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Energy Storage System Analysis Review for Optimal Unit Commitment

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Abstract: Energy storage systems (ESSs) are essential to ensure continuity of energy supply and maintain the reliability of modern power systems. Intermittency and uncertainty of renewable generations due to fluctuating weather conditions as well as uncertain behavior of load demand make ESSs an integral part of power system flexibility management. Typically, the load demand profile can be categorized into peak and off-peak periods, and adding power from renewable generations makes the load-generation dynamics more complicated. Therefore, the thermal generation (TG) units need to be turned on and off more frequently to meet the system load demand. In view of this, several research efforts have been directed towards analyzing the benefits of ESSs in solving optimal unit commitment (UC) problems, minimizing operating costs, and maximizing profits while ensuring supply reliability. In this paper, some recent research works and relevant UC models incorporating ESSs towards solving the abovementioned power system operational issues are reviewed and summarized to give prospective researchers a clear concept and tip-off on finding efficient solutions for future power system flexibility management. Conclusively, an example problem is simulated for the visualization of the formulation of UC problems with ESSs and solutions.

Keywords: energy storage systems; power system flexibility management; renewable energy generations; load leveling; optimal unit commitment

1. Introduction

Energy production using renewable energy resources has been on the increase on a daily basis all over the world and will likely continue to increase over the next few years; on the other hand, fossil-fuel-based energy productions will likely decline. It is expected, in the future, that the lion's share of energy will be produced from alternative energy sources, such as solar and wind energy. There are many reasons behind the increasing renewable generation installations. For example, installations of renewable energies are increasing for saving fossil fuels [1]. Additionally, urbanization and industrialization are increasing the demand for fossil fuels; consequently, the price of fossil fuels is rising all over the world. In addition, the demand for electricity has been growing worldwide because of population growth and other socioeconomic factors [2]. Moreover, deregulation and liberalization of the power market have led to growing competition among power producers [3,4]; therefore, power companies are trying to reduce the operational costs of their services. Typically, the operational costs of renewable generations are comparatively lower than fossil-fuel-based thermal generations (TGs). Furthermore, burning fossil fuels continuously for power generation produces enormous CO_2 and other greenhouse gas emissions into the environment [5]. The United States Environmental Protection Agency (EPA) demonstrated that around 32% of CO_2 emissions are caused by fossil-fuel-based power generation [6]. However, power generation companies still depend mainly on fossil fuels to ensure adequacy, reliability, and flexibility of supply. TGs make use of a large quantity of fossil fuels to generate electricity; for instance, the U.S. Energy Information and Administration (EIA) states that the United States (U.S.) is producing more than 65% of its electricity by burning fossil fuels [7], having already installed (and planning to install) a large number of renewable generators.

However, both wind turbine generators (WTGs) and PV suffer from what is known as intermittency [8–12] because winds have a nasty habit of abruptly dying or springing up, while the sun will also disappear behind clouds and injects no power at night from PV. Sometimes due to these reasons, within short bursts of several seconds, there may be too much power, too little power, or total blackout within the grid. The power output of WTG and PV depends on weather conditions, and power smoothing of WTG and PV outputs remains a technically challenging task [13,14]. WTG has huge ramp up and down requirements, and PV generates power only during the day, besides, they have the uncertainty of power output [15–19]. Renewable generation also has frequency distortions due to the continuously changing mismatches between the generation and demand, instantaneously [20,21]. Due to these problems, the effective load after considering the power output from the renewable energy generators as a negative load fluctuates widely. Hence, the other fossil-fuel-based TGs cannot run optimally since achieving an effective optimal unit commitment (UC) becomes very difficult as a result of load uncertainties [22]. This is because the load curve becomes intractable after the penetration of the renewable generators and the peak and off-peak gap increase in most cases; therefore, TG in the grid needs to be frequently turned off and on. Although coal-based or quick-response generators can be run as spinning reserves for solving these kinds of problems, these generators are polluting the environment massively. Therefore, energy storage systems (ESSs) have currently been installed in the smart grid to smoothing the generators' power output [23]. Several research works have been carried out on the configuration and development of sufficient energy storage facilities for power system flexibility, reliable operation, and management [24].

