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Optimizing day-ahead power scheduling: A novel MIQCP approach for enhanced SCUC with renewable integration

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A R T I C L E I N F O

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A B S T R A C T

This paper introduces an innovative methodology aimed at enhancing day-ahead power system scheduling by incorporating adaptable technologies within the framework of security-constrained unit commitment. The methodology is tailored for power systems characterized by significant integration of photovoltaic energy, with the goal of reducing operational expenses linked to energy storage systems, demand response initiatives, solar power curtailment, and load shedding. The scheduling issue is structured as a mixed-integer quadratically-constrained programming model, which guarantees globally optimal solutions for intricate, real-world applications. The developed model has been implemented using the GAMS and tested through extensive case studies on the IEEE 24-bus system. The findings reveal that the strategic coordination of flexible resources leads to a 5.6 % reduction in scheduling costs compared to traditional methods. This result highlights the model's effectiveness in improving operational efficiency and cost savings for power systems with high renewable energy penetration, establishing it as an essential tool for sustainable management of power systems.

Nomenclature

$f(P_{PV})$	PDF representing the generating power of each photovoltaic
P_{PV}	Power output generated by each photovoltaic generator
$P_{PV}^{\max}$	Maximum achievable power output of each photovoltaic generator
α,β	Parameters defining the shape of the Beta distribution
$C_{Pvg,i}$	Total associated cost for photovoltaic generator i
$C_{pvg,i}^{d}$, $C_{pvg,i}^{under}$, $C_{pvg,i}^{over}$	Costs associated with direct, underestimated, and overestimated power output for photovoltaic generator i
$K_{pvg,i}^{d}$, $K_{pvg,i}^{under}$, $K_{pvg,i}^{over}$	Cost factors related to the three cost components per photovoltaic generator
P	Pre-determined power output scheduled for photovoltaic generation
$P_{pvg,i}$	Power capacity available for each photovoltaic generator
$f_{P_{pvg,i}}(P)$	Combined PDF of the power output for each photovoltaic generator
$C_{k,n,t}^{ESS}$	Capacity available in the kth compressed air energy storage during time period t
C_{NG}	Cost of natural gas required for operating the CAES
C_{k}^{OM}	Costs associated with maintenance and operation of the kth CAES
$P_{rated,k}^{ESS}$	Power rating of the kth CAES
S_{k}^{ESS}	Apparent power rating of the kth CAES
C_{k}^{ESS}	Total energy capacity rating of the kth compressed air energy storage
C_p	Cost of power rating per unit of ESS
C_E	Energy-related cost of operating the compressed air energy storage system
intr	Applicable interest rate for financial calculations
lf	Operational lifespan of the CAES
$P_{k,n,t}^{ch}$	Charging power for the CAES in a given scenario over a period
$P_{k,n,t}^{dch}$	Discharging power for the CAES in a given scenario over a period
η^{ch},η^{dch}	Efficiency of charging and discharging processes for CAES
$P_{g,n,t}$	Active power dispatched from the gth thermal unit at time t
$P_{i,n,t}^{Lsh}$	Amount of power reduced at the specified bus
$P_{pv,n,t}^{curt}$	Power curtailed (not used) from solar photovoltaic generation at a given hour
a_g, b_g and c_g	Cost factor related to the fuel consumption of the generator
$VOLL$	Monetary value assigned to unsupplied electricity
PC_p	Penalty cost associated with curtailing solar power generation
C_{de}^{D}	Adjusted demand in response to demand response programs for unit gg
$DeR_{de,n,t}^{upp}$, $DeR_{de,n,t}^{dnn}$	Scheduled times for increasing or decreasing load at time t

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(continued)

$I_{g,n,t}$	Operational status (on/off) of generator units
RD_g,RU_g	Maximum capacities for ramping up or down for conventional generators
$P_g^{\min}$, $P_g^{\max}$, $Q_g^{\min}$,$Q_g^{\max}$	Boundaries for both reactive and active power output for every traditional generator
T_g^{on}, T_g^{off}	Minimum required operational or shutdown time for generator units
$y_{g,n,t}$,$z_{g,n,t}$	Indicators for the start-up or shutdown state of generator unit gg at hour t
V_i,V_j	Voltage levels at nodes i and j within the grid
δ_{ij}	Difference in the phase angle of voltage between nodes i and j
G_{ij},B_{ij} j	Susceptance and conductance parameters
$P_{pv,i,n,t}^{inj}$, $Q_{pv,i,n,t}^{inj}$	Reactive and active power injected at nodes ii and j
$P_{k,n,t}^{ch}$, $P_{k,n,t}^{dch}$, $Q_{k,n,t}^{ch}$, $Q_{k,n,t}^{dch}$	Reactive and active power being charged or discharged by ESS unit k
$P_{D,t}$and $Q_{D,t}$	Reactive and active power demands at time t
$P_{i,n,t}^{ch}$, $P_{i,n,t}^{dch}$	Status of charging or discharging for the ESS unit at bus i during hour t
$P_{\max}^{ESS}$	Maximum allowable rate for charging or discharging energy storage systems
$P_{de,n,t}^{DeR}$	Power demand after the implementation of demand response programs at time t under scenario n

1. Introduction

1.1. Concept & motivation

In modern power systems, operators face various challenges, with a major issue being the increasing load demand [1]. This surge often triggers congestion within transmission grids, precipitating a cascade of issues including voltage depletion, heightened power dissipation, elevated energy costs, and a plethora of stability and security dilemmas [2]. Consequently, power system operators (SO) are incessantly in pursuit of viable congestion mitigation strategies [3,4]. Conventional approaches to congestion management encompass the deployment of high-capacity transmission lines and substations, alongside the integration of Flexible AC Transmission System (FACTS) devices like Static Synchronous Compensators (STATCOM). This approach is often not preferred because of high installation expenses and environmental limitations. With the emergence of smart-grid technologies, power SOs now have the capability to leverage these advancements for congestion management and enhancement of power system stability [5–8]. Another challenge faced by SOs stems from the widespread integration of wind and solar photovoltaic (PV) power sources. Despite their environmentally friendly and renewable nature, these sources introduce issues related to power quality, output variability, and exacerbate congestion concerns. In instances where power quality and transmission congestion become limiting factors, SOs may find themselves compelled to curtail portions of the PV output. While curtailing renewables output is not an ideal solution, it becomes necessary in certain circumstances to prevent violations of power system constraints.

To manage real-time resource distribution and reduce the impact of renewable energy variability and load changes, power system operators utilize STATCOM and ESS technologies. Through security-constrained unit commitment (SCUC) alongside real-time capacity assessment, they address the scheduling complexities of thermal units and incorporate demand response programs (DRP). Phase-shifting transformers are deployed to optimize power flow, while coordinated STATCOM operations provide enhanced system control. This research presents a model utilizing mixed-integer quadratically-constrained programming (MIQCP) combined with quasi-Monte Carlo simulation (QMCS) to account for uncertainties in solar PV generation, ensuring a reliable and secure power system.

1.2. Literature review

The integration of renewable energy sources (RESs) into power systems has been facilitated significantly by ESS, which store surplus energy during periods of excess generation for later dispatch. ESS helps mitigate the intermittent nature of RESs, particularly PV, by providing a buffer against fluctuations and ensuring reliable power supply. A novel probabilistic optimization problem proposed in reference [9] highlights the role of ESS in managing uncertainties associated with solar PV farms. The integration of DRPs, flexible AC transmission systems (FACTS) devices, and ESS contributes to minimizing these intermittencies, thereby enhancing the flexibility, reliability, and economic viability of power systems [10].

