. [3]this issue is addressed within the framework of security-constrained unit commitment (SCUC.

In the context of sustainable energy systems, UC has become a key tool for assessing and operating portfolios with high shares of wind, solar, and storage, while maintaining supply security and limiting emissions. Many studies have investigated the formulation and solution of UC in the presence of RES, proposing models and algorithms that address uncertainty, flexibility, and security in diverse system settings. These works provide mechanisms for modeling, monitoring, and optimizing the operation of generation

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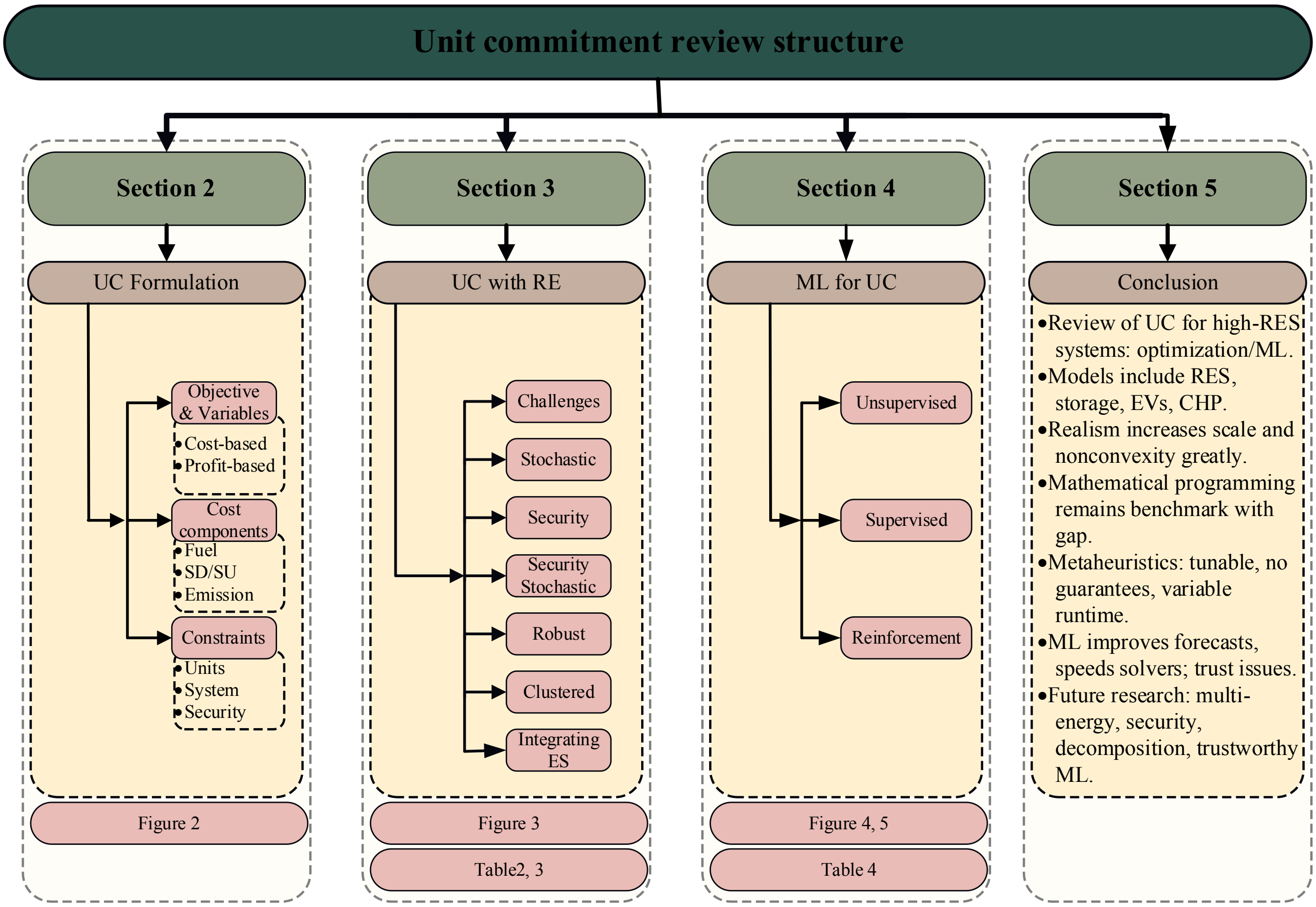

Fig. 1. Paper structure.

portfolios under a wide range of operating conditions. To synthesize this growing body of work, several review articles have examined UC with RES and the use of machine learning (ML) in related tasks such as forecasting. Existing reviews, however, often focus either on conventional and heuristic methodologies without considering ML-based approaches, or on a limited set of ML techniques applied mainly to thermal UC. Many are restricted to a single UC variant, such as stochastic UC, security-constrained UC, or profit-based UC. Table 1 presents a comparative analysis of these review studies.

Table 1 indicates that previous review studies have generally focused on selected aspects of the UC problem, such as conventional UC formulations, security-constrained UC, transmission-aware models, renewable integration, or specific computational methods. However, fewer studies provide an integrated synthesis that links RES-driven formulation changes with the suitability of classical optimization, metaheuristic, and ML-based solution methods. The distinctive contribution of this review is therefore its unified perspective on how high-RES penetration changes the UC problem structure and how different solution paradigms respond to these changes. In particular, this review connects renewable-integrated UC formulations with optimization and decomposition methods, metaheuristic approaches, and modern ML roles, including forecasting, scenario generation, surrogate modeling, solver acceleration, constraint screening, reinforcement learning, and decision support. This synthesis clarifies that ML is most promising not as a complete replacement for optimization, but as a complementary layer that improves uncertainty representation, computational efficiency, and operational decision support while still requiring feasibility validation and operator trust."

The present survey aims to provide an updated and integrated view of UC in RES-rich systems, encompassing both classical optimization and ML-based approaches. It reviews recent work on deterministic, stochastic, robust, and security-constrained UC formulations, as well as models that incorporate energy storage, electric vehicles, and multi-energy couplings. It also synthesizes the literature on ML for UC, including forecasting methods integrated into the UC model, hybrid ML–metaheuristic schemes, and ML techniques that support or approximate UC decisions.

In light of the extensive literature on UC with high-RES penetration, this survey does not attempt to simply re-list existing formulations and algorithms. Instead, it offers four

Table 1. A comparative evaluation of the extant review papers.

Ref	Year	UC	Mathematical formulation	RES	ML	Review focus	Comparative analysis tables			
							UC	**UC-RES**	**RES forecasting**	**UC-ML**
[2]	1998	Only thermal units	–	–	ANN	Conventional methodologies, GA, ES, and ANN for UC for thermal units	–	–	–	–
[4]	2012	Hydro and thermal units	–	–	–	Conventional methods, evolutionary algorithms	–	–	–	–
[5]	2013	Thermal units, uncertainties, and spinning reserve constraints	✓	WE	ANN	Conventional, ANN, ES, fuzzy, evolutionary, and hybrid algorithms	✓	–	–	–
[6]	2015	Short-term SUC	✓	WE, PV	–	A detailed review of the formulation of SUC. Solution using explicit formulation methodologies, no metaheuristic methods	✓	–	–	–
[7]	2017	Types of objectives in UC and impacts of RES and the ES devices	✓	WE, PV	–	Conventional, heuristic, and hybrid methodologies	✓	✓	–	–
[8]	2018	Deterministic, Price-based, stochastic, and in a deregulated environment	✓	WE, PV	ANN	Conventional, heuristic, and hybrid methodologies	✓	–	–	–
[9]	2018	Deterministic and uncertain UC in large-scale systems: thermal, hydro, RES, and DR	–	WE, PV	ANN	Conventional, heuristic, and hybrid methodologies	✓	–	–	–
[10]	2019	SUC	✓	WE, PV	–	Stochastic programming based on decomposition methods	✓	–	–	–
[11]	2021	PBUC	✓	WE, PV	–	Conventional, heuristic, and hybrid methodologies	✓	–	–	–
[12]	2021	Deterministic and Stochastic (with RES and ES devices) UC.	✓	WE, PV	ANN	Conventional, heuristic, and hybrid methodologies	✓	–	–	–
[13]	2021	SCUC	–	–	SVM, ANN RF	ML to the UC	–	–	–	–
[14]	2022	Conventional and uncertainty (RES and ES devices) formulation	–	WE, PV	ANN	Conventional, heuristic, hybrid, and decomposition methodologies. Accurate analysis of modeling detail, power system representation, and computational performance	✓	–	–	–
[15]	2022	SCUC	✓	WE, PV	ANN	Conventional, heuristic, and hybrid methodologies to solve the SCUC	–	–	–	–
[16]	2023	CBUC, PBUC, SCUC, SUC, Robust UC	✓	WE, PV	ML Approaches	Conventional, heuristic, hybrid, and decomposition methodologies	✓	–	–	✓
This study		**All generation units (TH, hydro, CHP, Heat only, etc.). CBUC, PBUC, SCUC, SUC, Robust UC, ES, and EV**	**Detailed formulation**	**WE, PV**	**ML approaches**	**Conventional, heuristic, hybrid, decomposition, and ML methodologies**	✓	✓	✓	✓

specific contributions:

- First, it provides an integrated synthesis of the UC development path from classical deterministic formulations to RES-integrated, stochastic, robust, and security-constrained models, highlighting how renewable uncertainty, flexibility resources, and network constraints have increased the complexity of the scheduling problem.
- Second, it compares classical optimization, decomposition methods, and metaheuristic algorithms not only in terms of their general advantages and limitations, but also in relation to formulation complexity, scalability, feasibility guarantees, and suitability for RES-integrated UC.
- Third, it reviews recent ML-assisted UC studies using a primary-role-based taxonomy that distinguishes input and uncertainty learning, learning-assisted optimization, and assurance, validation, and deployment.
- Fourth, it identifies a key methodological insight that is not fully developed in previous reviews: future UC research should not treat optimization, metaheuristics, and ML as competing paradigms, but as complementary components of hybrid scheduling frameworks in which optimization ensures feasibility and auditability, metaheuristics provide flexibility for complex extended formulations, and ML supports forecasting, scenario generation, warm-starting, constraint screening, surrogate modeling, and decision support.

The remainder of this paper is organized as follows (Figure 1): Section 2 presents the UC formulation and constraints, and Section 3 provides a comprehensive review of existing literature addressing the UC problem in the context of renewable energy sources. Section 4 provides a survey on the machine learning approaches to the UC, considering the RES penetration in power systems. Finally, Section 5 concludes the paper, summarizing key findings and outlining potential future research directions.

2- UC formulation and constraints

The unit commitment problem in power systems is typically formulated as a mixed-integer optimization problem over a scheduling horizon, t = 1, …, T, and a set of generation units, i = 1, …, N. Two main formulations are commonly considered: cost-based UC (CBUC) and profit-based UC (PBUC). In CBUC, the system operator minimizes the total operating cost, whereas in PBUC, a generating company maximizes its profit under market prices and technical constraints. Security constraints and uncertainty can be further incorporated, leading to security-constrained UC (SCUC), stochastic UC (SUC), robust UC (RUC), and combined stochastic security-constrained UC (S-SCUC) formulations. [16]. Figure 2 presents a conceptual diagram of the UC formulation in renewable-rich power systems.

2- 1- Decision variables and objective functions

Let $P_i(t)$ denote the active power output of unit i at hour t, and $u_i(t)\in\{0,1\}$ its on/off status. Let $v_i(t)\in\{0,1\}$ and $w_i(t)\in\{0,1\}$ denotestart-upandshutdownindicators,respectively, when these are explicitly modelled. Additional variables (e.g., reserve, state of charge for storage, hydro release) are introduced as required by the specific UC variant.

In CBUC, the objective is to minimize the total cost over the horizon, as expressed in Eq. (1) [17].

$$\boldsymbol{min\, TC} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(FC_{i,t} + SUC_{i,t} + SDC_{i,t} + EMC_{i,t}\right) \tag{1}$$

In PBUC, the objective is to maximize the profit PF, defined as the total revenue TR minus the total cost TC (Eq. 2).

$$\boldsymbol{max\, PF = TR - TC} \tag{2}$$

In the PBUC formulation, the revenue term should be interpreted according to the market products considered in the model. If only the energy market is represented, revenue is obtained from the scheduled power output of each generating unit and the corresponding energy price. If reserve-market participation is also considered, the revenue term should additionally include the payment received for the reserve capacity offered by each unit. Therefore, energy revenue and reserve revenue should be clearly distinguished in the explanation of the PBUC objective. In this context, the reserve capacity variable represents the amount of reserve provided by a committed unit at a given hour. If reserve-market revenue is not included in a specific formulation, the reserve-revenue component is omitted from the profit calculation.

Revenue is usually computed from energy and reserve prices. For example, if π_t^E and π_t^R Denote the day-ahead energy and reserve prices at hour t; the revenue of thermal units can be written as in Eq. 3.

$$TR = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(\pi_t^E P_i(t)u_i(t) + \pi_t^R P_i(t)u_i(t)\right) \tag{3}$$

Alternative expressions are possible depending on the market design (e.g., separate reserve products, ancillary-service revenues, or bilateral contracts), but they all enter the PBUC objective through the same profit relation. $PF = \mathrm{TR} - \mathrm{TC}$.

2- 2- Cost components

The total cost TC is typically decomposed into the following components.

a) Fuel cost:

The fuel cost of thermal unit i at hour t is often modelled

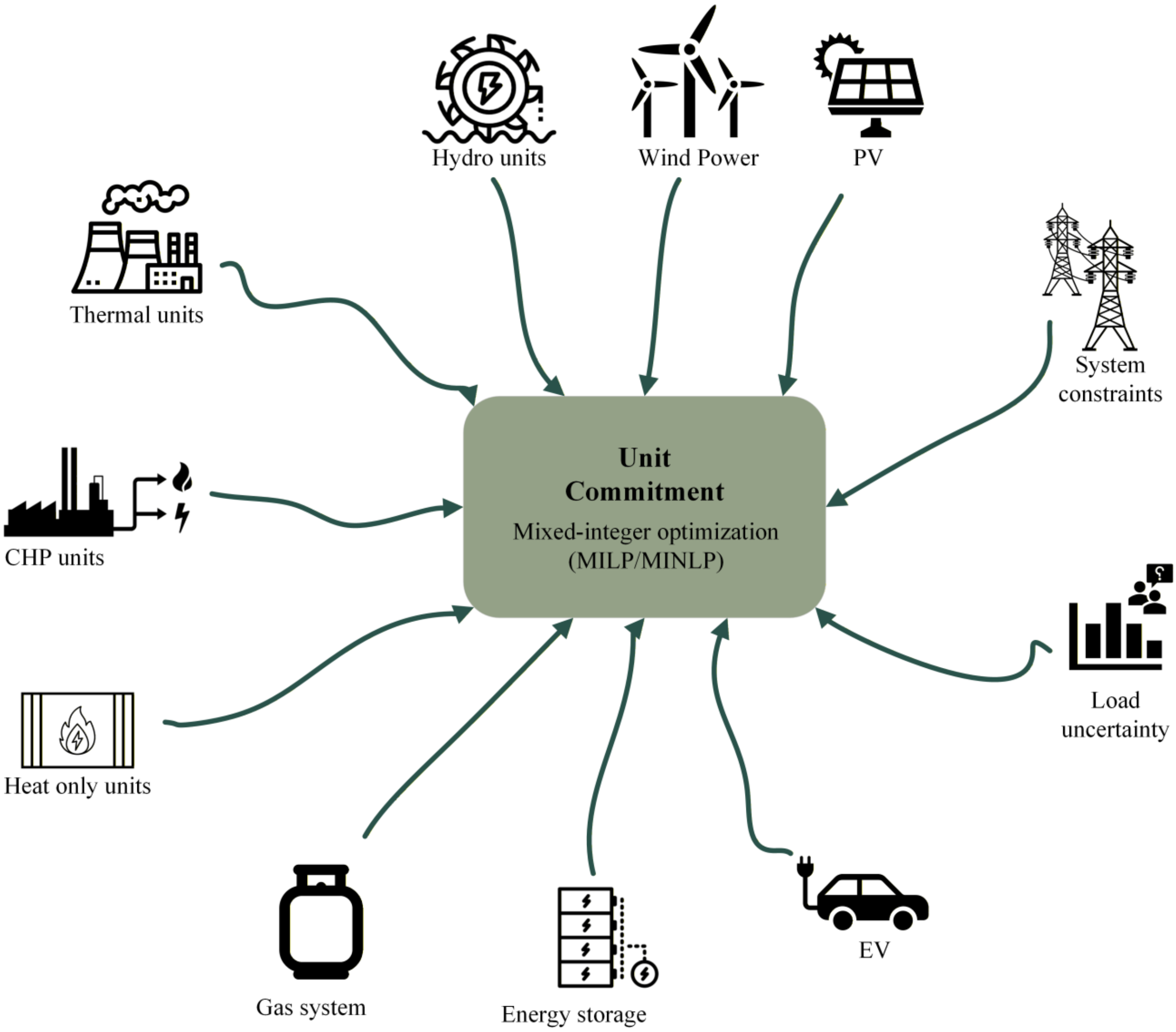

Fig. 2. Conceptual representation of the unit commitment problem.

by a quadratic function of its output, Eq.4 and Eq.5.

$$FC_{i,t} = f_i\big(P_i(t)\big)u_i(t) \quad (4)$$

With:

$$f_i\big(P_i(t)\big) = a_i.P_i^2(t) + b_iP_i(t) + c_i + \left|d_i.sin\Big(e_i\big(P_{min}(i) - P_i(t)\big)\Big)\right| \quad (5)$$

Where the sinusoidal term is included to describe the valve point effects [17].

b) Start-up cost:

The start-up cost accounts for the extra fuel and wear-and-tear incurred when a unit is brought online. A common model distinguishes between hot and cold start-ups based on the duration of the preceding off period, Eq.6.

$$SUC(i,t) = \begin{cases} HSUC_i & T_{t,i}^{off} \leq T_{t,i}^{down} + T_{t,i}^{cold} \\ CSUC_i & T_{t,i}^{off} > T_{t,i}^{down} + T_{t,i}^{cold} \end{cases} \quad (6)$$

c) Shutdown cost

The shutdown cost is typically considered a fixed value and is often disregarded due to its relatively insignificant magnitude compared to the start-up cost [18].

d)Emission cost

Thermal units inevitably emit harmful gases, such as CO2, throughout their operation. The emission cost is expressed in Eq. 7 [17].

$$EMC\big(P_i(t)\big) = \alpha_i + \beta_i . P_i(t) + \gamma_i . P_i^2(t) + \xi_i e^{(\lambda_i P_i(t))} \tag{7}$$

where: α_i , β_i , γ_i , ξ_i , λ_i denote the emission coefficients for the *i-th* thermal generation unit.