This review paper elaborates on the contribution of the ESS for optimal UC, which may involve the minimization of the operational costs or maximization of profit of the power systems under large-scale or small-scale renewable energy penetrations. Typically, renewable generations come with immense technical, economic, and environmental benefits for power system operators as well as the entire society. However, some technical challenges come with renewable energy integration, as highlighted in the previous paragraphs. Most of these problems that are directly related to optimal UC have been solved using the effective deployment of different energy storage facilities, and many review articles have already been published for summarizing the UC model. However, a thorough review of recent works of literature that have investigated the impacts associated with UC models when high penetrations of renewable energy are considered in the power system is reported in [25]. Another research is conducted to find a probabilistic model for UC operation to quantify the effect of the electric vehicle to the grid in different operational times in contrast. The research focuses on several producers and consumers within a microgrid based on cost-benefit analysis and it makes a comparison of the results with a deterministic model [26]. In Reference [27], the literate review for the past several years to demonstrate the modeling and computational aspects of stochastic optimization-based UC are reported. Reference [28] conducts a clear review by citing many peer-reviewed papers and then summarizes the latest techniques employed in optimizing UC problems for both stochastic and deterministic loads. Reference [29] tries to give a structured bibliographic survey for UC problems by applying a stochastic programming approach. However, this particular review work does not focus on ESSs contribution to the UC program.

2. A Short Literature Review on UC Models

The problem of UC is to determine which units of system generators to deploy and interconnect over the next operational periods, which is commonly 24 or 48 h; sometimes, it is also possible to solve UC for a week at a time. The problem is complex and can become more complicated by the consideration of intertemporal constraints. Several UC problems have been designed for solving various powers system operation problems, as reflected on the objective functions, simulation conditions, and optimization methods [30–32]. Succinctly, the UC problem in the power system can be defined as a broad set of mathematical optimization problems, where the production of a combination of power generators is coordinated in order to achieve some common targets. The usual targets are to maximize profit, minimize cost, and more.

2.1. Profit Maximization UC

The restructuring in conventional power systems has resulted in more challenges for the power producer. It becomes an essential strategy for the power company to make an optimal schedule for generations to survive in a competitive deregulated market. Many researchers have published articles related to profit maximization, which are summarized below [33–35].

2.1.1. Objective Function

The following problem formulation for UC in Equations (1) and (2) show the objective function for profit maximization.

$$\max\ F = \sum_{t=1}^{T}\sum_{g=1}^{G}\left[FP_t(P_t^g) - \left(f^g(P_t^g) + (SUC_i^g\left(1 - uc_{t-1}^g\right)\right)\right]uc_t^g. \tag{1}$$

$$f^g(P_t^g) = a^g + b^g P_t^g + c^g(P_t^g)^2 \qquad g \in [1, G],\ \ t \in [1, T]. \tag{2}$$

$$SUC^g \begin{cases} HS^g; & MTD^g \leq Toff_t^g \leq MTD^g + TOC^g, \\ CS^g; & Toff_t^g \geq MTD^g + TOC^g, \\ g \in [1, G],\ \ t \in [1, T]. \end{cases} \tag{3}$$

2.1.2. Decision Variables

The decision variables are two types; the binary variables (uc_t^g) 0 and 1 for the OFF and ON status of system generator units, respectively, and the real decision variable P_t^g that gives the scheduled power (MWh) of g^{th} committed unit at hour t (when (uc_t^g) = 1). The real decision variable range is $[p_{min}^g, p_{max}^g]$.