Various studies have examined the optimal scheduling of power systems incorporating FACTS devices and flexibility technologies. For instance, phase-shifting transformers and STATCOM devices are strategically utilized to manage high levels of solar PV generation, considering investment, load shedding, and PV power curtailment costs within an AC power flow model [11]. The deployment of STATCOM and ESS has been shown to effectively reduce cost components and alleviate congestion, thus optimizing the operation of power systems. Furthermore, reference [12] discusses transmission congestion management through optimal transmission switching and the use of STATCOM devices in AC optimal power flow scenarios, demonstrating that economic benefits can be achieved by leveraging the combined capabilities of these technologies rather than using them in isolation.

The integration of ESS in power system scheduling has gained traction, particularly for its role in the unit commitment problem. Reference [13] explores the use of ESS units to provide reserves, thereby reducing generating and renewable energy curtailment costs while preventing load shedding. A security-constrained unit commitment (SCUC) model incorporating battery energy storage and transmission switching is presented in [14], optimized using a mixed-integer linear programming (MILP) approach within the GAMS framework. This model aims to minimize total operating costs under DC power flow constraints [15].

Further literature suggests that ESS is pivotal for the enhanced integration of RESs, as it allows for the storage of excess energy for later dispatch. In reference [16], a stochastic SCUC model with compressed air energy storage (CAES) and renewable energy sources, incorporating DRP, is developed. Similarly, reference [17] emphasizes the integration of ESS in SCUC models to ensure static voltage stability in the presence of renewable energy. The focus on cost-effective and sustainable energy frameworks using ESS is evident in these studies. The mechanism for RES penetration into stochastic SCUC utilizing ESS, as described in [18], facilitates participation in ancillary services within the electricity market.

The combination of STATCOM and ESS technologies in SCUC problems is explored in reference [19], with the goal of minimizing generating and load shedding costs, albeit without specific consideration of RESs. The synergistic integration of ESS with STATCOM enhances system performance, offering significant improvements over standard STATCOM operations. The advantages of battery technology, such as higher energy densities, increased cycle life, improved reliability, and reduced costs, are highlighted in [20].

Within the framework of enhancing energy market standards, [21] presents a probabilistic approach for scheduling unit commitment and FACTS devices. The performance traits of energy storage systems and FACTS devices are analyzed in [22], highlighting the adaptive response needed for operations with frequent output variations. Reference [23] contributes to the optimization of SCUC problems by enhancing the deliverability of reserves through FACTS device integration, focusing on the incremental adjustment of STATCOM settings. The influence of these technologies on voltage levels and locational marginal pricing is also explored. Additionally, FACTS devices are used to enhance system reliability during re-dispatching situations, as detailed in [24], by employing AC optimal power flow for security.

Optimization algorithms [40–43], play a crucial role in effectively tackling complex problems like the SCUC, particularly when integrating various FACTS technologies. In [25], the use of the artificial bee colony

(ABC) algorithm is explored for addressing the SCUC problem, integrating multiple FACTS technologies. The unpredictable aspects of scheduling in power systems with ESS pose difficulties in ensuring non-anticaptivity and multi-stage resilience [26]. Stochastic SCUC, widely used for daily AC power grid management, supports the dispatch of both reactive and active power from thermal generators [27]. The co-optimization of ESS and STATCOM in economic dispatch scenarios with security constraints is discussed in [28], with the stochastic optimization method discretizing uncertainties to enhance tractability. However, the computational complexity increases with scenario size, necessitating scenario reduction algorithms [29] to maintain accuracy. Lastly, a novel stochastic optimization problem addressing the integration of solar energy into the power grid, considering the uncertainties of correlated solar PV farms, is proposed in [30]. The use of stochastic dual dynamic programming (SDDP) [31] is suggested as a means to manage the growing complexity of scenario-based optimization, though improvements in optimality and computational efficiency remain a key area for future research.

A probabilistic unit commitment model introduced in [32] showcases the integration of ESS and DRP to optimize power system operations. This model specifically addresses the optimal placement of DRP across transmission lines and includes decisions on line switching. The combined use of STATCOM and DRP, as demonstrated through simulations, effectively reduces network operational costs, wind power spillage, and congestion costs. The study relies on a DC power flow model for its analysis.

Further exploration into network optimization, particularly through bus-bar and line switching strategies, is detailed in [33]. These strategies aim to alleviate transmission congestion, an issue exacerbated by the variability of renewable energy sources. DRPs are highlighted as crucial tools for system operators, enabling them to balance supply and demand by adjusting energy usage in response to real-time changes in demand prices [34]. An incentive-driven demand response mechanism tailored for CAES is proposed in [35], utilizing particle swarm optimization to enhance system stability amidst the integration of distributed energy resources. This work significantly advances real-time scheduling problem models, integrating DRP and leveraging ESS units to enhance network flexibility and reduce solar PV power curtailment.

The application of DRP alongside STATCOM in power system scheduling remains underexplored, though some studies have begun to address this gap. For instance, [36] introduces a coordinated approach that integrates DRP with dynamic line rating within the SCUC model. This approach is particularly focused on cost reduction in wind farm scenarios and utilizes AC load flow equations alongside the nonlinear characteristics of DRP and STATCOM, resulting in a MINLP problem. The complexity of this model, due to its non-convex nature, presents challenges in achieving optimal solutions, and it is optimized using specialized GAMS solvers.

1.3. Novelty and contribution

This paper tackles an important gap in existing research by examining the integrated operation of ESS, STATCOM, and DRP within the context of stochastic SCUC. The goal is to create economical solutions for power systems by developing a MIQCP model that convexifies all relevant relationships, including the AC power flow issue. To manage the inherent complexity, a scenario reduction method is utilized along with QMCS, converting the stochastic optimization problem into a deterministic equivalent model covering various scenarios.

The research delves into the stochastic nature of PV generation in relation to electricity prices, alongside the charging and discharging dynamics of ESS and the role of STATCOM in voltage profile enhancement. An AC optimal power flow problem is formulated and solved, incorporating STATCOM devices, with PV generation and electricity prices treated as uncertain stochastic inputs.

- Create a stochastic SCUC strategy that integrates ESS and DRP, factoring in AC network constraints with the use of STATCOM devices, to reduce network congestion and bolster power system stability.
- Develop an advanced scenario generation model to represent QMCS approach to generate multiple scenarios of uncertain PV stochastic variables.
- Formulating the optimal power flow problem involves integrating the coordinated utilization of ESS, DRP, and STATCOM for enhanced system flexibility. Additionally, the task extends to the techno-economic scheduling of power systems featuring conventional thermal generation alongside the curtailment of solar PV power.

The novelty of this study lies in the integration of energy storage systems (ESS), STATCOM devices, and Demand Response Programs (DRP) within the security-constrained unit commitment (SCUC) framework, utilizing a Mixed-Integer Quadratically Constrained Programming (MIQCP) model. Unlike previous works, this research introduces a comprehensive approach by combining these flexible resources to tackle power system uncertainties, minimize curtailment, and reduce operational costs. A key innovation is the adoption of a quasi-Monte Carlo simulation (QMCS) approach for scenario generation, which allows for a more precise representation of stochastic solar PV generation and its impact on system performance. Moreover, the methodology employs the GAMS framework for global optimization, which facilitates the integration of renewable energy while maintaining system stability. The choice of GAMS is particularly significant because it offers advanced capabilities for solving large-scale, non-linear optimization problems, making it an ideal tool for handling the complexities of security-constrained unit commitment in power systems. The use of QMCS further enhances the accuracy of scenario generation, providing a better approximation of the uncertainty in renewable generation compared to traditional Monte Carlo methods. This combination of tools and methodologies has not been adequately addressed in prior studies, and it allows for a more robust and reliable optimization of power system operations. By incorporating these advanced techniques, this research pushes the boundaries of traditional optimization approaches, offering new avenues for future studies to explore real-time optimization, model simplification, and the enhancement of renewable energy integration. Additionally, the flexibility introduced by ESS, DRP, and STATCOM devices provides a pathway for addressing future challenges related to grid stability and energy management in the face of increasing renewable penetration.