2- 3- Operational constraints

The technical limitations and constraints associated with thermal, CHP, heat only, hydro and units, (PV) systems, (ES) units, load uncertainty, (EV), system security, and the natural gas infrastructure are detailed in items (A-A7), (B1-B2), C, (D1-D6), (E1-E), (F1-F3), (G1-G4), H, (I1-I8), (J1-J2), (K1-K5) and (L1-L5) respectively.

A1.Thermal units:

The initial on/off status and the time that each unit has been continuously on or off must be consistent with the minimum up/down-time requirements[1].

A2. Generation limits:

the generated power should be within the unit, Eq. 8 [19].

$$P_{min}(i)u_i(t) \le P_i(t) \le P_{max}(i)u_i(t) \tag{8}$$

A3. Ramp-up/down rate limits

Time-coupled constraints limit the rate of change in power output between consecutive hours as defined by Eq. 9 and Eq. 10, respectively [20].

$$P_i(t) - P_i(t-1) \le RU_i \tag{9}$$

$$P_i(t-1) - P_i(t) \le RD_i \tag{10}$$

A4. Minimum up/down-times constraints

once a unit is started (shut down), it must remain on (off) for at least $MUT(i)$ ($MDT(i)$) consecutive hours as defined by Eq. 11 and Eq. 12, to ensure that units remain on/off for specified durations [1].

$$T^{ON}(i,t) \ge MUT(i) \tag{11}$$

$$T^{OFF}(i,t) \ge MDT(i) \tag{12}$$

A5. Must-run/ must-off conditions

Certain units may be required to operate at specific times or may be subject to forced outages or scheduled maintenance due to operational constraints, reliability concerns, or economic factors [20].

A6. Prohibited Operating Zone (POZ)

A unit may encounter a range of output power levels that are technically or physically infeasible, referred to as the Prohibited Operating Zone (POZ). These limitations can significantly impact ED and UC decisions. [21].

A7. Additional constraints that may influence unit operation include fuel mix considerations, the ability to utilize dual or alternative fuels, fuel availability at the plant level, and crew constraints [22].

B. CHP units:

Several operational constraints faced by combined heat and power (CHP) units are analogous to those encountered by thermal units, including generation capacity limitations, minimum up- and down-time requirements, ramping rates, and power-heat coupling constraints.

Energy conversion points within the integrated power and heat systems must adhere to heat and power balance constraints [17].

C.Heat-only units

The operation of HO units is constrained by the generation capacity, minimum up/down time limits, and heat constraints [17].

D. Hydro units:

Water balance equation: This equation involves the physical balance of the water level in each reservoir and its connected reservoirs.

Water level limits.

Minimum up/down time.

State transitions.

Generating capacity.

Initial condition of the reservoirs [18]the pumped-storage units can reduce emissions of thermal generating units. The objective of this study is to investigate (a.

E. WE units

E1. To account for the inherent uncertainty in RES, the power system requires an estimation of its available power over the scheduling horizon. Given the potential errors in forecasting, it is essential to define a maximum power at risk, calculated based on the desired level of confidence (LC), as outlined in Eq.13, where P denotes the probability of the power at risk. [23]:

$$P\left(Power_{risk} \leq Power_{risk,max}\right) > LC \tag{13}$$

E2. To ensure the accuracy and reliability of the forecasting process, it is essential to establish forecasting limits.

E3. Generation capacity.

E4. WE curtailment refers to the process of reducing the output of wind turbines below their maximum generation capacity, as defined in Eq. (14) [23].

$$0 \leq P_w^t \leq P_{w,pr}^t \tag{14}$$

F. PV units

F1. Risk Constraint.
F2. Forecasting limits.
F3. Generation capacity[24].

G. ES units

G1. State of charge [25].
G2. Battery capacity limits [26].
G3. Not to charge and discharge at the same time period [25].
G4. Battery power balance [26].

H. Load uncertainty

the load uncertainty can be presented by a probability density function (PDF), like a normal or Gaussian distribution function [27]nonlinear and large-scale. In order to obtain a near optimal solution in low computational time and storage requirements, with respect to all specified constraints, a Genetic Algorithm using real-coded chromosomes is proposed in opposite to the more commonly used binary coded scheme. Gathering data from a list of strict priority order the Genetic Algorithm generates different candidate solutions to the problem, whereas Fuzzy Optimization guides the whole search process under an uncertain environment (varying load demand, renewable energy sources.

I. EV constraints

I1. EV fleet travel plan indicator.
I2. Upper and lower hourly energy limits for the EV fleet.
I3. Terminal energy conditions.
I4. EV Battery energy balance.
I5 EV aggregated battery SOC increment.
I6. Only a V2G EV fleet can discharge to the grid.
I7. Power exchange between EV fleet and grid.
I8. EV fleet state [28]

J. System constraints

J1. Power balance Eq. 15 [29]At each hour, total generation (including RES and storage discharging) plus imports must balance the total demand plus storage charging and losses.

$$\sum_{i=1}^{N} P_i(t)u_i(t) + P_t^{RES} + P_t^{ES,dis} = D_t + P_t^{ES,ch} + losses_t \tag{15}$$

J2. Spinning reserve requirements. The committed capacity must cover demand plus a specified reserve margin, Eq. 16 [29].

$$\sum_{i=1}^{N} P_i^{max}u_i(t) \geq D_t + R_t \tag{16}$$

K. Security constraints

K1. AC power flow constraints, Eq. 17 and Eq. 18 [3]

$$P_{Bg}(i,t) - P_{Bd}(i,t) - V(i,t) \times \sum_{j=1}^{N} V(j,t).\left(G_{ij}cos\theta_{ij} + B_{ij}sin\theta_{ij}\right) = 0 \tag{17}$$

$$Q_{Bg}(i,t) - Q_{Bd}(i,t) - V(i,t) \tag{18}$$

K2. Transmission line constraints: the total flowing power (MVA) through the transmission line should stay under the maximum line capacity [30].

K3. Voltage limits: the voltage value for every bus should be limited to a specific range.

K4. Phase angle value limits
K5. Frequency Limit Constraints [3.

L.Gas system constraints

L1. Gas source upper and lower limits
L2. Weymouth equation to govern the gas mass flux under steady-state
L3. Gas flow balance at each node
L4. Limits of the squared pressure between two nodes
L5. Power and gas network pairing constraints [31]

In addition to the previous constraints, the possibility of unit outages can be included as a contingency situation.

3- A literature review on the UC in the presence of RES

In recent decades, a plethora of algorithms have been developed to address the UC. Contemporary research efforts are increasingly focused on developing hybrid algorithms to enhance the tractability and effectiveness of solving the UC [14]. The PL method, a straightforward and expeditious approach to addressing the UC, is known to yield suboptimal solutions [2], [7], [4]. An adapted extended PL was proposed in [32], while in [33] this method was developed and tested on large-scale power systems. Previous research on the UC often focused solely on thermal units with simplified constraints. DP, a technique based on forward and backward problem decomposition, has been widely employed to address the UC. Early studies utilized DP to solve UCs involving ten thermal units. Different variations of DP were compared in [34]a large scale Unit Commitment (UC. While the LR method offers a solution to the computational challenges posed by DP, it may not always meet the stringent requirements and constraints of large-scale power systems. This can lead to suboptimal solutions, such as units operating unnecessarily [20].

The pursuit of enhanced accuracy and reduced operating costs for generation units has necessitated the development of novel algorithms. Numerous optimization techniques have been devised, drawing inspiration from the intricate and sophisticated behaviors observed in nature. GA was employed to address UC in [29]. Despite the flexibility of GA, it can be computationally intensive and does not guarantee optimal solutions. To mitigate these limitations,[27] introduced a hybrid approach combining GA with fuzzy optimization (FO). This integration enhances GA's search capabilities, leading to more accurate solutions. Nevertheless, reducing computational time may compromise the accuracy of the solution. To address the computational challenges associated with GA, the BF optimization algorithm, inspired by the behavior of E. coli bacteria, was employed in [19]. While BF offers computational efficiency, it may not effectively handle the minimum up/down time constraints of the cost function. Additionally, BF can be less effective in solving high-dimensional and multi-objective scheduling problems. Similarly, despite its advantages in terms of speed and simplicity, the PSO algorithm may be prone to becoming trapped in local optima within high-dimensional spaces and exhibit a slow convergence rate during the iterative process [35]. To mitigate computational complexity, the optimization process in [23] excluded the explicit evaluation of stochastic wind and solar power generation scenarios. An evolutionary algorithm, specifically the SFL, was employed in [36]. A notable advantage of SFL is its rapid convergence speed. In [22], ICA was proposed. Comparative analysis revealed that the total cost achieved by the ICA was lower than that obtained by GA, PSO, and BF. Nonetheless, ICA is computationally demanding. In [37], ICA was applied to a more complex variant of the problem, incorporating a novel objective function that considered the impact of load shedding on power generation scheduling. A novel optimization methodology (NOM) was proposed in [18] to address the pumped-storage UC, considering energy demand, economic factors, and environmental constraints. The perspective of the generation company, driven by profit maximization, was explored in [17] within the context of the UC. Utilizing a deterministic approach centered around the derivative of a newly formulated fitness function, the proposed heuristic optimization algorithm effectively achieves lower environmental CO2 emissions and higher economic profits for generation companies. BFMO is a nature-inspired optimization algorithm grounded in the grayling fish reproductive evolution model. In [21], BFMO was introduced as a novel approach to address the UC. To enhance the search capabilities of BFMO and mitigate the challenges of stagnation and local optima, the adaptive binary fish migration optimization (ABFMO) algorithm was proposed. While ABFMO has shown promise, further research is needed to fully explore its potential and identify areas for improvement. Although metaheuristic methods have been widely applied to UC because of their flexibility in handling nonlinear, nonconvex, and mixed-integer formulations, their practical limitations should be recognized. Unlike exact optimization and decomposition-based methods, metaheuristics generally do not provide rigorous optimality guarantees or certified optimality gaps. Their performance is often sensitive to parameter tuning, population size, stopping criteria, initialization strategy, and penalty-factor selection, which can lead to inconsistent reproducibility across test systems and studies. In addition, while methods such as GA, PSO, BF, SFL, ICA, and BFMO may perform well on small or medium-sized UC benchmarks, their application to large-scale SCUC with detailed transmission constraints, reserve requirements, ramping limits, and uncertainty scenarios remains challenging. The lack of deterministic convergence behavior, limited scalability evidence, and difficulty in satisfying all operational constraints without repair mechanisms have also restricted their industrial acceptance. Therefore, metaheuristics are better viewed as flexible research tools or components of hybrid frameworks rather than standalone replacements for established optimization-based UC solvers in real-world control-room applications. To provide a more transparent comparison of the reviewed UC solution approaches, Table 2 summarizes not only the main advantages and limitations of each method, but also the reported benchmark evidence, test-system scale, and applicability to RES-integrated UC formulations. Since the reviewed studies differ in terms of test systems, constraints, hardware platforms, programming environments, solvers, and stopping criteria, the reported computational evidence should not be interpreted as a direct ranking of the algorithms. Instead, it is intended to indicate the typical scalability, computational behavior, and practical suitability of each method for different UC settings.

The recent orientation to generate more electrical energy from RES has made the UC more complex. In light of the growing unpredictability in real-time operations, it is crucial to develop a process that delivers reliable UC decisions and ensures system dependability. This leads to significant differences in the general framework of the problem. Accurate forecasts of both load and RES must be integrated into the UC input data. When considering ES devices, it is essential to incorporate the initial terminal state-of-charge (SOC) and depth of discharge (DOD) values of these devices.

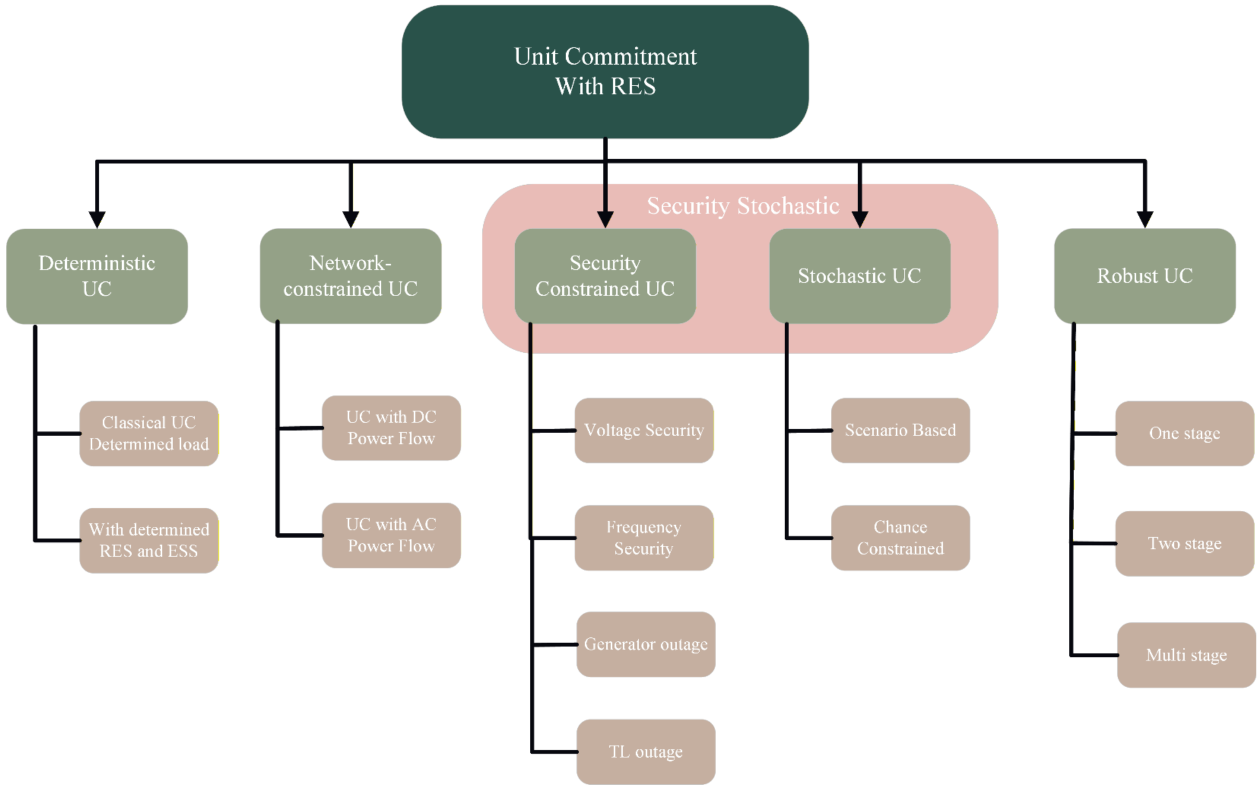

Fig. 3. Taxonomy of unit commitment formulations in power systems with RES.

[3]this issue is addressed within the framework of security-constrained unit commitment (SCUC. The general framework of UC can be summarized in the following points:

- Accurate forecasts of load and RES.
- The SOC and DOD of ES devices must be considered to ensure optimal operation and efficient utilization of storage resources.
- The previous data is integrated into the UC model to formulate the comprehensive optimization problem, considering the constraints imposed by other generation units, system limitations, and security requirements.

To provide a structured overview of the different UC formulations considered in renewable-rich systems, Figure 3 presents a taxonomy of UC with RES, distinguishing deterministic, network-constrained, security-constrained, stochastic, and robust models and their main subtypes.

3- 1- Challenges introduced by high penetration of renewable energy sources

High penetration of variable RES fundamentally alters the UC by increasing net-load volatility, forecast uncertainty, and the need for operational flexibility. First, wind and photovoltaic generation exhibit strong temporal variability and non-negligible forecast errors, which amplify reserve requirements and tighten ramping constraints on conventional units and storage. Second, the stochastic nature of RES injections makes it more challenging to satisfy security criteria (e.g., N-1 contingencies, frequency, and voltage limits), motivating the co-optimization of energy and reserves in security-constrained UC formulations. Third, the explicit representation of uncertainty through scenarios or uncertainty sets, combined with the integration of storage, electric vehicles, and multi-energy couplings, results in very large-scale mixed-integer problems that exceed the limits of classical deterministic UC formulations and solvers. These challenges have driven the development of stochastic, robust, and security-constrained UC variants, which are reviewed in the following subsections.