2.1.3. UC Constraints

(i) Spinning reserve constraint

$$\sum_{g=1}^{G} p_{max}^g uc_t^g \leq LD_t + MSR_t \quad g \in [1, G],\ \ t \in [1, T]. \tag{4}$$

(ii) Minimum OFF time and ON time constraints

$$\left(Ton_t^g - MUT^g\right)\left(uc_{t-1-uc_t^g}^g\right) \geq 0 \quad g \in [1, G],\ \ t \in [1, T]. \tag{5}$$

$$Ton_t^g = \left(Ton_{t-1}^g + 1\right)uc_t^g \quad g \in [1, G],\ \ t \in [1, T]. \tag{6}$$

$$\left(Toff_t^g - MDT^g\right)\left(uc_t^g - uc_{t-1}^g\right) \geq 0 \quad g \in [1, G], \ \ t \in [1, T]. \tag{7}$$

$$Toff_t^g = \left(Toff_{t-1}^g + 1\right)\left(1 - uc_t^g\right) \quad g \in [1, G], \ \ t \in [1, T]. \tag{8}$$

(iii) Initial status of Unit

$$uc_{t=0}^g \begin{cases} 0; IS^g < 0, \\ 1; IS^g > 0, \\ g \in [1, G]. \end{cases} \tag{9}$$

(iv) Load Demand Constraints

$$\sum_{g=1}^{G} P_t^g uc_t^g \leq L_t \quad g \in [1, G], \ \ t \in [1, T]. \tag{10}$$

(v) Generator's output power constraints

$$P_{min}^g \leq P_t^g \leq P_{max}^g \quad g \in [1, G], \ \ t \in [1, T]. \tag{11}$$

(vi) Generation Ramp rate

$$P_t^g - P_{t-1}^g \leq RU^g \quad g \in [1, G], \ \ t \in [1, T]. \tag{12}$$

$$P_{t-1}^g - P^g \leq RD^g \quad g \in [1, G], \ \ t \in [1, T]. \tag{13}$$

2.2. Cost Minimization UC

There are several papers on UC for minimizing system costs, but each of them is distinct from each author's viewpoint. Each manuscript solves UC problem by considering different conditions and constraints [36–39]. Reference [40] represents a UC problem formulation for minimizing cost as follows:

Objective Function

The objective function is to minimize the total production cost; Equation (14) expressed the objective function, and the fuel cost f and start-up cost SUC are as expressed in Equation (2) and (3), respectively. This minimization UC problem considers the same thermal UC constraints like profit maximization (see Section 2.1.2).

$$\min F = \sum_{t=1}^{T} \sum_{g=1}^{G} \left[f^g(P_t^g) + (SUC_i^g(1 - uc_{t-1}^g) \right] \quad g \in [1, G], \ \ t \in [1, T]. \tag{14}$$

2.3. Stochastic UC Problem

In recent times, the stochastic UC problem has been an interesting area for researchers due to the high penetration of renewable generation into the grid [41–47]. Renewable generations have the uncertainty of power output; that is why the introduction of stochastic UC programming is becoming very necessary [48,49]. Most of the recent papers have considered two or multistage stochastic UC [50–55]. Some articles considered hybrid scholastic UC to manage uncertainty on the expected net load [56]. The hybrid UC scheme applies the stochastic formulation to the initial operating hours of the optimization horizon so as to get a more accurate expected generation [57]. All of these stochastic UC models have been proven to increase the system efficiency using different optimization algorithms. A probabilistic UC problem considering incentive-based demand response (DR) and a high level of wind power are described in [58]:

2.3.1. Main Program Formulation for Stochastic UC

This proposed probabilistic thermal UC model lays emphasis on reducing the operational cost. The objective function F is shown in Equation (15).

$$\min F = \sum_{t=1}^{T} \left(\sum_{g=1}^{G} \left[f_t^g uc_t^g + \pi_{g,t}^{up} + \pi_{g,t}^{dn} \right) + A_t (D_t^o - D_t \right) \quad g \in [1, G], \ t \in [1, T]. \tag{15}$$

Here, fuel cost f_t^g is conditioned on the fuel type k and the generator's constraints are expressed considering the fuel types in Equation (16).

$$f_t^g = \alpha_{g,k}^1 + \alpha_{g,k}^2 P_t^g + \alpha_{g,k}^3 (P_t^g)^2 \left| \alpha_{g,k}^4 \times \sin \left\{ \alpha_{g,k}^5 \left(P_{g,k}^{min} - P_{g,k} \right) \right\} \right| \quad g \in [1, G], \ t \in [1, T]. \tag{16}$$

2.3.2. Constraints

Program constraints and some related formulations to fulfill the requirement for optimal objective values are listed below.