1.4. Paper organization

The structure of this paper unfolds as follows: In Section 2, the stochastic sources are delineated through modeling. Section 3 delves into the mathematical model underpinning the problem at hand. Methodology of the proposed scheme is expounded upon in Section 4. The numerical study and simulation findings find their place in Section 5, while Section 6 draws conclusions and outlines future prospects.

2. Distributed energy resources modelling

2.1. Solar power

The assumption is made that the output power of the photovoltaic (PV) generator can be precisely represented by a Beta distribution, as outlined in [37].

$$f(P_{PV}) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left(\frac{P_{PV}}{P_{PV}^{\max}}\right)^{\alpha-1}\left(1-\frac{P_{PV}}{P_{PV}^{\max}}\right)^{\beta-1} \tag{1}$$

As with wind energy generation, the overall cost of PV generator output can be determined using the method described in [38].

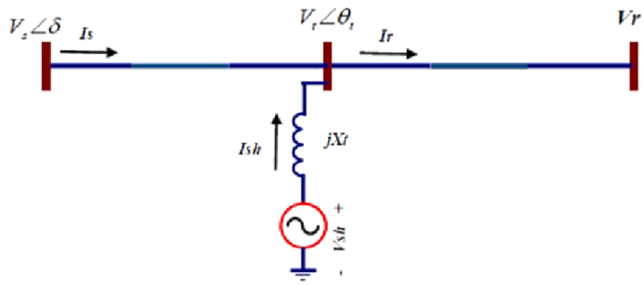

Fig. 1. STATCOM device circuit equivalent.

$$C_{Pvg,i} = C^{d}_{pvg,i} + C^{under}_{pvg,i} + C^{over}_{pvg,i} \tag{2}$$

These three cost components can be computed using the method delineated in [38].

$$C^{d}_{pvg,i} = K^{d}_{pvg,i} \times P_{pvg,i} \tag{3}$$

$$C^{under}_{pvg,i} = K^{under}_{pvg,i} \int_{P_{pvg,i}}^{P^{max}_{pvg,i}} (P - P_{pvg,i}) f_{P_{pvg}}\left(p_{pvg}\right) dp_{pvg} \tag{4}$$

$$C^{over}_{pvg,i} = K^{over}_{pvg,i} \int_{0}^{P_{pvg,i}} (P_{pvg,i} - P) f_{P_{pvg}}\left(p_{pvg}\right) dp_{pvg} \tag{5}$$

3. Mathematical modelling of STATCOM devices

A STATCOM comprises a single VSC paired with a shunt-connected transformer. Due to the absence of moving parts, it can generate and absorb reactive power more rapidly compared to a traditional spinning synchronous condenser. Functionally, it serves a similar voltage regulation role as an SVC, but with greater robustness. Unlike the SVC, the STATCOM's performance remains unaffected even at low voltage levels, making it more reliable in maintaining voltage stability. In steady-state analysis, the STATCOM can be equivalently modeled as a synchronous condenser. This analogy allows for its representation in power system simulations in a manner similar to how a synchronous generator is modeled for active power generation. Fig. 1 in the referenced material illustrates the STATCOM's equivalent circuit, which highlights its operational similarity to synchronous condensers in regular system studies. For practical applications, various operational models can be developed to integrate the STATCOM into power systems, considering different electrical configurations such as series networks. These models help in accurately assessing the STATCOM's impact on enhancing system stability and mitigating voltage fluctuations [22].

The reactive and active powers in the functioning system are established by enforcing particular key limitations. $V_{sh} = V_{sh}\angle\delta_{sh}$and $V_s = V_s\angle 0$with and as the voltage linking point and the essential section of the voltage source converter.

$$P_{\nu R} = \frac{V_{sh}V_s}{X_t}\sin\delta_{sh} \tag{6}$$

$$Q_{\nu R} = \frac{V_s^2}{X_t} - \frac{V_s V_{sh}}{X_t}\cos\delta_{sh} \tag{7}$$

$$P_i = V_i^2 G_{\nu R} + V_{\nu R} V_i (G_{\nu R}\cos(\theta_i - \delta_{\nu R}) + B_{\nu R}\sin(\theta_i - \delta_{\nu R})) \tag{8}$$

$$Q_i = -V_i^2 G_{\nu R} + V_{\nu R} V_i (G_{\nu R}\sin(\theta_i - \delta_{\nu R}) - B_{\nu R}\cos(\theta_i - \delta_{\nu R})) \tag{9}$$

3.1. Energy storage system

CAES is a highly effective technology for storing energy when electricity demand and prices are low, utilizing both traditional and renewable energy sources. This accumulated energy can be released during high-demand times when electricity costs are elevated, offering significant financial advantages. CAES's ability to balance load and optimize energy usage makes it a valuable asset for achieving cost-effectiveness and enhancing grid reliability, aligning well with the objectives of this study. The economic evaluation of CAES involves calculating various costs associated with its operation and deployment. These include the hourly variable operation costs (HVOC), which account for the fluctuating expenses of running the system, and the hourly fixed operation and maintenance costs (HFMC), which cover regular upkeep and maintenance. Additionally, the hourly arbitrage reflects the financial gains from buying and storing energy at low prices and selling it at high prices. Investment costs (IC) represent the initial capital required for setting up CAES units, while hourly conversion costs (HC) pertain to the expenses of converting stored energy back into electricity. This structured approach ensures a comprehensive assessment of CAES's economic and technical viability.

$$HVOC^{ESS}_{k,n,t} = \sum_{k=1}^{N_k} HR \times C^{ESS}_{k,n,t} \times C_{NG} \tag{10}$$

$$HFMC = \frac{\sum_{k=1}^{N_k} C^{OM}_{k}\left(P^{ESS}_{rated,k}\right)}{365 \times 24} \tag{11}$$

$$IC = \sum_{k=1}^{N_K} C_p \times S^{ESS}_k + C_c \times S^{ESS}_k + C_E \times C^{ESS}_k \tag{12}$$

$$HC = \frac{IC}{365 \times 24} \times \frac{\text{intr}(1+\text{intr})^{lf}}{(1+\text{intr})^{lf} - 1} \tag{13}$$

The total hourly operational cost of all designated CAESs (THC) in each scenario can be calculated by amalgamating various cost elements. THC can be effectively determined across different scenarios, offering insights into operational expenses.

$$THC^{ESS}_{k,n,t} = \left(HVOC^{ESS}_{k,n,t} + HFMC + HIC\right) \tag{14}$$

The functioning of ESS units is described through their charging and discharging procedures as well as their stored energy, referred to as the state of charge (SoC). These dynamics are represented by Eq. (15), where the energy level at a given hour depends on the energy from the preceding hour. The powers for charging and discharging are to be calculated by the optimization algorithm [28].

$$SOC_{k,n,t} = SOC_{k,n,t-1} + P^{ch}_{k,n,t} \times \eta^{ch} - P^{dch}_{k,n,t} \times \eta^{dch} \tag{15}$$

3.2. Problem formulation

3.2.1. Objective function

This research aims to reduce the overall operational expenses for the upcoming 24-hour period, as detailed in Eq. (16). The objective function (OF) integrates several cost components: the operational costs of thermal generators, expenses related to energy storage systems (ESS), costs incurred from load shedding, and the curtailment of solar PV power, along with the expenses associated with demand response programs (DRP). These cost components are depicted by the initial, second, third, and fourth terms of the objective function, respectively.