High-RES penetration affects UC decisions through several interacting operational mechanisms. Forecast uncertainty in wind and PV generation increases the need for flexible reserves and uncertainty-aware scheduling. Rapid net-load ramps require committing units with sufficient ramping capability or coordinating storage and demand-side flexibility. RES variability may also increase renewable curtailment when minimum generation limits, transmission constraints, or insufficient flexibility prevent full renewable absorption. In low-inertia systems, UC decisions must additionally account for frequency-security requirements, since fewer synchronous units online may reduce inertial response and primary frequency support. Energy storage can mitigate variability and ramping stress, but its operation introduces inter-temporal constraints related to state of charge, charging/discharging limits, and degradation. Similarly,

Table 2. Evidence-based comparison of UC solution methodologies. (Continued)

Method	Category	Main advantages	Main limitations	Reported test scale/benchmark evidence	Applicability to RES-integrated UC	Refs.
EE	Exact enumeration	Guarantees the global optimum for small systems; conceptually simple and useful as a benchmark.	Computationally impractical for large systems because all feasible on/off combinations must be examined.	Reported mainly as a theoretical or small-system benchmark, the number of possible unit-status combinations grows rapidly with the number of units and time periods.	Low; mainly useful for validation of small-scale UC models.	[2], [3], [32], [33]
PL	Heuristic / priority-based	Simple, fast, deterministic, and easy to implement; suitable for generating initial feasible schedules.	Highly heuristic; may produce higher operating cost; conventional PL may neglect start-up cost, ramp-rate limits, and other time-coupled constraints.	Applied to 10-, 20-, 40-, 60-, 80-, and 100-unit systems. Reported execution times for one PL-based study range from 7.24 s for 10 units to 374.03 s for 100 units, while improved PL variants report lower times.	Medium: useful for initialization, screening, and fast approximate scheduling, but limited for detailed SCUC/SUC with RES uncertainty.	[2], [4], [20], [29], [32], [33]
CDP	Dynamic programming	Maintains feasibility and can handle non-convex, nonlinear, and time-dependent UC decisions.	Suffers from the curse of dimensionality; memory and computation increase rapidly with system size.	Classical DP is mainly suitable for small systems or reduced-state formulations; complete-state enumeration becomes prohibitive for medium and large systems.	Low–Medium; useful for small systems or decomposed subproblems, but not suitable for large RES-rich SCUC/SUC without simplification.	[2], [4], [7], [20], [27], [33]
SDP	Dynamic programming variant	Reduces the computational burden of CDP by limiting the search sequence.	Less accurate than CDP because the search space is reduced using heuristic assumptions.	Sequential DP variants reduce computation compared with full DP, but the obtained solutions are generally suboptimal because not all combinations are retained.	Low–Medium; applicable only when the RES-UC model is simplified.	[2], [4], [33]
TDP	Dynamic programming variant	Reduces the number of evaluated states and can improve tractability compared with CDP.	May require extended processing time when a larger search window is used; solution quality depends on the truncation rule.	Truncated DP variants improve the solution quality compared with strict sequential DP, but require longer processing time than more aggressive truncation methods.	Low–Medium; useful only for reduced-size UC formulations.	[2], [4], [33]

Table 2. Evidence-based comparison of UC solution methodologies. (Continued)

LP	Mathematical programming/relaxation	Simple and computationally efficient when the problem can be linearized.	Cannot directly capture the non-convexity and binary commitment structure of UC without additional integer variables or approximations.	Mostly used as a relaxation, subproblem, or supporting technique rather than a complete UC solver.	Low; useful only inside larger MILP, decomposition, or relaxation frameworks.	[2] [23]
MILP	Mathematical programming	Provides a strong and systematic modeling framework; supports binary commitment variables, network constraints, and commercial solver implementation.	Computational burden increases with the number of units, time periods, scenarios, network constraints, and security constraints.	Reported UC comparisons include MILP execution times from 0.97 s for 10 units to about 123 s for 100 units in one benchmark table; however, these values depend strongly on formulation, solver, and hardware.	High; widely used for deterministic UC, SCUC, stochastic approximations, storage-integrated UC, and RES-rich scheduling.	[3], [33] [34]
LR	Decomposition/relaxation	Scalable for large UC problems; provides a dual bound and a quantitative measure of solution quality.	May suffer from duality gap, unstable convergence, and difficulty in recovering feasible primal schedules; heuristic repair is often required.	Reported as more scalable than general MIP for large UC problems, commonly with small duality gaps around 1–2% in practical applications; benchmark tables also report LR execution times increasing with system size.	Medium–High; useful for large systems and decomposition-based UC, but feasibility recovery is critical for RES-rich SCUC/SUC.	[2], [20], [33] [27], [33]
SA	Metaheuristic	Can handle nonlinear, nonconvex, and combinatorial UC structures; can escape some local minima.	Requires careful cooling schedule and parameter selection; convergence time can be long, and results may vary between runs.	Reported mainly as a stochastic metaheuristic alternative to DP and exact search methods, uniform runtime evidence is not consistently available across reviewed UC studies.	Medium; applicable to nonlinear RES-UC, but limited by tuning and runtime uncertainty.	[2], [3], [7]
B&B	Exact search / mathematical programming	Systematic search method; does not require priority ordering; can handle time-dependent start-up costs and binary decisions.	Requires large memory and computational effort for large-scale UC; branching effort increases rapidly with binary variables and constraints.	Reported mainly as an exact or MIP-based benchmark method. Instead of stating unsupported “exponential growth” quantitatively, the revised wording emphasizes rapid growth in computational burden and limited scalability for large UC/SCUC.	Medium for small/medium UC and as part of MILP solvers; low for direct solution of large RES-rich SCUC/SUC without decomposition or pruning.	[2], [3] [8], [32] [19], [34]
TB / TS	Metaheuristic / local search with memory	Uses adaptive memory to avoid cycling; can move beyond local neighborhoods and handle nonlinear objective functions.	Does not guarantee global optimality; performance depends on tabu-list design, neighborhood structure, and parameter tuning.	Reported as suitable for simplified UC and related OPF/economic-dispatch problems; comparative tables report TS-based results for some 10-unit cases, but large-scale runtime evidence is not uniformly available.	Medium; useful for heuristic RES-UC, but limited for strict large-scale SCUC due to feasibility and tuning issues.	[3], [7], [34]

Table 2. Evidence-based comparison of UC solution methodologies. (Continued)

GA	Metaheuristic / evolutionary	Flexible; handles nonlinear, nonconvex, time-dependent, and coupling constraints; suitable for parallel implementation.	No guarantee of global optimality; relatively high execution time; constraint handling may require repair operators or penalty functions.	Applied to systems up to 100 units. One benchmark reports average GA execution times increasing from 221s for 10 units to 15,733 s for 100 units, with best–worst solution differences below 0.74% in the tested cases.	Medium; useful for academic RES-UC and hybrid methods, but less attractive for real-time industrial SCUC without acceleration.	[2], [3], [4], [7] [4], [20], [27], [29]
PSO	Metaheuristic/swarm intelligence	Simple implementation; fast convergence in many cases; efficient global search compared with GA in several studies.	May suffer from premature convergence, weak local search, and sensitivity to inertia and learning parameters.	Applied in binary, improved binary, and LR-assisted PSO forms; benchmark comparisons include PSO-LR execution times from 42 s for 10 units to 730 s for 100 units in one reported table.	Medium; useful for nonlinear and RES-integrated UC, but feasibility enforcement and parameter tuning remain important.	[19], [23], [33], [35]
EP	Metaheuristic / evolutionary	Robust to nonlinear and non-smooth objective functions; can handle different operating constraints and load variations.	Parameter selection affects convergence; it may converge prematurely and does not guarantee global optimality.	A benchmark comparison reports EP execution times ranging from 100 s for 10 units to 6,120 s for 100 units in one large-scale UC comparison.	Medium; useful for nonlinear UC studies, but less common for large SCUC/SUC with detailed RES uncertainty.	[7] [27] [33] [34]
DE	Metaheuristic / evolutionary	Handles nonlinear and complex objective functions; has good global-search capability and often better convergence than classical GA.	Performance depends on mutation factor, crossover rate, and population settings; premature convergence may occur.	Applied to risk-constrained UC with PV and wind farms, where renewable uncertainty is represented using confidence intervals and forecast-error analysis.	Medium–High for RES-integrated UC; suitable for nonlinear risk-constrained formulations, but scalability and parameter tuning remain concerns.	[23], [35]
BF	Metaheuristic / bacterial foraging	Integer coding improves robustness and reduces chromosome size; minimum up/down-time constraints can be directly encoded without penalty functions.	Parameter selection is difficult; balancing exploration and exploitation is challenging; local optima may occur.	Applied to 10-, 20-, 40-, 60-, 80-, and 100-unit systems and seven-day scheduling. Reported results show improved feasible solutions compared with LR and GA in several large-scale cases, with lower computation time than the first BF version.	Medium; useful for nonlinear UC and larger test systems, but less established for detailed RES-rich SCUC/SUC.	[19], [27]

Table 2. Evidence-based comparison of UC solution methodologies.

SFL / SFLA	Metaheuristic / memetic-swarm hybrid	Combines memetic local search and PSO-like social behavior; high convergence speed; integer coding can directly satisfy minimum up/down-time constraints.	Execution time still increases with system size; parameter settings influence solution quality and convergence.	Applied to 10–100 generating units with one-day and seven-day scheduling periods; compared with LR, GA, PSO, and BF.	Medium; promising for nonlinear UC, but limited evidence for large-scale security-constrained RES-UC.	[3] [23] [36]
ICA	Metaheuristic / imperialistic competition	Handles integer variables, nonlinear constraints, and minimum up/down-time constraints; can provide high-quality schedules.	Requires several control parameters; computational effort can be high; no global optimality guarantee.	Applied to 10-100-unit systems over a one-day scheduling horizon. Reported comparisons show higher-quality solutions than BF in some cases and lower execution time than BF, although execution time can exceed ICGA.	Medium; useful for academic nonlinear UC and PBUC studies, but industrial use is limited by tuning and reproducibilit y issues.	[3], [22], [36]
FWPH	Decomposition / stochastic optimization	Combines progressive hedging with Frank-Wolfe-type linearization; can improve convergence behavior and Lagrangian dual bounds in stochastic/security-constrained UC.	Computationally demanding for large scenario sets; convergence depends on scenario structure, penalty parameters, and stopping criteria.	Reported for stochastic/security-constrained UC formulations where uncertainty is represented by scenarios; evidence should be reported using the correct FWPHA/FWPH reference rather than unrelated UC papers.	High for stochastic RES-UC in principle, but practical scalability depends on decomposition and parallelization .	[38]
BFMO / ABFMO	Metaheuristic / binary fish migration	Designed for binary optimization; can generate stable low-cost commitment schedules and improve exploration compared with simpler binary search methods.	Sensitive to algorithmic parameters; may stagnate or converge to local optima; large-scale and RES-rich validation remains limited.	Reported as a nature-inspired binary method for UC, the revised manuscript should cite the original BFMO/ABFMO UC reference directly.	Medium; potentially useful for binary UC decisions, but limited evidence for detailed RES-rich SCUC/SUC.	[21]

EVs and demand response can provide flexibility, but their availability, user behavior, and aggregation constraints must be modeled carefully. Network congestion is another important factor, as renewable-rich areas may be far from load centers, making transmission constraints and security-constrained UC increasingly important. Table 3 summarizes these renewable-related challenges, their effects on UC decisions, and the corresponding modeling solutions.

As shown in Table 3, high-RES penetration not only increases uncertainty in UC but also changes reserve requirements, ramping needs, network-constrained scheduling, frequency-security considerations, and the role of flexible resources such as storage, EVs, and demand response.

3- 2- Stochastic unit commitment (SUC)

SUC is a model for generating units' scheduling that addresses finding the optimal solution in the presence of uncertainties in generation and transmission availability through representative scenarios. A three-level formulation of the SUC, incorporating WF, solar units, and concentrating solar power (CSP), was presented in[25]. A novel SUC model considering the Renewable Portfolio Standard (RPS) was proposed in[39], highlighting the regulatory requirement for a specific proportion of RES in overall energy consumption. This model was expanded in [31]. By considering the gas cost, the elasticity and fast response property of the combined-cycle units can be exploited to overcome the problem of instability in generation from RES. A novel stochastic linear model was

Table 3. Renewable-related challenges and their implications for UC modelling.

Renewable-related challenge	Effect on UC decisions	Typical modeling solution
Forecast uncertainty of wind/PV	Increases scheduling risk, reserve needs, and possible imbalance costs	Stochastic UC, robust UC, chance-constrained UC, scenario-based UC
Net-load ramps	Requires units with sufficient ramping capability and fast flexibility	Ramping constraints, flexible reserves, storage coordination, demand response
Renewable curtailment	Occurs when RES output exceeds demand, flexibility, or network capacity	Curtailment variables, penalty terms, flexibility constraints, storage charging
Low inertia and frequency security	Fewer synchronous units online may weaken the frequency response	Frequency-constrained UC, inertia constraints, primary reserve constraints
Storage operation	Provides flexibility but introduces inter-temporal coupling	State-of-charge constraints, charge/discharge limits, degradation-aware scheduling
EV and demand-side flexibility	Can shift load or provide reserves, but depends on user availability	Aggregated EV models, demand response constraints, and flexibility windows
Network congestion	Limits renewable delivery and affects the commitment of local generators	SCUC, transmission constraints, DC/AC power-flow constraints, congestion management

suggested in [40]on daily horizon, the optimal schedule of generation units along with the required flexible ramp and spinning reserves under uncertainties of wind power and demand. Point estimate method (PEM to study the network-constrained UC under WE and load demand fluctuations. The role of real-time modification cost was integrated into the SUC model.[41]. The SUC-reviewed studies showed promising results but still require improvements in computational efficiency. Additionally, considering the system's frequency response and large-scale energy devices is essential for future studies.

3- 3- Security-constrained unit commitment (SCUC)

Here, the problem is aimed to be solved in terms of the power transmission network limitations (frequency and voltage ranges) before and after the loss or failure of a part of the power system. [3]this issue is addressed within the framework of security-constrained unit commitment (SCUC. The temporal relationship derived from historical uncertainty sequences related to the forecasting deviations of WP and load demand, and the probability of outages of generation, was enhanced through the structure of a double-phase robust SCUC, where a set of linear cost constraints was introduced in [42]. A coordinated solution for the SCUC traffic assignment problem (TAP) to mitigate congestion in coupled electrical transportation and power network systems with large-scale RES integration, with optimal scheduling of EV charging, was proposed [28]. Benders decomposition was exploited to solve the model in these two papers. A modified objective function was introduced in [43] by adding the probability of the occurrence of the worst WE scenarios in solving the day-ahead security-constrained ED.

3- 4- Security stochastic constrained unit commitment (S-SCUC)

A novel S-SCUC model was proposed and effectively solved using the FWPHA algorithms, resulting in improved Lagrangian dual bounds [38]. The study demonstrated that the optimality gap converges to zero with increasing iterations, paving the way for future extensions by incorporating PV and EVs.

3- 5- Robust unit commitment (RUC)

Robust optimization adopts a deterministic, set-based representation of uncertainty, whereas stochastic programming relies on probabilistic descriptions. Its main objective is to mitigate the adverse effects of unfavorable parameter realizations by safeguarding the solution against worst-case scenarios. Robust methods have been widely applied in many industries and can be designed at local or global levels to ensure resilience against both moderate and severe parameter deviations.

In [44] A robust UC and ED model was proposed to ensure system security even under worst-case realizations of uncertain parameters. By exploiting strong duality, the resulting formulation was reformulated as a single-stage optimization problem, making it more computationally tractable. In [45] UC was studied for a large-scale system comprising a power distribution network and a district heating network. A rolling look-ahead multistage distributionally robust UC model was developed, utilizing a probabilistic forecast-based uncertainty set to describe prediction errors. The model in [46] was shown to improve on standard RUC formulations that rely on pre-specified uncertainty sets, although computational complexity remains a challenge.

RUC was further investigated in [47] where uncertainty in load, renewable generation, and AC grid modeling was considered. An integrated-energy-system perspective was adopted in [48]where a network-constrained UC problem, including multiple energy carriers—such as gas, hydrogen, cooling, and heating—was formulated. Analysis of a larger power system revealed how multi-energy integration can enhance overall efficiency and reliability. In [49] A robust SCUC model was introduced that simultaneously accounts for wind energy and plug-in EVs, as well as both power and gas costs.

In summary, robust UC provides an effective framework for handling uncertainty in UC formulations by explicitly protecting against adverse realizations. Its main advantage lies in the ability to maintain solution quality under parameter variations; however, this often comes at the expense of increased model size and computational burden, particularly in large-scale, realistic systems.

3- 6- Clustered unit commitment CUC

It involves grouping generation units based on specific criteria to minimize the total generation cost while satisfying operational constraints. In this context, a network-CUC was proposed for planning purposes in [30] and the cost of load shedding was added to the objective function, considering WE and PV units. More constraints were added in [50] to the formulation to deal with the overestimation of ramping and reserve flexibility in the classic CUC.