(i) Power output constraint of unit g

$$P_{g,k}^{min} \leq P_t^g \leq P_{g,k}^{max} \quad g \in [1, G], \ t \in [1, T]. \tag{17}$$

(ii) Start-up function

$$\pi_{g,t}^{up} = \begin{cases} \pi_g^h uc_t^g (1 - uc_{t-1}^g), & \text{if } \sum_{t'=t-HS^g-CS^g}^{t-1} uc_{t'}^g > 0, \\ \pi_g^c uc_t^g & \text{otherwise}, \\ g \in [1, G], \ t \in [1, T]. \end{cases} \tag{18}$$

(iii) Start-off function

$$\pi_{g,t}^{dn} = \pi_{g,fix}^{dn} uc_{t-1}^g (1 - uc_t^g) \quad g \in [1, G], \ t \in [1, T]. \tag{19}$$

(iv) Power balance constraint

$$\sum_{g=1}^{G} = P_t^g u_t^g = D_t \quad g \in [1, G], \ t \in [1, T]. \tag{20}$$

$$D_t = (1 - \eta) D_t^o + D_t^e \quad g \in [1, G], \ t \in [1, T]. \tag{21}$$

$$D_t^e = \eta D_t^o \left(1 + \sum_{t'-1}^{G} E_{t,t'} \frac{\pi_{t'} - \pi_{t'}^o + A_t}{\pi_{t'}^o} \right). \tag{22}$$

(v) Incentive value limit

$$A_t^{min} \leq A_t \leq A_t^{max} \quad t \in [1, T]. \tag{23}$$

(vi) Power output constraint of unit g

$$P_{g,t}^{min} u_t^g \leq P_t^g u_t^g \leq P_{g,t}^{max} uc_t^g \quad g \in [1, G], \ t \in [1, T]. \tag{24}$$

$$P_{g,t}^{min} = \min \left(p_g^{max}, P_{t-1}^g + \Delta P_i^{up} \right) \quad g \in [1, G], \ t \in [1, T]. \tag{25}$$

$$P_{g,t}^{max} = \max \left(p_g^{min}, P_{t-1}^g + \Delta P_i^{dn} \right) \quad g \in [1, G], \ t \in [1, T]. \tag{26}$$

(vii) Turned on constraint

$$\sum_{t'=t-MUT^g}^{t-1} = MUT^g \text{ if } uc_t^g - uc_{t-1}^g = -1 \quad g \in [1, G], \ t \in [1, T]. \tag{27}$$

(viii) Turned off constraint

$$\sum_{t'=t-MTD^g}^{t-1} = MTD^g \text{ if } uc_t^g - uc_{t-1}^g = 1 \quad g \in [1, G], \ t \in [1, T]. \tag{28}$$

(ix) Up/Down reserves constraints

$$r_t^{up} = \sum \min\left(P_g^{max} - P_t^g, 10\Delta, P_i^{max}\right) uc_t^g \quad g \in [1, G], \ t \in [1, T]. \tag{29}$$

$$r_t^{dn} = \sum \min\left(P_t^g - P_g^{min}, 10\Delta P_i^{max}\right) uc_t^g \quad g \in [1, G], \ t \in [1, T]. \tag{30}$$

(x) Probability function (Prob)

$$\sum_k \left\{ p_k^{out} Prob\Big(-r_t^{dn} \le D_t P_{(\omega t, t)}^w - D_t^o \le r_t^{up} \Big) \right\} \ge \Big(1 - \varepsilon\Big) \quad g \in [1, G], \ t \in [1, T]. \tag{31}$$

The proposed stochastic UC improves the conventional form of the UC problem by integrating short-term security restriction in Equation (15). In Equation (15), a simultaneous probability occurrence of forecasting error of the residual demand is imposed on one hand; and a limit on the generator's outage beyond the balancing capacity of the scheduled up/down spinning reserves is imposed on the other. To satisfy Equation (15), in addition to the hourly power outputs of conventional generating units and on/off UC status, the system operator can set up four types of hourly decision variables; which are (1) the traditional up/down spinning reserve, (2) the amount of incentive value, (3) the wind curtailment levels, and (4) loads provided by incentive-based demand response program.