$$\min OF = \sum_{n=1}^{N_n} \rho_n \sum_{t=1}^{N_T} \left\{ \begin{array}{l} \sum_{g=1}^{N_G} \left(a_g P_{g,n,t}^2 + b_g P_{g,n,t} + c_g \right) I_{g,n,t} + THC_{k,n,t}^{ESS} + \sum_{b=1}^{N_b} \left(VOLL \times P_{i,n,t}^{Lsh} \right) \\ +PC_p \sum_{i=1}^{N_{pv}} P_{pv,i,n,t}^{curt} + \sum_{de=1}^{N_{de}} \left(DeR_{de,n,t}^{upp} + DeR_{de,n,t}^{dnn} \right) C_{de}^D \end{array} \right\} \tag{16}$$

To implement the proposed SCUC model, we utilized GAMS and formulated the problem as a Mixed-Integer Quadratically Constrained Programming (MIQCP) model. The decision variables include binary variables for unit commitment status and continuous variables for power generation levels, energy storage states, and demand response participation. The objective function, as represented in Eq. (16), integrates multiple cost components and is minimized using the GUROBI solver. This solver was selected due to its efficiency in handling large-scale mixed-integer optimization problems, ensuring optimal and computationally feasible solutions within a reasonable time frame.

3.2.2. Constraints

The stochastic SCUC model needs to adhere to the constraints outlined below:

a) Thermal generator constraints

The planned power outputs of the thermal generation units must comply with the requirements set forth in conditions (14) to (17). Furthermore, expressions (17) and (18) specify the maximum and minimum limits for both reactive and active powers. The constraints related to the ramp-up and ramp-down rates of the units are detailed in Eqs. (19) and (20) respectively. Additionally, minimum up and down time constraints are outlined in Eqs. (21) and (22), while start-up and shut-down constraints are detailed in Eqs. (23) and (24). Power demand constraints are specified in Eq. (25). The stochastic SCUC model under review includes ramp rate constraints for thermal units, addressing both active and reactive power limits, as expressed in Eqs. (19) and (20) for each solar PV scenario sample.

$$P_g^{\min} \le P_{g,n,t} \le P_g^{\max}, \ \forall g, n, t \tag{17}$$

$$Q_g^{\min} \le Q_{g,n,t} \le Q_g^{\max}, \ \forall g, n, t \tag{18}$$

$$P_{g,n,t} - P_{g,n,t-1} \le RU_g, \ \forall g, n, t \tag{19}$$

$$P_{g,n,t-1} - P_{g,n,t} \le RD_g, \ \forall g, n, t \tag{20}$$

$$\sum_{g\in\tau}^{N_G} y_{g,n,\tau} \le I_{g,n,t} \tau = \max\left(1, t - T_{gu}^{on} + 1\right), \ \forall g, t \tag{21}$$

$$\sum_{g\in\tau}^{N_G} z_{g,n,\tau} \le 1 - I_{g,n,t} \tau = \max\left(1, t - T_g^{off} + 1\right), \ \forall g, t \tag{22}$$

$$y_{g,n,t} - z_{g,n,t-1} = I_{g,n,t} - I_{g,n,t-1}, \ \forall g, t \tag{23}$$

$$y_{g,n,t} + z_{g,n,t} \le 1, \ \forall g, t \tag{24}$$

$$0 \le P_{D,t} \le P_{d,t}^{\max}, \ \forall t, d \tag{25}$$

b) Solar PV power constraints

As per Eq. (26), the wind power scheduled by the optimization should not exceed its maximum potential value as defined in Eq. (2). In cases where it's necessary for the scheduled solar PV power to remain below its maximum capacity, the portion that remains undelivered is referred to as solar PV power curtailment, as detailed in Eq. (19). Typically, curtailment occurs due to operational constraints within the power system, such as voltage and loading limitations.

$$P_{pv,i,n,t} \le P_{i,t}^{pv,\max}, \ \forall i, t \tag{26}$$

$$P_{pv,i,n,t}^{curt} = P_{i,t}^{pv,\max} - P_{pv,i,n,t}, \ \forall i, t \tag{27}$$

c) Power balance constraints

The power flow equations serve as critical constraints for system operations, presenting a linear AC load flow model integrating solar energy sources and ESS. These equations establish the interdependence among load, generation, and active/reactive flows within network branches. Moreover, Eqs. (28)-(29) outline the connections between these variables. Furthermore, (30) and (31) specify transmission needs, emphasizing line capacity and voltage constraints.

$$\sum_{g=1}^{N_G} P_{g,n,t} + \sum_{i=1}^{N_{pv}} P_{pv,i,n,t}^{inj} + \sum_{k=1}^{N_k} \left(P_{k,n,t}^{dch} - P_{k,n,t}^{ch} \right) - P_{D,t} = \sum_{j=1}^{N_b} V_{i,n,t} V_{j,n,t} \left(G_{ij} \cos\delta_{ij,n,t} + B_{ij} \sin\delta_{ij,n,t} \right) \tag{28}$$

$$\sum_{g=1}^{N_G} Q_{g,n,t} + \sum_{i=1}^{N_{pv}} Q_{pv,i,n,t}^{inj} + \sum_{k=1}^{N_k} \left(Q_{k,n,t}^{dch} - Q_{k,n,t}^{ch} \right) - Q_{D,t} = \sum_{j=1}^{N_b} V_{i,n,t} V_{j,n,t} \left(G_{ij} \sin\delta_{ij,n,t} - B_{ij} \cos\delta_{ij,n,t} \right) \tag{29}$$

$$V_i^{\min} \le V_{i,n,t} \le V_i^{\max}, \ \forall i, t \tag{30}$$

$$\delta_i^{\min} \le \delta_{i,n,t} \le \delta_i^{\max}, \ \forall i, t \tag{31}$$

d) ESS constraints

Buses equipped with ESS units must comply with constraints (32)-(36). It's important to note that the ESS can charge and discharge simultaneously. The SOC reflects the energy level of the ESS, which must be maintained within acceptable boundaries, represented by $SOC_i^{\min}$and$SOC_i^{\max}$, for each hour.

$$SoC_{i,n,t} = SoC_{i,n,t-1} + P_{i,n,t}^{ch} \eta^{ch} - P_{i,n,t}^{dch} \eta^{dch} \tag{32}$$

$$SoC_i^{\min} \le SoC_{k,i,n,t} \le SoC_i^{\max} \tag{33}$$

$$0 \le P_{i,n,t}^{ch} \le ch_{i,t} P_{\max}^{ESS} \tag{34}$$

$$0 \le P_{i,n,t}^{dch} \le dch_{i,t} P_{\max}^{ESS} \tag{35}$$

$$ch_{i,t} + dch_{i,t} \leq 1 \quad (36)$$

e) DRP constraints

The Demand Response (DR) program in this study operates on an incentive-based model, with its cost function incorporated into the objective function outlined in Eq. (16). DR programs are designed to adjust consumer demand for electricity through various stages, ensuring the overall efficiency and reliability of the power system. By offering incentives, these programs encourage consumers to reduce or shift their electricity usage during peak periods, thereby helping to balance supply and demand and alleviate stress on the grid. Implementing DR programs requires careful consideration of several constraints to ensure effective operation. These constraints include the availability and willingness of consumers to participate, the timing and extent of load adjustments, and the impact on overall system reliability. Additionally, the response of consumers to different incentive levels and the coordination with other system operations, such as the integration of renewable energy sources and energy storage systems, must be managed. By addressing these factors, DR programs can significantly contribute to reducing operational costs and enhancing the stability of the power system.