3- 7- Integrating (ES) devices into the UC

Given the increasing significance of ES devices, numerous studies have been conducted in this domain. A multi-objective PSO was proposed by [26] to address the intricacies posed by the UC, which arise due to the imprecision of RES forecasting and evolving demand patterns while incorporating ES. The inclusion of WE curtailment cost in the objective function was undertaken in this study. Maintaining equilibrium between real-time electricity supply and demand is imperative to minimize redundant power quality caused by the WP inverse peak regulation feature. The PSO algorithm can be employed to optimize WP utilization to achieve this objective. A comprehensive optimal model for UC, which identifies the optimal WP curtailment, was introduced in [51] and represented a significant advancement in the field. In the work [24]A novel MILP approach was introduced to address the day-ahead UC. The proposed approach incorporated a hybrid power plant scheme integrating WE, PV, and ES units connected to the grid. This method provided a new perspective and offered potential solutions for addressing the challenges associated with integrating renewable energy. A very significant category of techniques where uncertainty is explicitly included within the formulation using a set of discrete scenarios with associated probabilities is the SCUC. A wide variety of papers were published on this concern. An OVF was employed in [52] A MILP formulation with numerous parameters and a fragmentary programming approach was presented to determine the optimal volume of ES, directly linked to costs.

Upon thoroughly examining the references, it can be deduced that the approaches employed prove efficacious in providing an economical solution to the UC. Nevertheless, heuristic techniques still present challenges, which can be summarized as follows: first, the complexities involved in parameter tuning for specific techniques require careful consideration and decision-making on the user's part. Additionally, determining whether a solution is globally optimal poses a challenge, and the computational demands of these methods make them less suitable for real-time applications.

While there is potential to find improved solutions with each iteration, it's important to note that identical results with the same tuning parameters may not always be attainable. Setting stopping criteria can also be a difficult task. Thus, these solutions are not yet widely accepted within industry circles. To improve readability and avoid an overly dense comparison table, the reviewed UC studies are summarized in two separate tables. Table 4 presents conventional UC studies and classical solution approaches, mainly involving thermal or hydrothermal systems, while Table 5 presents RES-integrated and extended UC studies that include renewable generation, energy storage, electric vehicles, CHP units, heat networks, natural-gas networks, or other additional system components. In both tables, the UC constraints are reported according to the notation and order used in the mathematical formulation section.

The second group of studies reflects the gradual extension of UC formulations toward renewable uncertainty, storage flexibility, multi-energy coupling, and additional operational constraints, as summarized in Table 5.

4- Leveraging ML for Solving UC in the Presence of RES

In the ensuing section, we aim to provide a comprehensive review of the most pivotal academic literature on the application of machine learning methodologies for addressing the UC in the context of RES integration.

ML techniques involve using data to construct models that simulate the interactions and processes within a system. These models can then be used to develop decision-making rules for responses. ML algorithms are refined through an iterative learning process and can be categorized into three main types. [13]such as the unit commitment (UC:

- Unsupervised learning: algorithms that learn from unlabeled data to discover patterns or structures within the data (K-Means and hidden Markov models)
- Supervised learning: algorithms are trained on labeled datasets to learn patterns and make predictions or decisions. Common examples include linear regression, support vector machines (SVMs), decision trees, and neural networks.

Table 4. Summary of conventional UC studies and classical solution approaches.

Year	Ref.	Resource scope	Studied system/case study	Objective terms considered	UC constraints	Solving method
1996	[29]	Thermal units	10, 20, 40, 60, 80, and 100 units	FC, SU, SD	J1, J2, A1, A4	GA
1999	[1]	Thermal units	10, 20, 40, 60, 80, and 100 units	FC, SU, SD	J1, J2, A1, A4	EP
2003	[20]	Thermal and hydro units	10 and 26 units	FC, SU, SD	J1, J2, A1, A4, A5, A3, D1, D2, D4	LR, MIP
2003	[32]	Thermal units	10, 20, 40, 60, 80, and 100 units	FC, SU	J1, J2, A1, A2, A4	EPL
2009	[19]	Thermal units	10, 20, 40, 60, 80, and 100 units	FC, SU, SD	J1, J2, A1, A2, A4, A3	BF
2010	[27]	Thermal units	10 units	FC, SU, SD	J1, A2, A4, A3, H	GA, FO
2010	[35]	Thermal units	20, 40, 60, 80, and 100 units	FC, SU	J1, J2, A2, A4, A3	PSO
2010	[18]	Thermal and pumped-storage units	2 pumped-storage units and 26 thermal units	FC, SU, R	J1, J2, A1, A4, D1, D6	NOM
2011	[36]	Thermal units	10, 20, 40, 60, 80, and 100 units	FC, SU, SD, E	J1, J2, A1, A2, A3	SFL
2011	[34]	Thermal units	4 and 10 units	FC, SU	J1, J2, A1, A2	DP
2012	[22]	Thermal units	10, 20, 40, 60, 80, and 100 units	FC, SU	J1, J2, A1, A2, A4, A3, A7	ICA
2015	[37]	Thermal units	IEEE 118-bus system	FC, R	J1, A2	ICA
2017	[33]	Thermal units	10, 20, 40, 60, 80, and 100 units	FC, SU, E	J1, J2, A1, A4, A3	New PL
2019	[50]	Thermal units	IEEE 39-bus system with 90 units; IEEE 118-bus system with 540 units	FC, SU	J1, J2, A1, A2, A4, A5, A3, K2, E2	MIP
2021	[21]	Thermal units	IEEE 30-bus system with 6 thermal units; 56-bus system with 7 thermal units; IEEE 118-bus system with 19 units; 10, 20, 40, 60, 80, and 100 units	FC, SU, SD	J1, J2, A1–A4, A6	BF

Table 5. Literature review of the ML-related references. (Continued)

Year	Ref.	Resource scope	Studied system/case study	Objective terms considered	UC constraints	Solving method
2011	[23]	Thermal, wind, and PV units	10 thermal units, 1 PV unit, and 1 wind unit	FC, SU	J1, J2, A1, A2, A4, A3, E1	DE
2014	[3]	Thermal and wind units	6-bus system with 3 thermal units and 3 wind units; IEEE 118-bus system with 54 thermal units and 186 lines	FC, SU, SD	J1, A2, A4, A3, K5	B&B
2017	[17]	Thermal, CHP, and heat-only units	2 CHP, 8 thermal, and 1 heat-only units; 2 CHP, 10 thermal, and 1 heat-only units	FC, SU, E	A2, A4, A3, C, B1, B2	Heuristic algorithm
2019	[24]	Wind, PV, and energy storage	1 wind farm, 1 PV park, and 1 energy storage unit		E2, F1, F2, F3, G3	MILP
2019	[25]	Thermal, wind, PV, and energy storage	IEEE RTS-79; modified IEEE 24-node system	FC, SU	J1, J2, A1, A2, A4, A3, K2, E2, G3, G1	MILP
2019	[30]	Thermal, wind, and PV units	IEEE RTS-79; modified IEEE 24-node system	FC, SU	J1, J2, A1, A4, A5, A3, K2, E2, K4	MILP
2019	[38]	Thermal and wind units	IEEE RTS-96 with 26 thermal units and 1 wind turbine generator; IEEE 118-bus system with 54 generators and 10 wind turbine generators		J1, J2, A1, A2, A4, A3, K2, H, E2	FW-PHA
2019	[28]	Thermal, wind, and electric vehicles	6-bus system with 24-link traffic network; IEEE 118-bus system with 3 traffic networks	FC, SU, SD	J1, J2, A1, A2, A4, A3, K2, H, E2, I1–I8	Heuristic B-B
2019	[39]	Thermal, wind, and PV units	43 units, 197 buses, and 232 transmission lines	FC, SU, SD	J1, J2, A1, A2, A4, A5, A3, K2, H, E2	
2019	[26]	Thermal, wind, and battery energy storage	8-bus system with 6 renewable/heat units, 1 wind unit, and 1 BES; 26 thermal units, 1 wind unit, and 1 BES	FC, SU, SD, E, R	J1, J2, A2, A4, A3, K2, G3, G2, G4	RL-MOPSO
2019	[42]	Thermal and wind units	Modified IEEE RTS-96 system	FC, SU, SD	J1, A2, A4, A3, K2, H, E1, E2	BD and dual theory
2020	[49]	Thermal, wind, and electric vehicles	IEEE RTS 24-bus system; IEEE 118-bus system	FC, SU, SD	J1, J2, A1, A2, A4, A5, A3, K2, I1–I8	NBI
2020	[40]	Thermal and wind units	IEEE 118-bus system with 5 wind farms	FC, SU, SD	J1, J2, A1, A2, A4, A3, K2, H, E1	CPLEX solver
2020	[31]	Thermal, wind, and integrated electricity-gas system	IEEE 24-bus system with 20-node gas network	FC, SU, SD	J1, J2, A1, A2, A4, A5, A3, H, E1, L2–L3	ADP

Table 5. Literature review of the ML-related references.

2020	[51]	Thermal and wind units	10 thermal units and 1 wind unit	FC, SU, SD	J1, J2, A1, A2, A4, A3	PSO
2020	[44]	Thermal, wind, and energy storage	IEEE 39-bus system with 10 thermal units, 2 energy storage units, 2 wind farms, and 46 transmission lines	FC, SU, SD	J1, J2, A1, A2, A4, A5, A3, K2, G2–G3	MILP (CPLEX)
2020	[46]	Thermal and wind units	IEEE 6-bus system with 4 thermal units and 100 MW wind farm	FC, SU, SD	J1, J2, A1, A2, A4, A5, A3, K2, E1	MOSEK solver
2020	[45]	Thermal, CHP, heat-only, wind, PV, and heat network	9-bus system with 32-node heat network; 123-bus system with 32-node heat network; 4-bus system with 5-node heat network	FC, SU, SD, NL	J1, A1, A2, A4, A5, A3, K2, C, K3, 70	MOSEK solver
2020	[43]	Thermal and wind units	IEEE 118-bus system	FC, SU	J1, J2, A1, A2, A4, A3, K2, 72	Heuristic algorithm
2021	[47]	Thermal and wind units	6-bus and IEEE 118-bus systems	FC, SU, SD	J1, J2, A1–A5, K2, K4, E1, K3	Decomposition algorithm
2021	[52]	Thermal, wind, and energy storage	IEEE 9-bus and IEEE 118-bus systems	FC, SU, SD	J1, A1–A5, K2, G1–G4, 38, 73	CPLEX 12.6
2021	[48]	Thermal, CHP, heat-only, wind, energy storage, heat network, and natural-gas network	30-node heat network, 6-bus system, and 6-node natural-gas network	FC, SU, SD	J1, J2, A1–A5, K2, C, G3, 60, L3–L5, B, 75, 76	MIP (CPLEX)
2021	[41]	Thermal and wind units	Modified IEEE RTS-96 system	FC, SU, SD	J1, A1–A5, K2–K4, H, E1	MILP (CPLEX)

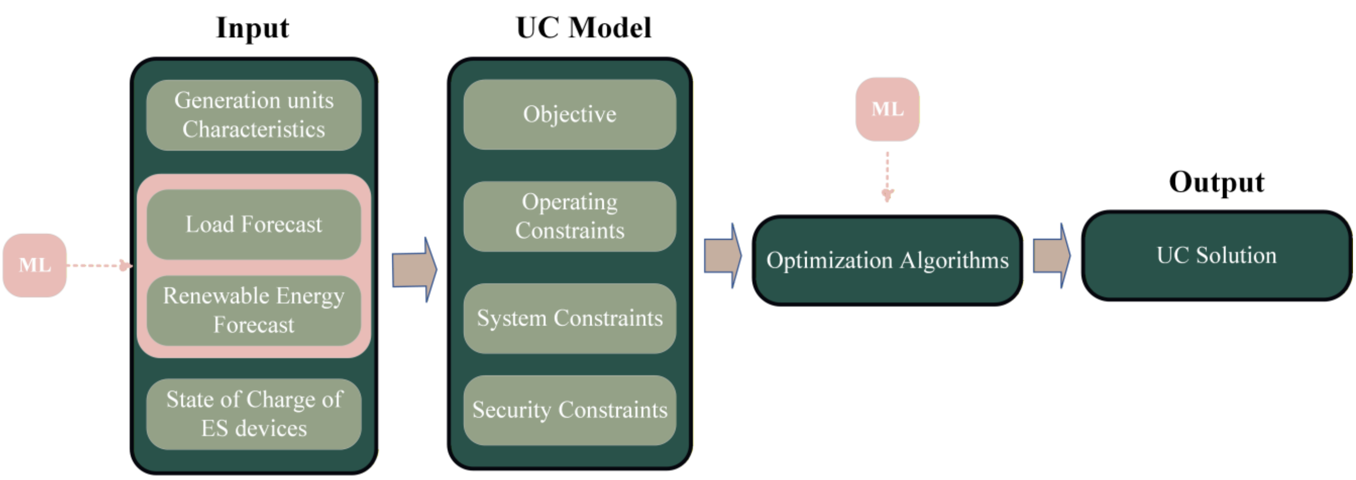

Fig. 4. ML roles within the UC workflow.

- Reinforcement learning: these algorithms learn to make sequential decisions through interaction with an environment, receiving feedback as rewards. Examples include Q-learning and deep Q-networks.

Based on the ML application, the studies can be classified into three main categories. The main roles of ML within the UC workflow, from improved input forecasting to ML-enhanced optimization algorithms, are summarized in Figure 4.

Since several ML-based UC studies contribute to more than one stage of the decision-making workflow, the following classification is based on the primary role of each method. Secondary contributions, such as uncertainty representation, solver acceleration, feasibility verification, or decision support, are discussed in the text where relevant.

4- 1- Input and uncertainty learning for UC

The earliest applications of ML in the UC were largely devoted to short-term forecasting of electrical load and renewable generation, as forecast accuracy directly impacts reserve requirements, commitment decisions, and operating costs in systems with high renewable energy (RES) penetration. A wide range of supervised learning models has been applied for this purpose, including feed-forward and recurrent neural networks, support vector machines, random vector functional link networks, k-nearest neighbors, and extreme learning machines, often in combination with signal-processing techniques such as wavelet or empirical mode decomposition to handle non-stationary time series [53]– [54]many critical challenges to the grid operators have been emerged in terms of the power balance, power quality, voltage support, frequency stability, load scheduling, unit commitment and spinning reserve calculations. To overcome such problems, numerous studies have been conducted to predict the wind power production, but a small number of them have attempted to improve the prediction accuracy by employing the multidimensional meteorological input data. The novelties of this study lie in the proposal of an efficient and easy to implement very short-term wind power prediction model based on the k-nearest neighbor classifier (kNN, [55]using historical output power data and performed by hybrid statistical models based on Least Square Support Vector Machines (LS-SVM, [56], [57], [58]. These studies consistently reported improved load, wind, and PV forecasting performance compared with traditional statistical approaches, thereby providing more reliable input data for UC formulations.

In UC-oriented works, ML-based forecasts are typically integrated as exogenous inputs to deterministic, stochastic, or robust UC models rather than altering the mathematical structure of the optimization problem itself. Forecasts of load, wind, and PV output obtained from neural networks or other ML models have been embedded in mixed-integer UC formulations for microgrids and distribution-level systems, leading to reduced operating costs and improved scheduling performance [59], [60], [61]. Hybrid schemes have also been proposed in which ML-based forecasters and data-driven models of generation units are combined with metaheuristics or evolutionary algorithms—such as genetic algorithms, particle swarm optimization, differential evolution and imperialist competitive algorithms—to address UC under uncertainty and to schedule conventional units, hydro plants and RES [62]– [63], [64], [65], [66], [67]. More recently, deep neural networks and advanced DL architectures have been adopted for forecasting and for constructing intelligent load models, and have been coupled with UC solvers or reinforcement learning frameworks to handle varying load and renewable availability in multi-agent or hierarchical settings [68]– [69]it has a drawback that weather conditions influence the generation output significantly. Thus, it is not easy to perform Economic Load Dispatch (ELD, [70]. Overall, the dominant role of ML in this literature is to provide more accurate point or probabilistic forecasts and uncertainty characterizations that feed established UC formulations; the underlying optimization models and solution techniques remain largely unchanged, and the reported benefits are primarily attributed to the improved quality of the forecasting stage.

Recent studies show that ML is increasingly used not only for point forecasting but also for uncertainty-aware inputs to stochastic and RES-integrated UC. Predictive-prescription frameworks based on boosting ensemble learning have been used to exploit contextual covariates, such as weather and calendar information, for improving UC decisions under uncertain load [71]. In parallel, generative models have recently emerged for renewable scenario generation. Conditional latent diffusion models and two-stage Transformer–diffusion frameworks have been proposed to generate short-term wind and offshore wind power scenarios, providing richer probabilistic inputs for stochastic UC, reserve scheduling, and reliability-aware operation under high-RES penetration [72], [73]the scenario generation community has conducted numerous studies employing generative models. Among these generative models, diffusion models have shown remarkable capabilities with excellent posterior representation. However, diffusion models are seldom used to quantify renewable energy uncertainty. To fill this research gap, this manuscript proposes a novel conditional latent diffusion model (CLDM.