$$P^{DeR}_{de,n,t} = P^{FD}_{de,t} + P^{SH}_{de,n,t} \quad (37)$$

$$P^{SH}_{de,n,t} = \left(DeR^{upp}_{de,n,t} - DeR^{dnn}_{de,n,t}\right)P^{FD}_{de,t} \quad (38)$$

$$\sum_{t \in T} P^{SH}_{de,n,t} = 0 \quad (39)$$

$$0 \leq DeR^{upp}_{de,n,t} \leq DeR^{\max}_{de,t} \quad (40)$$

$$0 \leq DeR^{dnn}_{de,n,t} \leq DeR^{\max}_{d,t} \quad (41)$$

Following the implementation of DRPs, constraint (37) illustrates the net demand of the grid network. Moreover, the net load shift within the scheduled time interval must equal zero, as indicated in Eq. (39). Additionally, constraints (40) and (41) outline the restrictions for day-ahead adjustable loads. Regarding the power constraints, the model indeed incorporates both active and reactive power constraints as inequality constraints to ensure that the power output from both thermal and renewable generators does not exceed the specified limits for each time period. These power constraints are critical for ensuring the system's operational feasibility, as they account for both the maximum and minimum power that can be dispatched by each unit. The inclusion of these constraints in the inequality form ensures that the power flows and the system's stability are maintained within acceptable boundaries, while also addressing the potential issues arising from renewable energy fluctuations, such as solar power curtailment.

4. Implementation method

In this research, the stochastic optimization issue involving ESS is addressed using a MINLP model in GAMS with the GUROBI solver. The approach includes using initial grid data to determine the charging and discharging patterns of ESS, governed by specific constraints. The scheduling of ESS is based on battery capacity and electricity market prices, with an optimal dispatch strategy that integrates ESS with wind power generation for a 24-hour period. Stochastic scheduling with solar PV power is combined with VRP to optimize the hourly dispatch of ESS and energy transporters. The goal is to minimize ESS operational expenses while meeting all relevant constraints. This method is executed in GAMS using the GUROBI solver. The figure also illustrates the proposed stochastic optimization process, showing how the integration of ESS, solar PV, and transportation logistics is managed to achieve efficient and cost-effective energy system operations.

4.1. Data and methodology

The input data for the optimization study includes several key components that define the system's behavior and constraints. Thermal generation data encompasses the installed capacity, power output limits, ramp-up and ramp-down rates, and fuel costs for each of the 26 thermal generators in the IEEE 24-bus system. Renewable energy data focuses on solar photovoltaic (PV) generation, where power profiles are forecasted on an hourly basis and modeled using stochastic methods, specifically the quasi-Monte Carlo simulation (QMCS) technique to account for uncertainties. Energy storage system (ESS) data includes the capacity, charging and discharging limits, state-of-charge dynamics, and both fixed and variable costs for each ESS unit. Demand response program (DRP) data outlines the participation rates of consumers, the maximum demand reduction achievable, and the associated cost-benefit analysis for DRP implementation.

Transmission network data includes critical information about line capacities, voltage limits, and reactive power constraints for the 38 transmission lines in the IEEE 24-bus system, along with voltage stability limits at each bus. Additionally, scenario data for solar PV generation is included, with 1000 stochastic scenarios generated through the QMCS method. To reduce the complexity of these scenarios, scenario reduction is applied using K-means clustering, which reduces the scenarios to 10 per hour. These input data components are essential for the optimization process, providing a comprehensive view of the system's parameters and constraints to ensure realistic and efficient outcomes under varying

5. Case study

The methodology outlined in this research leverages GAMS as a powerful instrument for tackling optimization challenges [37]. Initially conceived as a non-convex model, it undergoes transformation into a MIQCP model. By employing the "GUROBI" solver within GAMS, the study achieves access to its globally optimal solution [38].

5.1. Test system

The developed model is evaluated using the IEEE 24-bus system, as depicted in Fig. 2. This test system features 26 thermal generators, 38 transmission lines, and 3 load blocks, as described in [39]. It also integrates renewable energy sources, including five PV farms and CAES units located at buses 1, 3, 7, 21, and 23. With a combined capacity of 100 MW for the renewable components, the significant presence of solar PV power highlights the necessity for effective scheduling strategies to manage and optimize energy generation and storage.

The IEEE 24-bus system has a peak generator load of 2850 MW and a

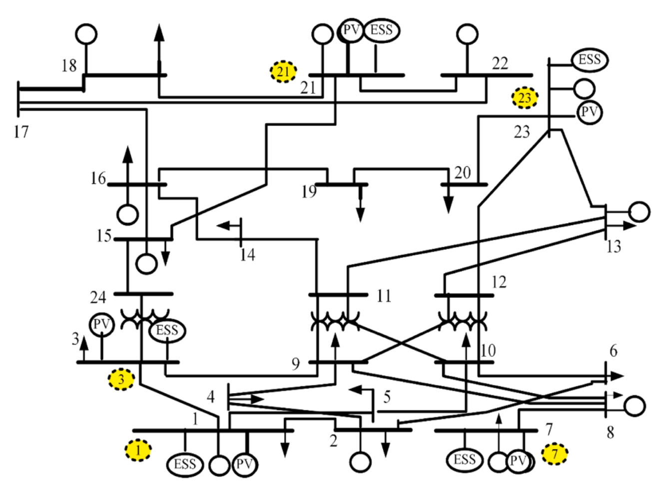

Fig. 2. Modified IEEE 24-bus network.

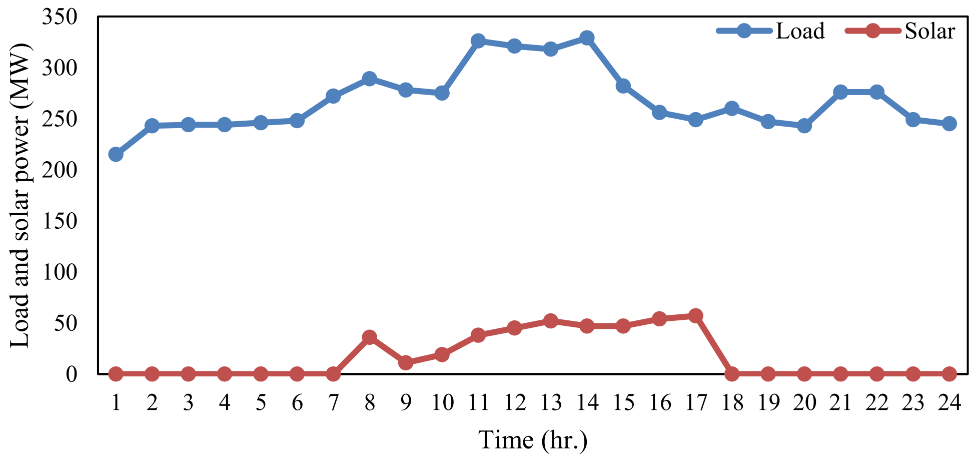

Fig. 3. Forecasted load and solar PV data.

total installed capacity of 3105 MW. Fig. 3 provides the hourly load profile data, which is essential for assessing the model's performance. Additionally, the study assumes that each demand point can participate DRPs with a maximum participation rate of 0.3. This setup ensures a comprehensive evaluation of the model's capability to handle both conventional and renewable energy sources while optimizing scheduling and operational costs.

The proposed ESS has an anticipated capacity range between a minimum of 100 MW and a maximum of 1000 MW. Released power levels are designed to vary from 5 MW to a maximum of 100 MW, with injected power similarly constrained between 5 MW and 100 MW. FACTS devices are assumed to have the flexibility to adjust network line reactance by up to ±50 %. Given that STATCOM devices are well-suited for large transmission lines prone to congestion, they are particularly practical for installation on frequently congested lines, such as major interconnections or heavily utilized segments within the network. As a result, FACTS devices are strategically assigned to lines 3 and 21. To optimize voltage stability and relieve congestion within network lines, this strategy also incorporates CAES and DRP. The cost of curtailing solar PV output is set at $87 per MWh, and the value attributed to unserved load is $1000 per MWh [38]. The variability in solar PV output is represented through a scenario generation and reduction method. A probabilistic MILP problem is proposed to tackle the uncertainties associated with solar photovoltaic systems. Initially, 1000 scenarios were created using the QMCS technique and subsequently reduced to 10 scenarios per hour through the K-means clustering method.

5.2. *Case studies*

To showcase the effectiveness of the proposed stochastic SCUC model in optimizing power distribution and demand response programs while minimizing three objectives, we apply the model to a 24-bus power system. This analysis focuses on optimizing the thermal generation, CAES systems, and DRP under the influence of correlated random variables, assessing their impact on system performance with the inclusion of STATCOM devices. The flexibility of these resources is evaluated through two distinct scenarios: (case1) baseline operation without DRP and CAES, (case2) combined optimization of thermal units, CAES, and DRP to evaluate the comprehensive benefits on system performance.

- Ø **Case I**

This section examines how incorporating thermal generation and solar PV affects system operating expenses. Fig. 4 displays the dispatch schedules for both thermal units and the solar PV facility. Units G1 through G3, G10 through G21, and G24 through G26 are continuously operational throughout the entire 24-hour period. In contrast, units G8, G9, and G23 are active only between the hours of 9 AM and 7 PM, while units G4 and G5 operate from 4 AM to midnight. The total operational expenditure, including the solar PV facility, amounts to $632,322.84. This is notably lower than the $653,244.12 expense incurred without the solar PV installation. The reduction in cost underscores the economic benefit of integrating solar PV into the energy mix. By leveraging renewable energy, the system can reduce reliance on more expensive thermal generation, thereby decreasing overall operational costs. In Case 1, the operational costs are primarily driven by thermal generation,

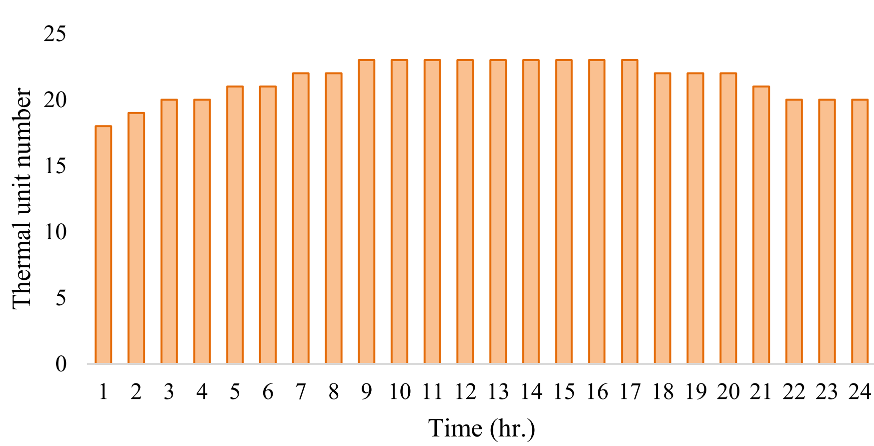

Fig. 4. Scheduling of thermal units alongside projected solar PV installations.

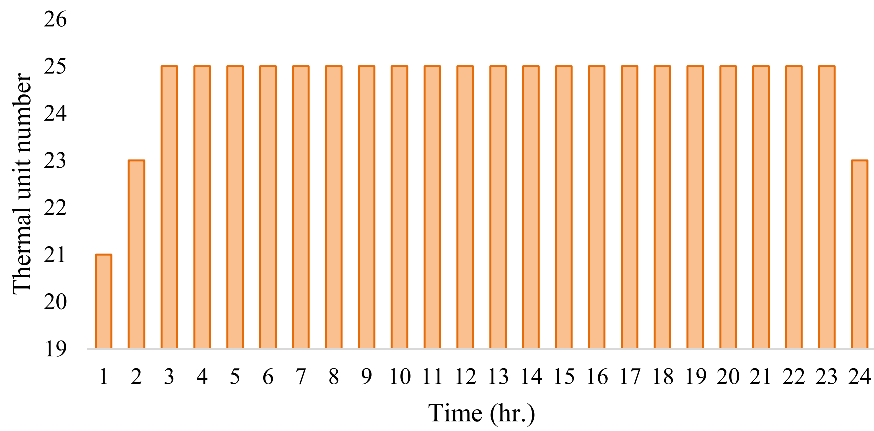

Fig. 5. Scheduling of thermal units alongside solar PV power, ESS, DRP, and incorporating STATCOM devices.

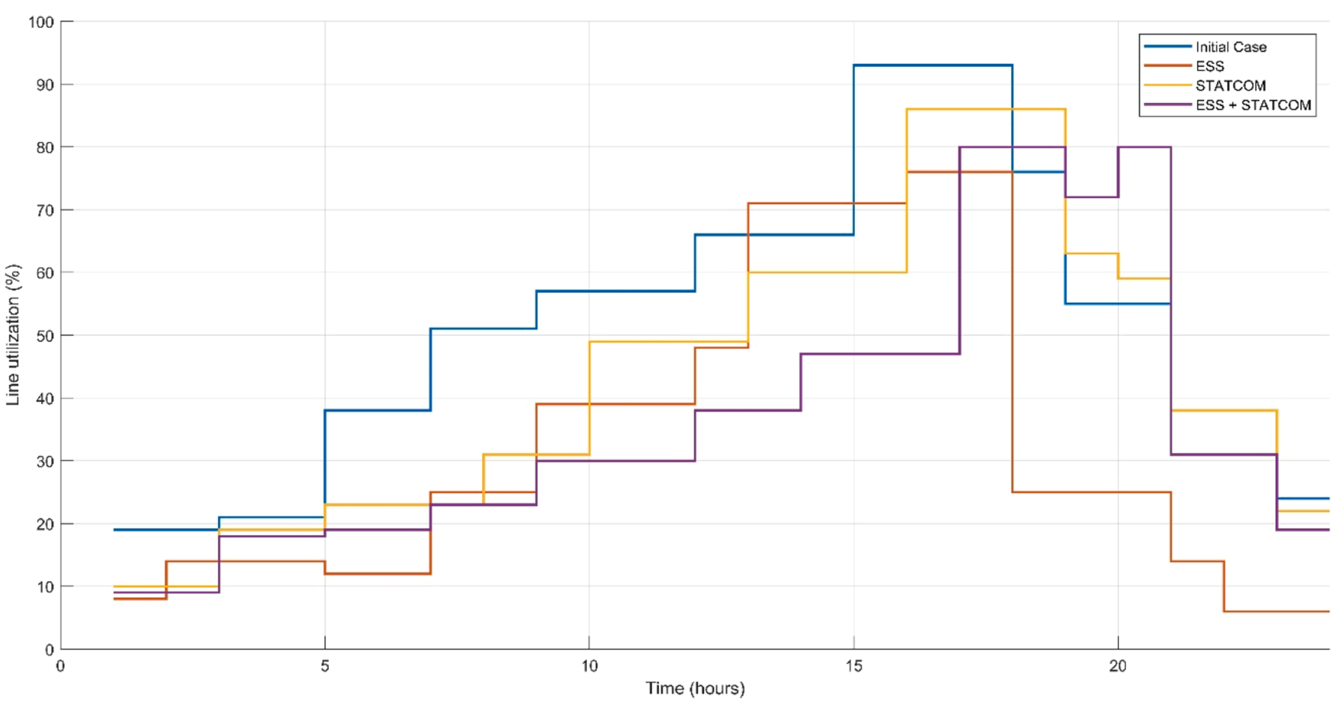

Fig. 6. Line utilization of solar PV.