4- 2- Learning-assisted UC optimization

The literature on ML as a direct optimization tool for UC can be grouped into three broad streams:

(i) RL-based decision and policy learning,
(ii) deep learning and other surrogate models that approximate cost and constraint relationships, and
(iii) data-driven screening and acceleration techniques.

RL has been applied to ED and UC to learn scheduling policies from interaction with a simulated environment [74], [75]. Most studies consider systems with a limited number of thermal units and enforce only basic operational constraints, such as start-up/shutdown and generation limits, yet they demonstrate that RL can handle very large decision spaces and nonlinear objective functions [76]. Numerical experiments indicate that repeatedly solving short-term UC problems and updating decisions as new information becomes available can be more cost-effective than relying solely on day-ahead schedules, although forecast errors increase with the planning horizon and reduce the quality of long-term decisions [76]. In addition, Monte Carlo methods combined with ML have been used to generate and evaluate uncertainty scenarios for day-ahead UC and ED, thereby contributing primarily to uncertainty representation while also supporting the optimization stage [77].

Several contributions embed ML models within heuristic or metaheuristic optimization frameworks. Priority-list and PSO-based schemes have been coupled with AI components to address UC with RES and energy storage [78]. ANNs have been trained as fast approximators of nonlinear mixed-integer solvers, enabling near-optimal operating strategies to be obtained with significantly lower computational effort [79]making otherwise straightforward problems highly computationally intensive. A sufficiently trained artificial neural network (ANN. Monte Carlo methods combined with ML have also been used to generate and evaluate large sets of scenarios for day-ahead UC and ED, improving the representation of uncertainty in the scheduling process while indirectly supporting the optimization stage [77].

Recent ML-assisted UC studies have moved from simple forecast integration toward direct prediction and warm-starting of UC decisions. DNN-based models have been trained to predict UC solutions directly, while SVM-based predictors with performance guarantees have been proposed to warm-start optimization solvers and reduce computational time [80], [81]its NP-hard nature places a prohibitive computational burden on classical mixed-integer programming (MIP. Other works use multi-label classification to estimate generator commitment and dispatch in large grids while incorporating weather measurements and verifying feasibility through AC-OPF calculations [82]. These studies indicate that ML can accelerate UC, but they also confirm that optimization-based feasibility checks remain essential when strict operational reliability is required.

Neural networks have been employed to model complex components and contexts within the UC problem. For example, BP networks have been applied to UC with cascaded hydropower stations, although forecast accuracy in the load component remains a limitation and motivates further NN optimization. [89]. Adaptive contextual learning has been used to solve microgrid UC without requiring a priori information on RES and demand uncertainties, by learning data-driven policies from observed operating states. [94] we study a unit commitment (UC. In parallel, relaxed DL-based controllers have been proposed for real-time economic dispatch and generation control, with potential extensions to automatic voltage control and stability applications in large-scale interconnected systems [95].

Deep architectures are increasingly used to approximate the feasibility regions of UC or post-contingency security metrics. CNNs have been trained to solve SCUC with uncertain wind generation and battery energy storage, while DNNs have been used to encode frequency constraints in preventive UC formulations, reducing computation time and improving cost and forecasting performance [104], [105]. Nearest-neighbor methods can act as short-term proxies for UC solvers, substantially reducing computational effort by reusing solutions from similar historical operating points [93]. Data-driven models of transmission line constraints and power-flow relationships have been integrated into UC formulations to capture network limits without explicit AC or DC power-flow calculations [98], [103]. Other works construct non-parametric, Gaussian-based models of cost functions [101] or exploit ensemble ANNs in parallel to accelerate large-scale UC evaluations [100].

Another important trend is the integration of ML within mathematical optimization rather than replacing optimization entirely. Recent approaches include ML-assisted decomposition for UC with energy storage, automated formulation tightening for storage resources, ML-based cutting-plane generation, and ML-enhanced surrogate Lagrangian relaxation [106], [107], [108], [109]. These methods aim to reduce problem size, improve warm-start quality, screen inactive constraints, or learn good-enough subproblem solutions while preserving an optimization layer for feasibility and optimality verification. Such hybrid ML–optimization frameworks are particularly relevant for large-scale SCUC, where direct end-to-end learning remains difficult because of binary decisions, network constraints, and reliability requirements.

RL-guided tree-search algorithms have also been proposed to explore the UC decision space more efficiently [99], [102]. In these approaches, learned policies reduce the branching factor of the search tree and guide the search toward promising regions, thereby decreasing computation time and mitigating the curse of dimensionality. Overall, the existing literature demonstrates that ML can support or partially replace traditional UC solvers in selected settings, but a unified and widely adopted ML-based solution framework for UC has not yet emerged.

Graph-based and decision-support learning methods have also become prominent in recent UC research. GNN, GCN-GRU, and spatio-temporal GNN-LSTM frameworks have been used to capture network topology, temporal load patterns, generator commitment status, and critical transmission constraints for accelerating UC and SCUC solutions [110], [111], [112]. In addition, learning-enabled SCUC with storage, Markov decision process-based microgrid scheduling, and quality-diversity learning for multi-alternative UC show how ML can support faster online decisions and provide alternative feasible schedules for operational preparedness[113], [114], [115]. These developments strengthen the role of ML as a decision-support and acceleration layer, while emphasizing the continued need for validation, feasibility screening, and operator trust before practical deployment.

4- 3- Assurance, validation, and deployment of ML-based UC tools

The practical value of ML in UC depends strongly on the

Table 6. Literature review of the ML-related references. (Continued)

year	ref	ML Technique	Training Data	Study Case	Application of the ML	Optimization problem	Other used Alg.
2010	[53]	6- ANN-feedforward backpropagation	Years 1997 to 2007: peak load, energy consumption humidity, rainfall, wind speed consumer price & industrial indexes	Electricity Generating Authority of Thailand	Load forecasting		
2010	[83]	ACO-based SVM	Historical daily data: load, temperature, rainfall, wind speed, cloud cover	SHAANXI province in, China	Load forecasting		Ant colony
2011	[74]	RL (Greedy & Pursuit algorithms)	Cost function coefficient. Generation units' limits. Resolved ED results. Rate of Exploration and Exploitation. Discount parameter. Rate of modification.	Three-generator system IEEE 30-bus 10 G system 20 G system (T losses)	ED	ED as a multi-stage decision-making problem Only thermal units	
2012	[84]	Adaptive wavelet & feed-forward NN	The time series data for wind speed and wind power, year 2004.	National Renewable Energy Laboratory website, Site 7263 in the Midwest ISO region, USA	WE forecasting		
2012	[62]	Developed ES to handle UC constraints	No data: 4 rules to handle the constraints	100-unit system, An actual Tai Power 40-unit system over a week	UC constraints	Large-scale UC, TH units. **O.F.** FC+SU+SD. **St.** A1, A2, A3, A4, A5, J1 and J2.	elite PSO
2012	[59]	Feed-forward NN	National Environment Agency (NEA)	Islanded and grid-connected MG	WE and PV forecasting	Optimal size of BESS. UC (Microturbines and fuel cells, WE, PV). **St.** A1, A2, A3, A4, A5, J1 and J2.	MILP using AMPL, CPLEX Checking using KNITRO
2012	[85]	Probabilistic NN and ANFISs	Synthetic data is generated through power flow calculations and time-domain simulations for training and testing processes	17-G 163-bus Iowa PS. 50-G 145-bus IEEE.	Preventive control	Dynamic SCUC. Control variables are included. 3-ph-g faults are considered	GA

Table 6. Literature review of the ML-related references. (Continued)

2012	[86]	Recurrent NN	12months data (10-50) m hub: Time series, Wind speed, Direction, Temperature, atmospheric pressure, Wind Distribution	Slangkop Weather Station	WE forecasting		
2013	[63]	SVR	Boston Housing Data Set Half-hourly load in New South Wales, (10 to 24) May 2007	UCI standard data set Electric load data set in New South Wales	Load forecasting		APSO Optimizing the SVR
2013	[87]	Wavelet decomposition (WD)	Temperature Humidity Wind speed Historical peak load	Iran National Grid in 3 cities (Tehran, Tabriz and Ahvaz)	Load forecasting		GA Optimizing the ANN
2013	[60]	Backpropagation ANN	Historical patterns of electric and water consumption	MG in Chile (2PVs, 2WT, a diesel generator, and an ESS)	Electrical and Water Consumption forecasting	UC with EMS and DSM. **O.F.** FC+SU unserved power unserved water using the LABB **St.** A1, A2 and J1	MILP by CPLEX solver
2013	[64]	Levenberg-Marquardt ANN	Extracted points in the Hill Diagram	The hydroelectric plant of Tres Marias in Brazil 6 units upstream of the São Francisco River	Model the production function	UC min the water discharge of Hydroelectric units. **St.** D1, D2, D3, D4, D5 and D6.	differential evolution PSO
2014	[65]	ANN	Temperature, wind speed, wind direction, humidity, and pressure.	Summerside Wind Farm in Prince Edward, Canada	Short-term prediction of WE		ICA to optimize the NN weights
2015	[55]	Least Squares SVM & WD	05/03/2012 to 05/03/2013 every 10 min: The hourly average value of the PV power, module, and ambient temperature, and irradiance on a plane inclined at a tilt angle of 3 and 15 degrees	PV system located in Apulia – South East of Italy	PV forecasting		
2015	[88]	Nonparametric NN	The Wind Power in 2012	10 TH units and WF in Alberta, Canada	WE forecasting	UC **O.F.** FC+SU+SD+R unserved power **St.** A1, A2, A3, A4, A5, J1 and J2.	PSO to construct NN GA for SCUC
2015	[75]	RL- Q-learning	Solved UC using PL	3 TH units' system	ED and UC solving	UC **O.F.** FC+SU+SD **St.** A2	PL

Table 6. Literature review of the ML-related references. (Continued)

2016	[89]	Backpropagation NN	Number of units The capacity of every unit in each hydropower station The reservoir's average water level and reservoir storage, etc.	3-level cascaded hydropower stations on the Qingjiang River basin	Solve the UC	UC of Hydro units. **O.F.** min water consumption **St.** D1, D2, D3, D4, D5 and D6.	
2016	[76]	RL-NN	No need for labeled input/output pairs.	10 TH + PV system	function Approximation	**O.F.** UC FC+SU **St.** A1, A2, A3, A4, J1 and F1.	
2016	[90]	SVR	Electric load data on a half-hourly basis: (2 to 7 May 2007). (2 to 24 May 2007). (1 Jan to 12Jan 2015). (1 Jan to 1 Feb 2015).	New South Wales market in Australia New York Independent System Operator, USA	Load forecasting		Differential EMD to optimize the SVR
2016	[91]	SLNN with random weights	Short-term electricity load data	Data sets from the Australian Energy Market Operator.	Load forecasting		
2016	[92]	Empirical mode decomposition and (SVR)	Wind speed time series	An anemometer installed on top of an apartment building located at 78 Marine Drive, Singapore	Wind speed forecasting		
2017	[56]	ELM	Historical data (1 Oct 2015 to 30 Sep 2016: hourly average solar radiation, wind speed, ambient and module temperature, and PV power output.	Three grid-connected PV systems installed on the rooftop of the Power Electronics and RE Laboratory at the University of Malaya, Malaysia	PV forecasting		
2017	[61]	Levenberg-Marquardt learning for SL-NN	May, June, and July of 2012, 5-min resolution: Ambient temperature. Time of day. Time-of-use price. Peak demand imposed by the microgrid operator.	Realistic data from an actual energy hub management system	Modeling the smart loads in an MG	UC **O.F.** FC +SU+ SD +load curtailment **St.** A1, A2, A3, A4, A5, J1, G1, G2, G3, G4 and DR capacity	MINLP solvers, in the DICOPT solver
2017	[54]	K-nearest neighbors classifier KNN	Historical data in 10-min intervals at 60 m height: Wind speed and direction. Pressure. Air temperature.	The historical dataset from the Database on Wind Characteristics	WE forecasting		

Table 6. Literature review of the ML-related references. (Continued)

2018	[93]	Nearest Neighbor classification	Pre-solved UC problems data sets	Updated versions of IEEE RTS-79 and IEEE-RTS96 (Thermal and wind units)	UC	UC **O.F.** FC +SU+ SD **St.** A1, A2, A3, A4, A5, J1, E1, E2, E3, E4	YALMIP, CPLEX solver
2018	[66]	Error BP-NN	Data (08/2009 to 08/2013): Hours, air flow, precipitation, and temperature.	IEEE-6 bus system: TH, PV, ESS, Demand response.	PV forecasting	SUC **O.F.** FC+SU+SD +capacity costs for reserve provision. **St.** A1, A2, A3, A4, A5 J1, F1, F2, F3, G1, G2, G3, G4, and demand response.	multi-objective GA
2018	[94]	Adaptively partitioned contextual learning algorithm	without requiring any a priori information **Context consisting of:** Current time. Load demand context. Weather context. Downtime of units.	Isolated microgrid system with 4TH +WT	UC	UC **O.F.** FC+SU+ Load shedding + Power curtailment **St.** A1, A2, A3, A4, A5 J1, J2	
2018	[78]	Time-varying acceleration coefficient-PSO	NO required data. They are designed based on mathematical functions and strategies to improve the algorithm's performance over time.	TH, RE, PV, ESS system	UC, ED	UC **O.F.** FC+SU **St.** A1, A2, A3, A4, A5 J1, J2, G1, G2, G3, G4	PL: ON/OFF scheduling TVAC-PSO to solve ED
2018	[95]	DNN & Relaxed-DL	Frequency deviation and Area control error of the i-th area.	IEEE 10-G 39-bus New-England. Hainan 8-G power grid, China. IEEE 118-bus power system	ED, UC, automatic generation control (AGC), generation command dispatch (GCD)	UC **O.F.** FC+SU or thermal units only **St.** A1, A2, A3, A4, A5, J1, J2	
2018	[68]	PSO-based RL	Historical data of WE and Load.	Modified IEEE 118 bus 54 units, 3 WF, 186 T-Lines	Load and WE forecasting	UC **O.F.** Operation costs with emission concerns; Value-at-Risk-based reliability measurement **St.** A1, A2, A3, A4, A5, J1, J2	Novel multi-objective PSO

Table 6. Literature review of the ML-related references. (Continued)

2019	[96]	Multi-agent RL	Demand load historical data	MG has two controllable and one uncontrollable generator; 10 total: 7 controllable and three uncontrollable.	Load forecastin g	Distributed SUC TH, WE, PV, ES **St.** A1, A2, A3, A4, A5, J1, F2, F2, F3, G1, G2, G3, G4.	
2019	[97]	Data-driven uncertainty set for WP forecast errors	Uncertainty-based data on the posterior predictive distribution of future WE forecast errors from historical data.	Six-bus and IEEE 118-bus	WE forecastin g	Two-stage adaptive robust UC model **O.F.** SU + SD + no-load, FC, and penalty costs for electricity demand. **St.** A1, A2, A3, A4, A5, J1, J2	Solved with CPLEX 12.8.0
2019	[69]	DNN Gaussian-Gaussian-Restricted-Boltzmann-Machine	PV output, temperature, and their variance.	Real data of PV system generation output in Japan	PV forecastin g		
2019	[79]	BP-Single- and multi-layer ANNs	Preserved UC by NLMIS solver	2 CHP generators, an electric utility with time-of-use energy rates, and one hot water tank. A university campus: gas turbines, fuel cells, chillers, diesel generators, and a heater.	UC	UC **O.F**. FC+SU **St.** A2, J1, G1	NLMIS solver
2019	[67]	DL (long short-term memory NNs)	Historical data power load and WE distribution.	Modified IEEE-118 bus test system: 54 TH, 3 WF, 186 TL	Load and WE forecastin g	Value-at-Risk-based UC model **O.F**. FC +SU+ Emission **St.** A1, A2, A3, A4, A5, J1, J2	GA
2020	[77]	Monte Carlo-based DL	Generated dataset of solved day-ahead UC and ED	IEEE-RTS96: 19 WF were added	UC	SUC **O.F**. FC +SU **St.** A1, A2, A3, A4, A5, J1, J2, E1, E2, E3, E4	

Table 6. Literature review of the ML-related references. (Continued)

2020	[98]	K-nearest neighbors	Historical data: hourly electricity demand at each bus and WF for 360 days. Hourly capacity factors of generating units Transmission lines statues	IEEE RTS-96 system 19WF, 73 nodes and 120 TL power system in Texas with 2000 buses and 3206 lines	UC	Generic single-period transmission constrained -UC DC power flow power balance generation limits	
2021	[99]	RL-guided tree search	(2016–2019) Data: National Grid Demand, Whitelee onshore WF, and Generators and UC data.	5,10, 20,30 generators systems	UC	SUC **O.F**. FC +SU **St.** A1, A2, A3, A4, A5, J1, J2, E1, E2, E3, E4	MILP for compariso n
2021	[57]	Simplified LSTM NNs &multilayer perceptron	Weather data acquisition. PV energy production.	Two geographically separated PV systems from 2 different countries (Chiang Rai, Thailand, and Kaohsiung, Taiwan)	PV forecastin g		
2021	[100]	ANN parallel processing	Solved UCs	IEEE 30-bus test system	UC	Multi-objective model of the UC **O.F**. FC +SU **St.** A1, A2, A3, A4, A5, J1, J2	
2021	[101]	Gaussian algorithm & Bayesian optimization	Historical and actively collected data during optimization in a non-parametric Bayesian fashion.	10 TH units' isolated power system characterized by identical generating units and RES	UC	UC **O.F**. FC+ SU **St.** A1, A2, A3, A4, A5, J1, J2 and Plant crew constraints	LR GA For comparing
2021	[58]	convolutional NN Long short-term memory	Historical time series half-hourly electric load data (Jan 2014 – Dec 2019)	Bangladesh power system for day-ahead and week-ahead forecasting	Load forecastin g		
2022	[70]	Deep-RL	The historical operations reports from New England ISO: Day-ahead WE forecast. Hourly generated WE. Historical UC decisions solved with Gurobi 9.1 MILP solver.	IEEE 39-bus 10 G, 46 TL /910-machine New England power system)	Load and WE forecastin g UC	UC **O.F**. FC +SD +SU +No load costs **St.** A1, A2, A3, A4, A5, J1, J2, E1	
2022	[102]	Guided A* & Guided Iterative-deepening-A* for RL	The initial policy uses random parameters and is trained via model-free RL in the simulation environment.	10–30-generator system WE and load historical data from the GB power system	ED, UC	ED, UC **O.F.** FC+ SU +LOLP **St.** A1, A2, A3, A4, A5, J1, J2, E1.	Heuristic PL algorithm

Table 6. Literature review of the ML-related references.