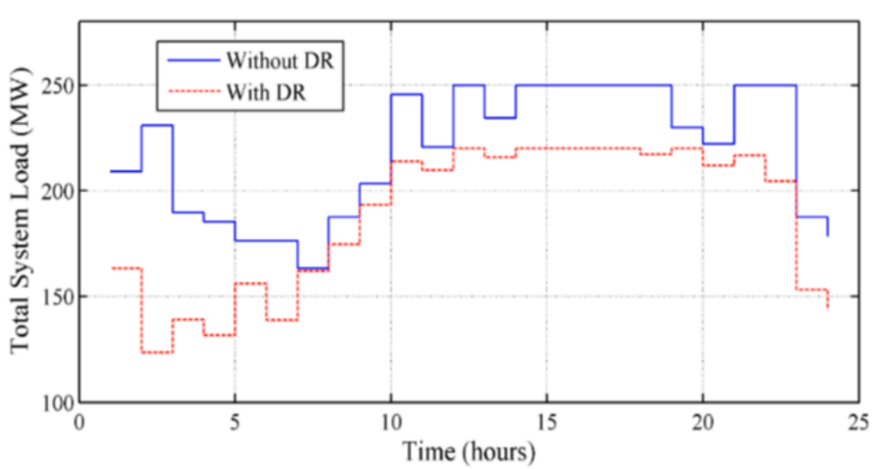

Fig. 7. Total system load of Case 2.

with minimal integration of renewable energy sources. The comparison with Case 2 shows a significant reduction in operational costs due to the incorporation of solar PV, ESS, and DRPs. Additionally, voltage stability is improved as the system utilizes flexible resources to balance load fluctuations more effectively.

Ø **Case II**

This research utilizes stochastic optimization within the SCUC framework, incorporating ESS, solar PV scenarios, and a DRP, alongside STATCOM devices. The QMCS technique addresses the variability in solar PV output. As illustrated in Fig. 5, the DRPs associated with each ESS substantially lower peak demands, improve troughs, and balance load distribution. This adjustment results in increased generation from the most cost-effective units (G1 to G3, G8 to G20) and decreased output from higher-cost thermal units (G6, G7, G21). The highest-cost unit at bus 23 is deactivated from hours 4 to 24. The total operational expenditure in this case is $598,765.32. The expense is influenced by the solar PV power uncertainty modeling, with an 85 % commitment for ESS, DRP, and STATCOM devices. The optimization of thermal units, CAES, and DRP under stochastic conditions significantly reduces the peak demand, balancing the load and improving the efficiency of renewable energy utilization. The DRPs help shift the demand to off-peak hours, thereby reducing the need for costly thermal generation, particularly during the high-cost periods.

In Fig. 6, for line 1, transmission usage is high in the morning and drops in the afternoon due to STATCOM devices. Under Case 2, line 1 is active continuously from hours 6 to 19, highlighting STATCOM's role in managing optimal power flow based on varying solar PV input.

Fig. 7 illustrates the total system load for Case 2, both with and without DR. Fig. 8 displays the results of scheduling for the charging and discharging of ESS in Case 2. ESS units are charged in the early hours when electricity prices are low and discharged between 7 AM and 1 PM. Charging activity is concentrated at nodes 1, 3, 7, 21, and 23, whereas discharging occurs primarily at nodes 4, 15, 16, 17, and 24. This demonstrates that efficient use of DRPs and ESS can enhance network performance.

ESS and STATCOM devices work together by providing voltage support and stabilizing the grid during periods of high demand or volatility. While ESS absorbs excess renewable energy during low demand and discharges during high demand, STATCOM optimizes the voltage profile and manages transmission congestion, ensuring more stable and efficient power delivery across the network. Table 1 provides insights into several parameters including the objective function, costs associated with ESS and DRP, fuel expenses, start-up charges, and the projected curtailment of renewable energy across Cases 1 to 3. Notably, the overall objective function value diminishes from Case 1 to Case 3, indicating a decrease in ESS costs alongside an escalation in DRP costs, which implies a decline in revenue. Given that renewable energy capacity is relatively small compared to thermal power units, the power system can achieve near-total efficiency in utilizing renewable energy, approaching 100 %. These results align with the optimized performance of the electricity market.

Table 1
Simulation outcomes for each scenario on the IEEE 24-bus network.

Cases	SCUC costs ($)	ESS costs ($)	DRP costs ($)	Solar Curtailment (MWh)	Computational Time (s)
1	574,838.94	–	–	120	314
2	543,139.41	97.85	1102.90	39.29	918

Based on Fig. 8(a), the 5.6 % reduction in scheduling costs compared to traditional methods can be explained through the impact of increasing renewable energy penetration on overall system costs. In the traditional approach, which relies more on fossil fuels, fuel expenses are significantly higher, leading to greater scheduling costs. In Case 1, where renewable energy penetration is only 20 %, the SCUC cost reaches $600,000 due to the high dependency on thermal power generation. Based on Fig. 8(b) renewable energy penetration increases, the reliance on fossil fuels decreases, leading to a reduction in fuel costs. In Case 2, with 50 % renewable energy integration, fuel costs drop to $350,000. Although additional costs arise from energy storage systems (ESS) and demand response programs (DRP) to manage renewable variability, the total scheduling cost decreases to $570,000, reflecting a 5 % cost reduction from the traditional method.In Case 3, where renewable energy penetration reaches 80 %, fuel costs further decline to $290,000. While ESS and DRP costs continue to rise, the overall scheduling cost decreases to $565,000, achieving the observed 5.6 % reduction. This demonstrates that despite the additional expenses for grid stability, the savings from reduced fuel consumption outweigh the increased costs. Furthermore, higher renewable energy integration leads to better utilization of available resources, minimizing curtailment. In Case 1, solar curtailment is 100 MWh, indicating inefficiencies in utilizing renewable generation. However, in Case 3, curtailment drops to just 10 MWh, signifying a more optimized use of renewable energy without excessive losses.

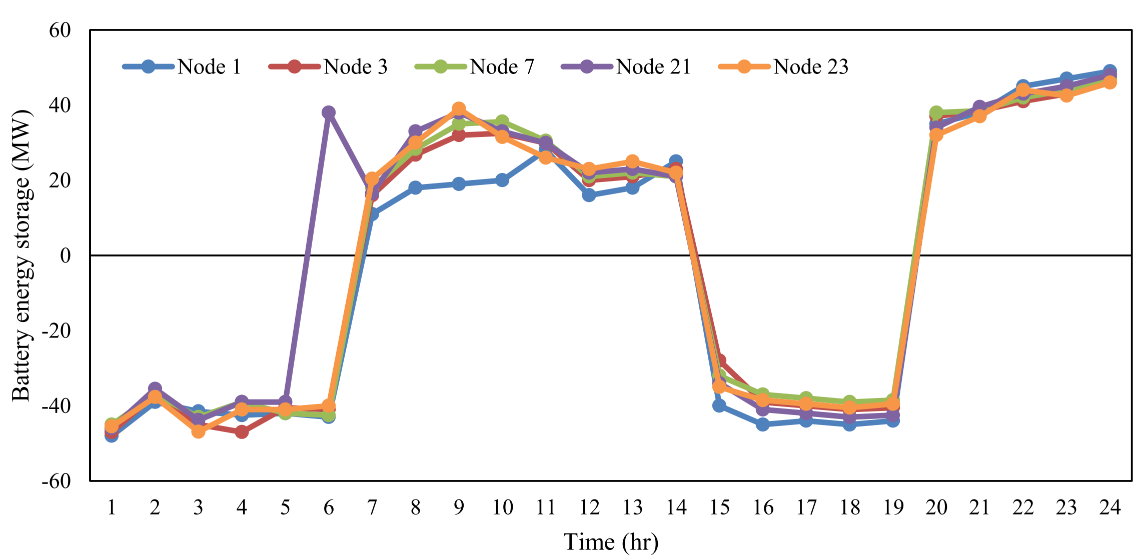

Fig. 8. Power levels for charging and discharging of each ESS in Case 2.