2022	[103]	Optimally compact-NN	UC and OPF solutions with hourly load profiles	14-, 57-, and 89-bus networks	UC, OPF	UC, OPF **O.F.** FC+ SU +LOLP **St.** A1, A2, A3, A4, A5, J1, J2, E1, K1, K2
2022	[104]	Convolutional-NN	WE data and UC decisions	Ten units and 100 units with WE and BESSs over 24 hours	UC	SCUC **O.F.** FC+ SU +SD **St.** A1, A2, A3, A4, A5, J1, J2, G1, G2, G3, G4, K1, K2, K3, K4, K5.
2022	[105]	Deep-NN	Synchronous generators (SG)Frequency response. Active and reactive power injections for SG, WTG, and Load.	IEEE 39-bus system, four WTGs	UC	Frequency-constrained-UC **O.F.** FC+ SU +SD **St.** A1, A2, A3, A4, A5, J1, J2, G1, G2, G3, G4, K1, K2, K3, K4, K5.

role that the ML model plays in the scheduling workflow. Forecasting and scenario-generation models mainly improve the quality of UC input data by providing load, wind, PV, price, or uncertainty information; however, they do not directly determine commitment decisions and must still be coupled with an optimization model. In contrast, ML-assisted optimization methods, such as surrogate models, warm-start predictors, constraint-screening tools, and GNN-based decision predictors, directly influence or approximate UC decisions and therefore require stricter feasibility and reliability checks. These methods may reduce computational time, but their deployment is limited by several issues, including the lack of guaranteed feasibility, weak generalization to unseen operating conditions, sensitivity to forecast errors and topology changes, scalability challenges in large SCUC problems, and the need for operator trust. Therefore, ML-based UC methods should be evaluated not only by prediction accuracy or speedup, but also by feasibility violations, optimality gaps, robustness, out-of-distribution performance, repair effort, and compatibility with existing optimization-based scheduling tools.

While ML-based methods have shown promising results for UC in terms of speed and, in some cases, cost performance, their adoption in industry remains limited. A central reason is the difficulty of trusting data-driven models in safety-critical, highly regulated environments such as power system operation. First, many ML approaches for UC are trained and evaluated on historical or simulated datasets that may not fully represent the operating conditions under which they will be deployed. Dataset shift, rare events, and changing market rules can lead to degradation in performance, particularly in the tails of the distribution, where security and economic impacts are most significant. It is therefore essential to perform rigorous out-of-sample evaluation and stress-testing of ML models, including extreme scenarios for RES, demand, and contingencies.

In addition to statistical reliability, several regulatory, operational, and interpretability barriers limit the deployment of learned UC policies in real control-room environments. From a regulatory perspective, UC schedules must satisfy reliability standards, market rules, reserve requirements, security constraints, and auditability requirements; therefore, operators must be able to justify why a unit is committed or decommitted under specific system conditions. Pure black-box ML policies often lack such traceability and may not provide certificates of feasibility, optimality gap, or security compliance. From an operational perspective, control-room tools require deterministic runtimes, robust fallback mechanisms, compatibility with existing EMS/MMS platforms, and stable performance under data-quality problems, topology changes, outages, and rare extreme events. Moreover, any computational benefit obtained from ML prediction may be reduced if extensive post-processing or solver-based repair is needed to restore feasibility. Finally, interpretability remains a major barrier because binary UC decisions are time-coupled and affected by many interacting constraints, including ramp limits, minimum up/down times, reserve margins, and transmission limits. Without clear explanations, confidence margins, and validation against trusted optimization solvers, learned UC policies are more likely to be accepted as advisory, warm-starting, screening, or decision-support tools than as standalone replacements for established optimization-based scheduling systems.

Second, pure ML models that directly output UC decisions may violate feasibility constraints (e.g., minimum up/down times, ramping limits, transmission limits) or produce solutions with unknown optimality gaps. Hybrid architectures that embed ML within an optimization framework - such as learning warm starts, surrogate cost or feasibility approximations, or screening inactive constraints - offer a compromise: they can accelerate solution times while maintaining feasibility guarantees and known optimality bounds from the underlying MILP or MINLP solver.

Third, comparisons with traditional methods are sometimes limited to small test systems or weak baselines, making it challenging to assess whether ML consistently provides benefits. Systematic benchmarking against strong MILP formulations and state-of-the-art decomposition or robust optimization techniques is needed to clarify when ML is genuinely advantageous and when it merely replicates existing capabilities.

A further barrier to the assessment and deployment of ML-based UC methods is the absence of a standardized benchmarking framework. Existing studies use different test systems, renewable penetration levels, uncertainty models, training datasets, hardware platforms, solvers, and performance metrics, which makes direct cross-comparison difficult. Future ML-UC research should therefore report results on a common set of benchmark systems, such as small systems for algorithmic validation, medium-scale IEEE RTS or IEEE 118-bus systems for network-constrained UC, and larger systems for scalability testing. These benchmarks should include standardized load, wind, PV, and forecast-error profiles, fixed training/validation/test splits, and clearly defined UC, reserve, ramping, minimum up/down time, and network constraints. In addition to objective cost and solution time, future studies should report optimality gaps, feasibility violations, reserve and transmission constraint violations, warm-start improvement, out-of-distribution performance, repair effort, and hardware/software specifications. Such a benchmarking protocol would improve reproducibility and allow a more meaningful comparison between learning-based UC methods and established optimization-based solvers.

Although supervised and reinforcement-learning approaches dominate the reviewed ML-UC literature, unsupervised learning remains an underexplored direction with several promising applications. Clustering techniques such as K-means, hierarchical clustering, Gaussian mixture models, spectral clustering, and self-organizing maps could be used to identify representative net-load regimes, renewable-generation patterns, or typical operating days, thereby reducing the number of scenarios that must be solved in stochastic or clustered UC. Similarly, autoencoders and variational autoencoders could compress high-dimensional load, wind, PV, and network-state data into low-dimensional latent representations that preserve the main uncertainty structure while reducing computational burden. Unsupervised scenario reduction may also help select representative forecast-error trajectories, detect rare operating regimes, and support adaptive training-set construction for ML-based UC predictors. These directions are particularly relevant for RES-integrated UC, where scalability is strongly affected by the number of uncertainty scenarios, temporal resolution, and network constraints.

Ultimately, optimization-based validation can play a crucial role in enhancing trust. For instance, one can use a trusted UC solver to (i) verify the feasibility of ML-generated schedules, (ii) quantify the cost and security margins relative to optimal solutions, and (iii) identify operating regions where the ML model is unreliable and must be overridden. Designing such validation loops and integrating them into real-time and day-ahead operation workflows is an important direction for future work.

Overall, the literature suggests that ML is most promising when used to support UC by improving forecasts, guiding search or screening constraints, rather than completely replacing optimization. Developing principled frameworks for certifiable, robust, and interpretable ML-enabled UC tools remains an open research challenge.

For a comprehensive overview of the literature surrounding the utilization of ML for UC, please refer to Table 6. In addition, Figure 5 provides an evidence map showing how the ML approaches are distributed across UC variants.

A comprehensive review of 115 relevant studies in the field of UC reveals the following key findings:

1. High penetration of RES transforms the UC into a large-scale, mixed-integer, nonlinear, and often nonconvex combinatorial problem, which substantially increases computational complexity and solution time for conventional optimization algorithms.
2. The use of ML for electrical load and RES forecasting generally improves prediction accuracy, which in turn enhances the quality of UC schedules and reduces operating costs.
3. ML-based approaches for decision-making in UC (e.g., direct schedule generation, policy learning, and hybrid ML–optimization schemes) are emerging as a promising complement to traditional mathematical programming and metaheuristic methods.
4. ML models can mitigate some limitations of traditional parametric representations of cost and constraint functions, enabling more flexible and data-driven modelling that may improve the effectiveness of UC solutions.
5. When appropriately designed and trained, ML-assisted UC frameworks have the potential to deliver faster solution times while maintaining satisfactory levels of accuracy, reliability, and adaptability to previously unseen operating conditions.
6. The field remains immature, and further research is required to assess the robustness and generality of ML-based UC methods in more realistic settings, including

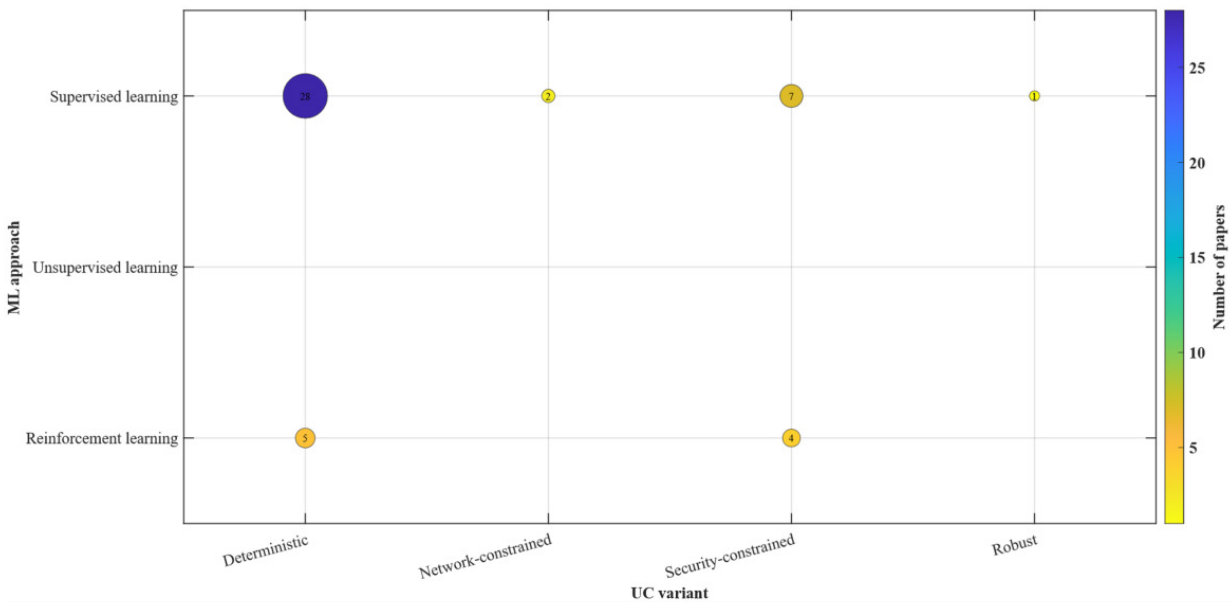

Fig. 5.Evidence map of ML-based unit commitment (UC) literature.

transmission network constraints, contingencies such as generator outages, and profit-driven market participants.

7. Future work should place greater emphasis on optimization-based validation and verification of ML models to rigorously assess performance, ensure feasibility, and build greater trust in learned models across broader operational regions.

5- Conclusion

This paper reviews unit commitment (UC) formulations and solution techniques for power systems with high penetration of renewable energy sources (RES), with a particular emphasis on the interplay between classical optimization, metaheuristics, and machine learning (ML). From the modelling perspective, the integration of RES, energy storage, electric vehicles, combined heat and power (CHP) units, heat-only plants, hydro resources, and multi-energy couplings has led to a broad family of UC variants, including deterministic, stochastic, robust, security-constrained, and network-constrained formulations. These models aim to capture the operational flexibility and security requirements of modern systems, but they also increase dimensionality and nonconvexity, making UC a large-scale mixed-integer problem that is challenging to solve in real time.

Regarding solution approaches, mathematical programming techniques - such as mixed-integer linear programming, Lagrangian relaxation, and decomposition methods - remain the reference for obtaining high-quality solutions with explicit optimality gaps. Metaheuristic algorithms have been widely explored to handle nonconvex cost functions, complex constraint sets, and large-scale instances. They can produce good solutions in many practical settings, but their performance is often sensitive to parameter tuning; they lack guarantees of global optimality, and they may exhibit long or variable computation times, which limits their industrial deployment.

ML has emerged as a complementary tool within the UC workflow in three main roles: improving forecasts of load and RES; accelerating or enhancing UC solvers through surrogate models, warm-starts, and constraint screening; and, more recently, learning UC decision policies via deep and reinforcement learning. The reviewed literature indicates that ML can substantially improve forecasting accuracy and reduce solution times, particularly when integrated with strong optimization models. However, concerns about feasibility, robustness, and performance guarantees continue to hinder the widespread use of purely data-driven UC solutions. The evidence map constructed from the ML-based studies shows that most applications rely on supervised learning for deterministic UC, while work on network-constrained, security-constrained, and robust UC remains limited, and unsupervised learning has not yet been explicitly exploited.

Based on this review, several specific directions can be identified for future research:

1. High-fidelity RES-integrated UC formulations:

Future UC models should represent renewable uncertainty together with storage degradation, EV availability, demand-response flexibility, low-inertia frequency-security constraints, renewable curtailment, and transmission congestion. This is especially important for systems where wind, PV, storage, and flexible loads interact across multiple time scales.

2. Scalable optimization and decomposition methods:

Future studies should develop more efficient decomposition, relaxation, and parallel computing strategies for large-scale stochastic UC, robust UC, and SCUC. Particular attention should be given to reducing scenario burden, improving convergence behavior, and preserving feasibility under network and reserve constraints.

3. Standardized benchmarking for ML-assisted UC:

Future ML-UC studies should use common benchmark systems, such as small systems for algorithmic validation, IEEE RTS or IEEE 118-bus systems for network-constrained UC, and larger systems for scalability testing. These benchmarks should include standardized load, wind, PV, and forecast-error profiles, fixed training/validation/test splits, and common reporting metrics such as objective cost, solution time, optimality gap, feasibility violations, repair effort, and hardware/software specifications.

4. Hybrid ML–optimization frameworks with feasibility guarantees:

Rather than replacing optimization solvers entirely, future research should focus on integrating ML into UC workflows through warm-starting, constraint screening, surrogate modelling, decomposition support, and scenario reduction. These methods should be coupled with optimization-based validation to guarantee feasibility, quantify optimality gaps, and identify cases where ML predictions should be repaired or rejected.

5. Unsupervised and generative learning for uncertainty reduction:

Clustering, autoencoders, variational autoencoders, and generative models can be explored for identifying representative net-load regimes, reducing renewable scenarios, detecting rare operating conditions, and constructing adaptive training datasets. These tools may help reduce the computational burden of stochastic and clustered UC while preserving the main uncertainty structure.

6. Deployment-oriented validation and operator trust:

Future ML-based UC tools should be evaluated under out-of-distribution conditions, topology changes, contingencies, data-quality problems, and extreme RES events. Research should also address interpretability, confidence margins, auditability, compatibility with EMS/MMS platforms, and robust fallback mechanisms so that ML-assisted UC can be accepted as a reliable decision-support layer in practical control-room environments.

In summary, UC in the presence of high-RES penetration remains a central and challenging issue in power system operation. Progress will require both richer, more realistic UC formulations and stronger optimization algorithms, as well as carefully designed ML components that enhance - rather than replace - the underlying mathematical models. Closer integration of power-system modelling, optimization theory, and data-driven techniques is likely to be decisive in translating recent academic advances into reliable tools for real-world system operation.

Highlights:

- Reviews UC formulations for power systems with high renewable penetration.
- Compares optimization, decomposition, and metaheuristic UC solution methods.
- Classifies ML roles in UC as forecasting, solver support, and decision support.
- Identifies key gaps in benchmarking, feasibility validation, and trusted deployment.
- Nomenclature

References

[1] K. A. Juste, H. Kita, E. Tanaka, and J. Hasegawa, “An evolutionary programming solution to the unit commitment problem,” IEEE Transactions on Power Systems, vol. 14, no. 4, pp. 1452–1459, Nov. 1999, doi: 10.1109/59.801925.

[2] S. Sen and D. P. Kothari, “Optimal thermal generating unit commitment: a review,” International Journal of Electrical Power & Energy Systems, vol. 20, no. 7, pp. 443–451, Oct. 1998, doi: 10.1016/S0142-0615(98)00013-1.

[3] H. Ahmadi and H. Ghasemi, “Security-Constrained Unit Commitment With Linearized System Frequency Limit Constraints,” IEEE Transactions on Power Systems, vol. 29, no. 4, pp. 1536–1545, Jul. 2014, doi: 10.1109/TPWRS.2014.2297997.

[4] A. Bhardwaj, V. K. Kamboj, V. K. Shukla, B. Singh, and P. Khurana, “Unit commitment in electrical power system-a literature review,” in 2012 IEEE International Power Engineering and Optimization Conference, Melaka, Malaysia, Jun. 2012, pp. 275–280. doi: 10.1109/PEOCO.2012.6230874.

[5] B. Saravanan, S. Das, S. Sikri, and D. P. Kothari, “A solution to the unit commitment problem—a review,” Front. Energy, vol. 7, no. 2, pp. 223–236, Jun. 2013, doi: 10.1007/s11708-013-0240-3.

[6] Q. P. Zheng, J. Wang, and A. L. Liu, “Stochastic Optimization for Unit Commitment—A Review,” IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 1913–1924, Jul. 2015, doi: 10.1109/TPWRS.2014.2355204.

[7] S. Y. Abujarad, M. W. Mustafa, and J. J. Jamian, “Recent approaches of unit commitment in the presence of intermittent renewable energy resources: A review,” Renewable and Sustainable Energy Reviews, vol. 70, pp. 215–223, Apr. 2017, doi: 10.1016/j.rser.2016.11.246.

[8] I. Abdou and M. Tkiouat, “Unit Commitment Problem in Electrical Power System: A Literature Review,” IJECE, vol. 8, no. 3, p. 1357, Jun. 2018, doi: 10.11591/ijece.v8i3.pp1357-1372.

[9] W. van Ackooij, I. Danti Lopez, A. Frangioni, F. Lacalandra, and M. Tahanan, “Large-scale unit commitment under uncertainty: an updated literature

survey," Ann Oper Res, vol. 271, no. 1, pp. 11–85, Dec. 2018, doi: 10.1007/s10479-018-3003-z.

[10] M. Håberg, "Fundamentals and recent developments in stochastic unit commitment," International Journal of Electrical Power & Energy Systems, vol. 109, pp. 38–48, Jul. 2019, doi: 10.1016/j.ijepes.2019.01.037.

[11] H. Abdi, "Profit-based unit commitment problem: A review of models, methods, challenges, and future directions," Renewable and Sustainable Energy Reviews, vol. 138, p. 110504, Mar. 2021, doi: 10.1016/j.rser.2020.110504.

[12] V. Kumar, R. Naresh, and A. Singh, "Investigation of solution techniques of unit commitment problems: A review," Wind Engineering, vol. 45, no. 6, pp. 1689–1713, Dec. 2021, doi: 10.1177/0309524X21992446.

[13] Y. Yang and L. Wu, "Machine learning approaches to the unit commitment problem: Current trends, emerging challenges, and new strategies," The Electricity Journal, vol. 34, no. 1, p. 106889, Jan. 2021, doi: 10.1016/j.tej.2020.106889.

[14] L. Montero, A. Bello, and J. Reneses, "A Review on the Unit Commitment Problem: Approaches, Techniques, and Resolution Methods," Energies, vol. 15, no. 4, Art. no. 4, Jan. 2022, doi: 10.3390/en15041296.

[15] N. Yang et al., "A Comprehensive Review of Security-constrained Unit Commitment," Journal of Modern Power Systems and Clean Energy, vol. 10, no. 3, pp. 562–576, May 2022, doi: 10.35833/MPCE.2021.000255.

[16] A. Aharwar, R. Naresh, V. Sharma, and V. Kumar, "Unit commitment problem for transmission system, models and approaches: A review," Electric Power Systems Research, vol. 223, p. 109671, Oct. 2023, doi: 10.1016/j.epsr.2023.109671.

[17] M. E. Nazari and M. M. Ardehali, "Profit-based unit commitment of integrated CHP-thermal-heat only units in energy and spinning reserve markets with considerations for environmental CO2 emission cost and valve-point effects," Energy, vol. 133, pp. 621–635, Aug. 2017, doi: 10.1016/j.energy.2017.05.164.

[18] M. E. Nazari, M. M. Ardehali, and S. Jafari, "Pumped-storage unit commitment with considerations for energy demand, economics, and environmental constraints," Energy, vol. 35, no. 10, pp. 4092–4101, Oct. 2010, doi: 10.1016/j.energy.2010.06.022.

[19] M. Eslamian, S. H. Hosseinian, and B. Vahidi, "Bacterial Foraging-Based Solution to the Unit-Commitment Problem," IEEE Transactions on Power Systems, vol. 24, no. 3, pp. 1478–1488, Aug. 2009, doi: 10.1109/TPWRS.2009.2021216.

[20] X. Guan, Q. Zhai, and A. Papalexopoulos, "Optimization-based methods for unit commitment: Lagrangian relaxation versus general mixed integer programming," in 2003 IEEE Power Engineering Society General Meeting (IEEE Cat. No.03CH37491), Jul. 2003, pp. 1095-1100, Vol. 2. doi: 10.1109/PES.2003.1270468.

[21] J.-S. Pan, P. Hu, and S.-C. Chu, "Binary fish migration optimization for solving unit commitment," Energy, vol. 226, p. 120329, Jul. 2021, doi: 10.1016/j.energy.2021.120329.

[22] M. Moghimi Hadji and B. Vahidi, "A Solution to the Unit Commitment Problem Using Imperialistic Competition Algorithm," IEEE Transactions on Power Systems, vol. 27, no. 1, pp. 117–124, Feb. 2012, doi: 10.1109/TPWRS.2011.2158010.

[23] S. Abedi, G. H. Riahy, S. H. Hosseinian, and A. Alimardani, "Risk-Constrained Unit Commitment of Power System Incorporating PV and Wind Farms," ISRN Renewable Energy, vol. 2011, pp. 1–8, Dec. 2011, doi: 10.5402/2011/309496.

[24] A. Dreher, S. Liebehentze, M. Wickert, and J. Schuett, "A Limit Order Book Based Unit Commitment of a Renewable Energy Unit Portfolio in the European Continuous Intraday Market," in 2019 16th International Conference on the European Energy Market (EEM), Sep. 2019, pp. 1–6. doi: 10.1109/EEM.2019.8916532.

[25] E. Du et al., "Operation of a High Renewable Penetrated Power System With CSP Plants: A Look-Ahead Stochastic Unit Commitment Model," IEEE Transactions on Power Systems, vol. 34, no. 1, pp. 140–151, Jan. 2019, doi: 10.1109/TPWRS.2018.2866486.

[26] B. Wang, M. Zhou, B. Xin, X. Zhao, and J. Watada, "Analysis of operation cost and wind curtailment using multi-objective unit commitment with battery energy storage," Energy, vol. 178, pp. 101–114, Jul. 2019, doi: 10.1016/j.energy.2019.04.108.

[27] A. Ademovic, S. Bisanovic, and M. Hajro, "A Genetic Algorithm solution to the Unit Commitment problem based on real-coded chromosomes and Fuzzy Optimization," in Melecon 2010 - 2010 15th IEEE Mediterranean Electrotechnical Conference, Apr. 2010, pp. 1476–1481. doi: 10.1109/MELCON.2010.5476238.

[28] Y. Sun, Z. Chen, Z. Li, W. Tian, and M. Shahidehpour, "EV Charging Schedule in Coupled Constrained Networks of Transportation and Power System," IEEE Transactions on Smart Grid, vol. 10, no. 5, pp. 4706–4716, Sep. 2019, doi: 10.1109/TSG.2018.2864258.

[29] S. A. Kazarlis, A. G. Bakirtzis, and V. Petridis, "A genetic algorithm solution to the unit commitment problem," IEEE Transactions on Power Systems, vol. 11, no. 1, pp. 83–92, Feb. 1996, doi: 10.1109/59.485989.

[30] E. Du, N. Zhang, C. Kang, and Q. Xia, "A High-Efficiency Network-Constrained Clustered Unit Commitment Model for Power System Planning Studies," IEEE Transactions on Power Systems, vol. 34, no. 4, pp. 2498–2508, Jul. 2019, doi: 10.1109/TPWRS.2018.2881512.

[31] Y. Xu, T. Ding, M. Qu, and P. Du, "Adaptive Dynamic Programming for Gas-Power Network Constrained Unit Commitment to Accommodate Renewable Energy With Combined-Cycle Units," IEEE Transactions on

Sustainable Energy, vol. 11, no. 3, pp. 2028–2039, Jul. 2020, doi: 10.1109/TSTE.2019.2951616.

[32] T. Senjyu, K. Shimabukuro, K. Uezato, and T. Funabashi, "A fast technique for unit commitment problem by extended priority list," IEEE Transactions on Power Systems, vol. 18, no. 2, pp. 882–888, May 2003, doi: 10.1109/TPWRS.2003.811000.

[33] A. M. Elsayed, A. M. Maklad, and S. M. Farrag, "A new priority list unit commitment method for large-scale power systems," in 2017 Nineteenth International Middle East Power Systems Conference (MEPCON), Dec. 2017, pp. 359–367. doi: 10.1109/MEPCON.2017.8301206.

[34] P. K. Singhal and R. N. Sharma, "Dynamic programming approach for solving power generating unit commitment problem," in 2011 2nd International Conference on Computer and Communication Technology (ICCCT-2011), Sep. 2011, pp. 298–303. doi: 10.1109/ICCCT.2011.6075161.

[35] T. Logenthiran and D. Srinivasan, "Particle Swarm Optimization for unit commitment problem," in 2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems, Jun. 2010, pp. 642–647. doi: 10.1109/PMAPS.2010.5528899.

[36] J. Ebrahimi, S. H. Hosseinian, and G. B. Gharehpetian, "Unit Commitment Problem Solution Using Shuffled Frog Leaping Algorithm," IEEE Transactions on Power Systems, vol. 26, no. 2, pp. 573–581, May 2011, doi: 10.1109/TPWRS.2010.2052639.

[37] A. Tavakoli, M. J. Sanjari, H. Karami, S. H. Hosseinian, and G. B. Gharehpetian, "Imperialistic Competitive Algorithm Based Unit Commitment Considering Risk of Cascading Blackout," Electric Power Components and Systems, vol. 43, no. 4, pp. 374–383, Feb. 2015, doi: 10.1080/15325008.2014.963261.

[38] A. M. Palani, H. Wu, and M. M. Morcos, "A Frank–Wolfe Progressive Hedging Algorithm for Improved Lower Bounds in Stochastic SCUC," IEEE Access, vol. 7, pp. 99398–99406, 2019, doi: 10.1109/ACCESS.2019.2927346.

[39] W. Tian, M. Shan, R. Lu, Y. Xu, and T. Ding, "Stochastic Unit Commitment to Accommodate Renewable Energy with Renewable Portfolio Standard," in 2019 IEEE Sustainable Power and Energy Conference (iSPEC), Nov. 2019, pp. 1401–1405. doi: 10.1109/iSPEC48194.2019.8974953.

[40] S. Naghdalian, T. Amraee, S. Kamali, and F. Capitanescu, "Stochastic Network-Constrained Unit Commitment to Determine Flexible Ramp Reserve for Handling Wind Power and Demand Uncertainties," IEEE Transactions on Industrial Informatics, vol. 16, no. 7, pp. 4580–4591, Jul. 2020, doi: 10.1109/TII.2019.2944234.

[41] S. Ranjan and A. R. Abhyankar, "Investigating the Need for Real-Time Adjustment Cost in Unit Commitment Framework for Wind-Integrated Power Systems," IEEE Systems Journal, vol. 15, no. 4, pp. 5355–5366, Dec. 2021, doi: 10.1109/JSYST.2021.3079584.

[42] Z. Zhang, Y. Chen, X. Liu, and W. Wang, "Two-Stage Robust Security-Constrained Unit Commitment Model Considering Time Autocorrelation of Wind/Load Prediction Error and Outage Contingency Probability of Units," IEEE Access, vol. 7, pp. 25398–25408, 2019, doi: 10.1109/ACCESS.2019.2900254.

[43] X. Zhu, Z. Yu, and X. Liu, "Security Constrained Unit Commitment with Extreme Wind Scenarios," Journal of Modern Power Systems and Clean Energy, vol. 8, no. 3, pp. 464–472, 2020, doi: 10.35833/MPCE.2018.000797.

[44] G. Zhang, F. Li, and C. Xie, "Flexible Robust Risk-Constrained Unit Commitment of Power System Incorporating Large Scale Wind Generation and Energy Storage," IEEE Access, vol. 8, pp. 209232–209241, 2020, doi: 10.1109/ACCESS.2020.3038685.

[45] Y. Zhou, M. Shahidehpour, Z. Wei, Z. Li, G. Sun, and S. Chen, "Distributionally Robust Unit Commitment in Coordinated Electricity and District Heating Networks," IEEE Transactions on Power Systems, vol. 35, no. 3, pp. 2155–2166, May 2020, doi: 10.1109/TPWRS.2019.2950987.

[46] X. Zheng, H. Chen, Y. Xu, Z. Li, Z. Lin, and Z. Liang, "A mixed-integer SDP solution to distributionally robust unit commitment with second-order moment constraints," CSEE Journal of Power and Energy Systems, vol. 6, no. 2, pp. 374–383, Jun. 2020, doi: 10.17775/CSEEJPES.2019.00930.

[47] S. Dehghan, P. Aristidou, N. Amjady, and A. J. Conejo, "A Distributionally Robust AC Network-Constrained Unit Commitment," IEEE Transactions on Power Systems, vol. 36, no. 6, pp. 5258–5270, Nov. 2021, doi: 10.1109/TPWRS.2021.3078801.

[48] M. A. Mirzaei, M. Nazari-Heris, B. Mohammadi-Ivatloo, K. Zare, M. Marzband, and S. A. Pourmousavi, "Robust Flexible Unit Commitment in Network-Constrained Multicarrier Energy Systems," IEEE Systems Journal, vol. 15, no. 4, pp. 5267–5276, Dec. 2021, doi: 10.1109/JSYST.2020.3012338.

[49] A. Ahmadi, A. Esmaeel Nezhad, P. Siano, B. Hredzak, and S. Saha, "Information-Gap Decision Theory for Robust Security-Constrained Unit Commitment of Joint Renewable Energy and Gridable Vehicles," IEEE Transactions on Industrial Informatics, vol. 16, no. 5, pp. 3064–3075, May 2020, doi: 10.1109/TII.2019.2908834.

[50] G. Morales-España and D. A. Tejada-Arango, "Modeling the Hidden Flexibility of Clustered Unit Commitment," IEEE Transactions on Power Systems, vol. 34, no. 4, pp. 3294–3296, Jul. 2019, doi: 10.1109/TPWRS.2019.2908051.

[51] B. Yang et al., "Unit Commitment Comprehensive Optimal Model Considering the Cost of Wind Power Curtailment and Deep Peak Regulation of Thermal Unit," IEEE Access, vol. 8, pp. 71318–71325, 2020, doi: 10.1109/ACCESS.2020.2983183.

[52] Z. Guo, W. Wei, L. Chen, M. Shahidehpour, and S. Mei, "Economic Value of Energy Storages in Unit Commitment With Renewables and Its Implication on Storage Sizing," IEEE Transactions on Sustainable Energy, vol. 12, no. 4, pp. 2219–2229, Oct. 2021, doi: 10.1109/TSTE.2021.3086953.

[53] P. Bunnoon, K. Chalermyanont, and C. Limsakul, "The Comparison of Mid-Term Load Forecasting between Multi-Regional and Whole Country Area Using Artificial Neural Network," IJCEE, pp. 334–338, 2010, doi: 10.7763/IJCEE.2010.V2.157.

[54] M. Yesilbudak, S. Sagiroglu, and I. Colak, "A novel implementation of kNN classifier based on multi-tupled meteorological input data for wind power prediction," Energy Conversion and Management, vol. 135, pp. 434–444, Mar. 2017, doi: 10.1016/j.enconman.2016.12.094.

[55] M. G. De Giorgi, P. M. Congedo, M. Malvoni, and D. Laforgia, "Error analysis of hybrid photovoltaic power forecasting models: A case study of Mediterranean climate," Energy Conversion and Management, vol. 100, pp. 117–130, Aug. 2015, doi: 10.1016/j.enconman.2015.04.078.

[56] M. Hossain, S. Mekhilef, M. Danesh, L. Olatomiwa, and S. Shamshirband, "Application of extreme learning machine for short-term output power forecasting of three grid-connected PV systems," Journal of Cleaner Production, vol. 167, pp. 395–405, Nov. 2017, doi: 10.1016/j.jclepro.2017.08.081.

[57] C.-H. Liu, J.-C. Gu, and M.-T. Yang, "A Simplified LSTM Neural Network for One-Day-Ahead Solar Power Forecasting," IEEE Access, vol. 9, pp. 17174–17195, 2021, doi: 10.1109/ACCESS.2021.3053638.

[58] S. H. Rafi, Nahid-Al-Masood, S. R. Deeba, and E. Hossain, "A Short-Term Load Forecasting Method Using Integrated CNN and LSTM Network," IEEE Access, vol. 9, pp. 32436–32448, 2021, doi: 10.1109/ACCESS.2021.3060654.

[59] S. X. Chen, H. B. Gooi, and M. Q. Wang, "Sizing of Energy Storage for Microgrids," IEEE Transactions on Smart Grid, vol. 3, no. 1, pp. 142–151, Mar. 2012, doi: 10.1109/TSG.2011.2160745.