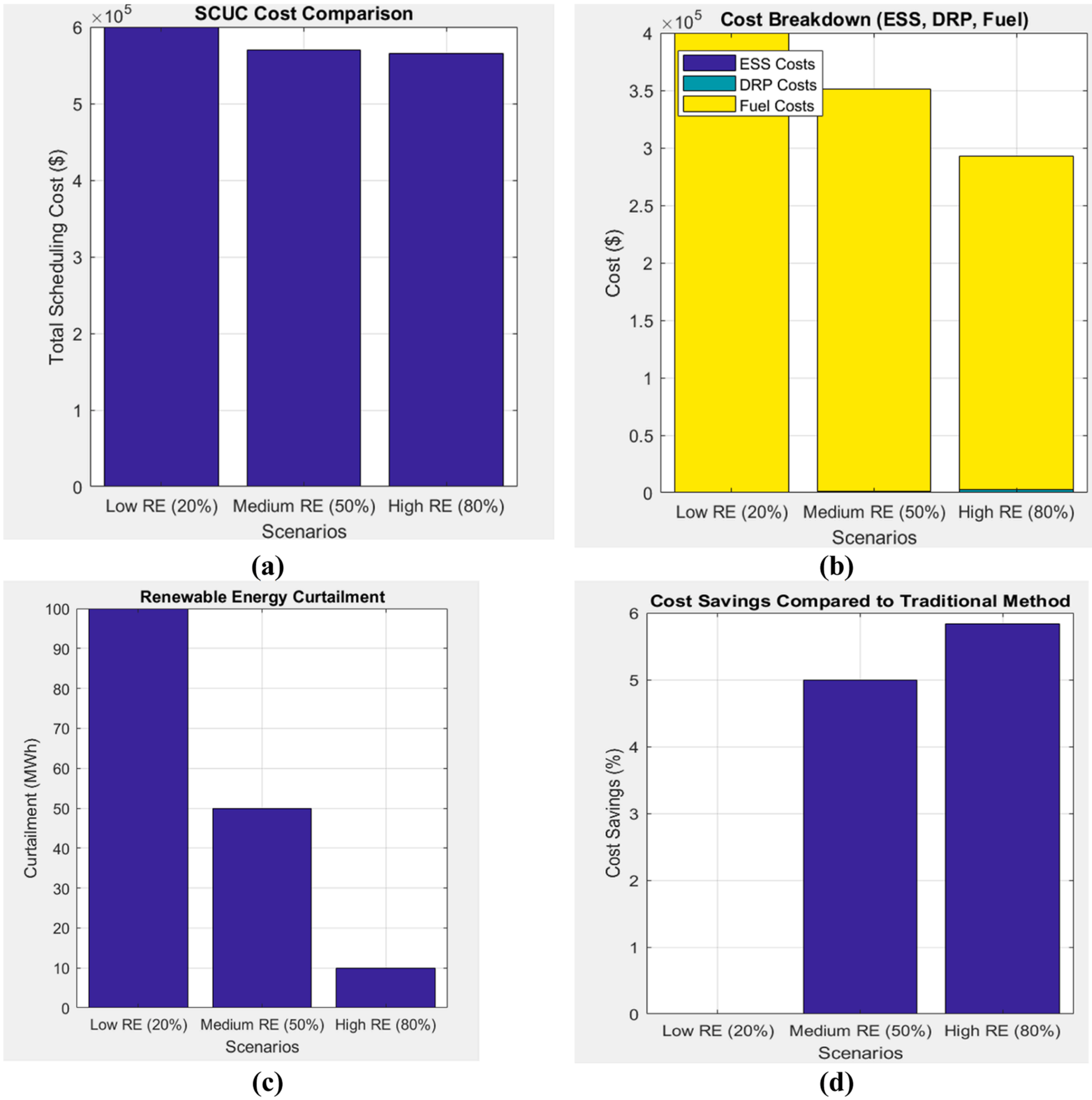

Fig. 9. Amount of Cost breakdown, cost saving and curtailment per scenarios.

According to Fig. 9, the 5.6 % cost savings can be attributed to improved efficiency in utilizing renewable energy. While ESS and DRP costs increase with higher renewable penetration, the substantial reduction in fuel consumption results in lower total scheduling costs. This highlights the economic advantage of transitioning towards a more renewable-dependent power system.

6. Conclusion

This study presents a comprehensive single-stage stochastic SCUC optimization model tailored for the IEEE 24-bus system, effectively incorporating PV uncertainties and STATCOM devices. The developed model, structured as a MIQCP problem, integrates all relevant operational constraints and AC power flow equations. By implementing this convex model in GAMS and optimizing it with GUROBI's global optimum solver, we have achieved a refined approach to optimizing the scheduling of ESS and DRP. The utilization of STATCOM devices within this framework addresses voltage stability challenges and enhances system reliability. The incorporation of QMCS alongside Cholesky decomposition for scenario generation ensures a precise and reliable representation of uncertainties while preserving the original correlation matrix. The optimization focuses on minimizing three key objectives: the total operational cost of ESS, the overall reserve costs, and the expenses associated with DR. The findings demonstrate that integrating solar PV farms with ESS and STATCOM devices not only improves voltage stability but also offers a cost-effective solution for managing energy markets and addressing network problems. This approach underscores the potential of advanced optimization techniques and strategic integration of renewable energy sources to enhance the efficiency and reliability of modern power systems.While the proposed model demonstrates promising results, there are several areas where further research could be pursued to enhance its applicability and performance. One potential direction for future work is the implementation of real-time optimization techniques, which would allow for dynamic adjustments based on changing grid conditions, such as fluctuations in solar power generation or demand. This would enable a more adaptive and responsive approach to energy management.

Additionally, the complexity of the model could be reduced while maintaining its accuracy. Techniques such as surrogate modeling, machine learning, or approximation methods could be explored to speed up the computations without sacrificing the quality of optimization. Another valuable avenue for future research would be the integration of other emerging technologies. For instance, incorporating advanced energy storage systems with higher capacities, decentralized energy systems like microgrids, or advanced demand-side management strategies could further enhance the performance and reliability of the system. Moreover, expanding the model to include multi-objective optimization could help balance trade-offs between different system goals, such as minimizing operational costs while ensuring environmental sustainability, grid reliability, and social welfare. Further studies could also focus on conducting sensitivity analysis to assess how changes in renewable energy penetration or other key parameters affect the performance of the model. This would provide insights into the robustness and adaptability of the approach under various conditions. Finally, exploring the impact of various policy and regulatory frameworks on the system could provide valuable insights. Understanding how different incentive schemes or regulatory restrictions influence the cost-effectiveness and feasibility of integrating renewable energy sources into the grid is an important research direction.

CRediT authorship contribution statement

Sina Samadi Gharehveran: Writing – original draft, Software, Methodology, Conceptualization. **Kimia Shirini:** Writing – review & editing, Methodology, Conceptualization. **Selma Cheshmeh Khavar:** Writing – review & editing, Methodology, Conceptualization. **Arya Abdollahi:** Writing – review & editing, Validation, Investigation.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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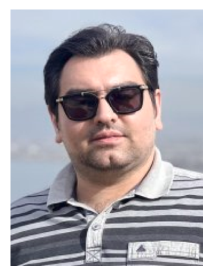

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