[60] R. Palma-Behnke et al., "A Microgrid Energy Management System Based on the Rolling Horizon Strategy," IEEE Transactions on Smart Grid, vol. 4, no. 2, pp. 996–1006, Jun. 2013, doi: 10.1109/TSG.2012.2231440.

[61] B. V. Solanki, A. Raghurajan, K. Bhattacharya, and C. A. Cañizares, "Including Smart Loads for Optimal Demand Response in Integrated Energy Management Systems for Isolated Microgrids," IEEE Transactions on Smart Grid, vol. 8, no. 4, pp. 1739–1748, Jul. 2017, doi: 10.1109/TSG.2015.2506152.

[62] P.-H. Chen, "Two-Level Hierarchical Approach to Unit Commitment Using Expert System and Elite PSO," IEEE Transactions on Power Systems, vol. 27, no. 2, pp. 780–789, May 2012, doi: 10.1109/TPWRS.2011.2171197.

[63] J. Che, "Support vector regression based on optimal training subset and adaptive particle swarm optimization algorithm," Applied Soft Computing, vol. 13, no. 8, pp. 3473–3481, Aug. 2013, doi: 10.1016/j.asoc.2013.04.003.

[64] Pedro de Lima Abrão, Elizabeth Fialho Wanner, and Paulo Eduardo Maciel de Almeida, "A novel movable partitions approach with neural networks and evolutionary algorithms for solving the hydroelectric unit commitment problem | Proceedings of the 15th annual conference on Genetic and evolutionary computation." Accessed: Dec. 29, 2022. [Online]. Available: https://dl.acm.org/doi/10.1145/2463372.2463523

[65] M. J. Ghadi, S. H. Gilani, H. Afrakhte, and A. Baghramian, "A novel heuristic method for wind farm power prediction: A case study," International Journal of Electrical Power & Energy Systems, vol. 63, pp. 962–970, Dec. 2014, doi: 10.1016/j.ijepes.2014.07.008.

[66] M. Furukakoi, O. B. Adewuyi, H. Matayoshi, A. M. Howlader, and T. Senjyu, "Multi-objective unit commitment with voltage stability and PV uncertainty," Applied Energy, vol. 228, pp. 618–623, Oct. 2018, doi: 10.1016/j.apenergy.2018.06.074.

[67] M. Zhou, B. Wang, and J. Watada, "Deep learning-based rolling horizon unit commitment under hybrid uncertainties," Energy, vol. 186, p. 115843, Nov. 2019, doi: 10.1016/j.energy.2019.07.173.

[68] M. Zhou, B. Wang, T. Li, and J. Watada, "A data-driven approach for multi-objective unit commitment under hybrid uncertainties," Energy, vol. 164, pp. 722–733, Dec. 2018, doi: 10.1016/j.energy.2018.09.008.

[69] S. Ogawa and H. Mori, "A Gaussian-Gaussian-Restricted-Boltzmann-Machine-based Deep Neural Network Technique for Photovoltaic System Generation Forecasting," IFAC-PapersOnLine, vol. 52, no. 4, pp. 87–92, Jan. 2019, doi: 10.1016/j.ifacol.2019.08.160.

[70] A. Ajagekar and F. You, "Deep Reinforcement Learning-based Solution Approach for Unit Commitment under Demand and Wind Power Uncertainty," in 2022 American Control Conference (ACC), Jun. 2022, pp. 4520–4525. doi: 10.23919/ACC53348.2022.9867273.

[71] O. Yurdakul, F. Qiu, and A. Meyer, "A Predictive Prescription Framework for Stochastic Unit Commitment Using Boosting Ensemble Learning Algorithms," IEEE Transactions on Power Systems, vol. 39, no. 4, pp. 5726–5740, Jul. 2024, doi: 10.1109/TPWRS.2023.3336902.

[72] X. Dong, Z. Mao, Y. Sun, and X. Xu, "Short-Term Wind Power Scenario Generation Based on Conditional Latent Diffusion Models," IEEE Transactions on Sustainable Energy, vol. 15, no. 2, pp. 1074–1085, Apr. 2024, doi: 10.1109/TSTE.2023.3327497.

[73] W. Zhao, J. Zhao, X. Shen, J. Liu, and S. Fan, "A two-stage uncertainty forecasting method for offshore wind power based on FEDformer and SDCDM," Energy, vol. 348, p. 140452, Apr. 2026, doi: 10.1016/j.

energy.2026.140452.

[74] E. A. Jasmin, T. P. Imthias Ahamed, and V. P. Jagathy Raj, "Reinforcement Learning approaches to Economic Dispatch problem," International Journal of Electrical Power & Energy Systems, vol. 33, no. 4, pp. 836–845, May 2011, doi: 10.1016/j.ijepes.2010.12.008.

[75] L. Raju, R. S. Milton, S. Suresh, and S. Sankar, "Reinforcement Learning in Adaptive Control of Power System Generation," Procedia Computer Science, vol. 46, pp. 202–209, Jan. 2015, doi: 10.1016/j.procs.2015.02.012.

[76] J. E. A., T. P. I. Ahamed, and R. T, "A function approximation approach to Reinforcement Learning for solving unit commitment problem with photovoltaic sources," in 2016 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), Dec. 2016, pp. 1–6. doi: 10.1109/PEDES.2016.7914428.

[77] L. Duchesne, E. Karangelos, A. Sutera, and L. Wehenkel, "Machine learning for ranking day-ahead decisions in the context of short-term operation planning," Electric Power Systems Research, vol. 189, p. 106548, Dec. 2020, doi: 10.1016/j.epsr.2020.106548.

[78] S. Tiwari, B. Dwivedi, and M. P. Dave, "A multi-stage hybrid artificial intelligence-based optimal solution for energy storage integrated mixed generation unit commitment problem," Journal of Intelligent & Fuzzy Systems, vol. 35, no. 5, pp. 4909–4919, Jan. 2018, doi: 10.3233/JIFS-169775.

[79] N. V. Panossian, D. McLarty, and M. E. Taylor, "Artificial Neural Network for Unit Commitment on Networks with Significant Energy Storage," in 2019 IEEE Green Technologies Conference(GreenTech), Apr. 2019, pp. 1–5. doi: 10.1109/GreenTech.2019.8767137.

[80] Z. Lyu, "A Deep Neural Network Model for Unit Commitment," in 2025 IEEE 23rd Student Conference on Research and Development (SCOReD), Nov. 2025, pp. 1–6. doi: 10.1109/SCOReD68498.2025.11399072.

[81] F. Pourahmadi and J. Kazempour, "Unit Commitment Predictor With a Performance Guarantee: A Support Vector Machine Classifier," IEEE Transactions on Power Systems, vol. 40, no. 1, pp. 715–727, Jan. 2025, doi: 10.1109/TPWRS.2024.3400405.

[82] F. Safdarian, J. Peeples, D. Richards, and T. J. Overbye, "A Fast Learning-Based Unit Commitment Strategy with AC Optimal Power Flow for Large Grids with Direct Inclusion of Weather," in 2024 IEEE Kansas Power and Energy Conference (KPEC), Apr. 2024, pp. 1–5. doi: 10.1109/KPEC61529.2024.10676027.

[83] D. Niu, Y. Wang, and D. D. Wu, "Power load forecasting using support vector machine and ant colony optimization," Expert Systems with Applications, vol. 37, no. 3, pp. 2531–2539, Mar. 2010, doi: 10.1016/j.eswa.2009.08.019.

[84] K. Bhaskar and S. N. Singh, "AWNN-Assisted Wind Power Forecasting Using Feed-Forward Neural Network," IEEE Transactions on Sustainable Energy, vol. 3, no. 2, pp. 306–315, Apr. 2012, doi: 10.1109/TSTE.2011.2182215.

[85] C. F. Kucuktezcan and V. M. I. Genc, "A new dynamic security enhancement method via genetic algorithms integrated with neural network-based tools," Electric Power Systems Research, vol. 83, no. 1, pp. 1–8, Feb. 2012, doi: 10.1016/j.epsr.2011.09.004.

[86] Z. O. Olaofe and K. A. Folly, "Wind power estimation using recurrent neural network technique," in IEEE Power and Energy Society Conference and Exposition in Africa: Intelligent Grid Integration of Renewable Energy Resources (PowerAfrica), Jul. 2012, pp. 1–7. doi: 10.1109/PowerAfrica.2012.6498633.

[87] M. Moazzami, A. Khodabakhshian, and R. Hooshmand, "A new hybrid day-ahead peak load forecasting method for Iran's National Grid," Applied Energy, vol. 101, pp. 489–501, Jan. 2013, doi: 10.1016/j.apenergy.2012.06.009.

[88] H. Quan, D. Srinivasan, and A. Khosravi, "Incorporating Wind Power Forecast Uncertainties Into Stochastic Unit Commitment Using Neural Network-Based Prediction Intervals," IEEE Transactions on Neural Networks and Learning Systems, vol. 26, no. 9, pp. 2123–2135, Sep. 2015, doi: 10.1109/TNNLS.2014.2376696.

[89] G. Bao, S. Wen, and W. Yu, "Neural network approach for modelling and solving the unit commitment problem of cascaded hydropower stations," in 2016 31st Youth Academic Annual Conference of Chinese Association of Automation (YAC), Nov. 2016, pp. 334–338. doi: 10.1109/YAC.2016.7804914.

[90] G.-F. Fan, L.-L. Peng, W.-C. Hong, and F. Sun, "Electric load forecasting by the SVR model with differential empirical mode decomposition and autoregression," Neurocomputing, vol. 173, pp. 958–970, Jan. 2016, doi: 10.1016/j.neucom.2015.08.051.

[91] Y. Ren, P. N. Suganthan, N. Srikanth, and G. Amaratunga, "Random vector functional link network for short-term electricity load demand forecasting," Information Sciences, vol. 367–368, pp. 1078–1093, Nov. 2016, doi: 10.1016/j.ins.2015.11.039.

[92] Y. Ren, P. N. Suganthan, and N. Srikanth, "A Novel Empirical Mode Decomposition With Support Vector Regression for Wind Speed Forecasting," IEEE Transactions on Neural Networks and Learning Systems, vol. 27, no. 8, pp. 1793–1798, Aug. 2016, doi: 10.1109/TNNLS.2014.2351391.

[93] G. Dalal, E. Gilboa, S. Mannor, and L. Wehenkel, "Unit Commitment Using Nearest Neighbor as a Short-Term Proxy," in 2018 Power Systems Computation Conference (PSCC), Jun. 2018, pp. 1–7. doi: 10.23919/PSCC.2018.8442516.

[94] H.-S. Lee, C. Tekin, M. van der Schaar, and J.-W. Lee, "Adaptive Contextual Learning for Unit Commitment in Microgrids With Renewable Energy Sources," IEEE Journal of Selected Topics in Signal Processing,

vol. 12, no. 4, pp. 688–702, Aug. 2018, doi: 10.1109/JSTSP.2018.2849855.

[95] L. Yin, T. Yu, X. Zhang, and B. Yang, “Relaxed deep learning for real-time economic generation dispatch and control with unified time scale,” Energy, vol. 149, pp. 11–23, Apr. 2018, doi: 10.1016/j.energy.2018.01.165.

[96] G. Farzaneh, A. Mohsen, and D. Vali, “A multi-agent reinforcement learning algorithm with fuzzy approximation for Distributed Stochastic Unit Commitment,” Journal of Intelligent & Fuzzy Systems, vol. 37, no. 5, pp. 6613–6628, Jan. 2019, doi: 10.3233/JIFS-182879.

[97] C. Ning and F. You, “Data-Driven Adaptive Robust Unit Commitment Under Wind Power Uncertainty: A Bayesian Nonparametric Approach,” IEEE Transactions on Power Systems, vol. 34, no. 3, pp. 2409–2418, May 2019, doi: 10.1109/TPWRS.2019.2891057.

[98] S. Pineda, J. M. Morales, and A. Jiménez-Cordero, “Data-Driven Screening of Network Constraints for Unit Commitment,” IEEE Transactions on Power Systems, vol. 35, no. 5, pp. 3695–3705, Sep. 2020, doi: 10.1109/TPWRS.2020.2980212.

[99] P. de Mars and A. O’Sullivan, “Applying reinforcement learning and tree search to the unit commitment problem,” Applied Energy, vol. 302, p. 117519, Nov. 2021, doi: 10.1016/j.apenergy.2021.117519.

[100] K. Mehmood et al., “Short-term power dispatch using neural network-based ensemble classifier,” Journal of Energy Storage, vol. 33, p. 102101, Jan. 2021, doi: 10.1016/j.est.2020.102101.

[101] P. Nikolaidis and S. Chatzis, “Gaussian process-based Bayesian optimization for data-driven unit commitment,” International Journal of Electrical Power & Energy Systems, vol. 130, p. 106930, Sep. 2021, doi: 10.1016/j.ijepes.2021.106930.

[102] P. de Mars and A. O’Sullivan, “Reinforcement learning and A* search for the unit commitment problem,” Energy and AI, vol. 9, p. 100179, Aug. 2022, doi: 10.1016/j.egyai.2022.100179.

[103] A. Kody, S. Chevalier, S. Chatzivasileiadis, and D. Molzahn, “Modeling the AC power flow equations with optimally compact neural networks: Application to unit commitment,” Electric Power Systems Research, vol. 213, p. 108282, Dec. 2022, doi: 10.1016/j.epsr.2022.108282.

[104] T. Wu, Y.-J. Angela Zhang, and S. Wang, “Deep Learning to Optimize: Security-Constrained Unit Commitment With Uncertain Wind Power Generation and BESSs,” IEEE Transactions on Sustainable Energy, vol. 13, no. 1, pp. 231–240, Jan. 2022, doi: 10.1109/TSTE.2021.3107848.

[105] Y. Zhang et al., “Encoding Frequency Constraints in Preventive Unit Commitment Using Deep Learning With Region-of-Interest Active Sampling,” IEEE Transactions on Power Systems, vol. 37, no. 3, pp. 1942–1955, May 2022, doi: 10.1109/TPWRS.2021.3110881.

[106] Q. Ding, L. Li, Y. Chen, and S. Xu, “A Machine Learning-Assisted Decomposition Method for Efficient Unit Commitment Solving in ESS System,” in 2024 IEEE 8th Conference on Energy Internet and Energy System Integration (EI2), Nov. 2024, pp. 1778–1783. doi: 10.1109/EI264398.2024.10991462.

[107] F. Hyder, U. N. Quang, and B. Yan, “A Novel Machine Learning-Based Automated Formulation Tightening Approach for Energy Storage Resources in Unit Commitment,” IEEE Transactions on Automation Science and Engineering, vol. 23, pp. 4039–4052, 2026, doi: 10.1109/TASE.2025.3648951.

[108] M. Wang and H. Ye, “Data-Driven Technologies to Accelerate Unit Commitment Problem,” in 2025 4th Asia Power and Electrical Technology Conference (APET), Dec. 2025, pp. 128–131. doi: 10.1109/APET68390.2025.11429007.

[109] J. Wu, P. B. Luh, Y. Chen, B. Yan, and M. A. Bragin, “Synergistic Integration of Machine Learning and Mathematical Optimization for Unit Commitment,” IEEE Transactions on Power Systems, vol. 39, no. 1, pp. 391–401, Jan. 2024, doi: 10.1109/TPWRS.2023.3240106.

[110] C. Shi, S. Liu, and Y. Yu, “Graph Neural Network and Dynamic Neighborhood Search for Solving Unit Commitment,” in 2025 IEEE International Conference on Energy Technologies for Future Grids (ETFG), Dec. 2025, pp. 1–6. doi: 10.1109/ETFG61999.2025.11401168.

[111] S. Du et al., “Learning-Integrated Unit Commitment Optimization Based on GCN-GRU and Load Scenario Clustering,” in 2024 6th International Conference on Energy, Power and Grid (ICEPG), Sep. 2024, pp. 1056–1060. doi: 10.1109/ICEPG63230.2024.10775416.

[112] A. Moradpour and Z. Wang, “Spatio-Temporal Deep Learning for Accelerating Security-Constrained Unit Commitment via Adaptive Constraint Filtering,” in 2025 57th North American Power Symposium (NAPS), Oct. 2025, pp. 1–6. doi: 10.1109/NAPS66256.2025.11272309.

[113] W. Xu, J. Lin, X. Sheng, O. Zhang, X. Jiang, and X. Wang, “Learning-Enabled Optimization for Security-Constrained Unit Commitment with Energy Storage,” in 2024 IEEE 8th Conference on Energy Internet and Energy System Integration (EI2), Nov. 2024, pp. 4159–4165. doi: 10.1109/EI264398.2024.10990692.

[114] R. Panda, “Optimal Scheduling of Renewable-Integrated Microgrid Using Markov Decision Process-Based Security-Constrained Unit Commitment,” in 2026 4th Odisha International Conference on Electrical Power Engineering, Communication and Computing Technology (ODICON), Feb. 2026, pp. 1–5. doi: 10.1109/ODICON66687.2026.11470654.

[115] Y. Chen, J. Zhu, and C. Zeng, “Quality-Diversity Learning Enabled Multi-Alternative Unit Commitment Optimization,” IEEE Transactions on Power Systems, vol. 41, no. 1, pp. 805–808, Jan. 2026, doi: 10.1109/TPWRS.2025.3631269.

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