2.4. Multiobjective UC Problem

Most of the multiobjective UC problems are formulated as an extension of the stochastic UC problems for the simultaneous realization of more than one objective of system operators. A novel multipurpose operation planning method for minimizing the prediction error of power generated from solar PV generators to achieve the optimal reduction of the operating cost and improve the voltage stability of power systems, simultaneously, was reported in [59]. An optimally scheduled demand response (DR) program and properly sized storage system are considered as the main parameters for voltage stability improvement and PV output prediction error minimization. The stochastic programming algorithm is deemed to provide adequate treatment of the uncertainty of PV output and coordination of demand response for consumer side management. The multiobjective genetic algorithm (MOGA) and the neural network toolbox in MATLAB library were used in the research study. The detailed problem formulation is described below.

2.4.1. Problem Formulation

The operation approach is divided into three parts: the prediction section, the UC section, and the multi-objective schedule section of the stochastic UC problem. Equation (32) shows the objective function for minimizing the total operation cost, and a two-stage stochastic programming problem for UC was implemented as described below:

$$\min \ OC = \sum_t \left[\sum_g c_i(\hat{u}_{gt}, \hat{P}_{gt}, \hat{r}_{gt}) + h(\hat{D}r_t) + \sigma(P\hat{V}_t^{curt}) + \mathbf{E}[\phi(\hat{\mathbf{x}}, \omega)] \right]. \tag{32}$$

2.4.2. Constraint Functions

$$s.t. \quad \sum_{s}(\hat{P}_{st} \cdot \hat{u}_{st}) + \hat{Ess}_{st} + \sum_{j} S_{jt} = d_{st}^{fr} - \hat{PV}_{st}. \tag{33}$$

$$(\hat{u}_{gt}, \hat{P}_{gt}, \hat{r}_{gt}) \in \mathcal{Q}_i. \tag{34}$$

$$(\hat{Dr}_t) \in \mathcal{D}. \tag{35}$$

$$(\hat{Ess}_t) \in \mathcal{E}. \tag{36}$$

$$0 \leq \hat{PV}_t \leq PV_t^{max}. \tag{37}$$

$$\hat{PV}_t^{curt} = PV_t^{max} - \hat{PV}_t. \tag{38}$$

Physical operations of the generator, such as generator output limits, generator ramp limits, and minimum up- and down-time constraints, belong to the constraint set $\mathcal{Q}$ in Equation (34). Demand response and energy storage system constraints set are $\mathcal{D}$ in Equation (35) and $\mathcal{E}$ in Equation (36). PV output control constraints are determined by Equations (37) and (38).

The second-stage objective function, which consists of the resource cost ϕ for each scenario ω, is derived below:

$$\begin{aligned}\phi(\hat{\mathbf{x}}, \omega) = \min \sum_{g} q_g(\tilde{r}_{gt}^{up}(\omega), \tilde{r}_{gt}^{dn}(\omega)) + v \cdot \tilde{l}_t(\omega) + \theta(\tilde{Dr}_t(\omega)) \\ + \beta(\tilde{PV}_t^{curt}(\omega)) + \gamma(\tilde{Ess}_t^{up}(\omega), \tilde{Ess}_t^{dn}(\omega)).\end{aligned} \tag{39}$$

$$\begin{aligned} s.t. \quad \sum_{k}[\hat{g}_{kt} \cdot \hat{u}_{kt} + \tilde{r}_{kt}^{up}(\omega) - \tilde{r}_{kt}^{dn}(\omega)] + \sum_{j} S_{jt} + \hat{Ess}_{kt} + \tilde{Ess}_{kt}^{up}(\omega) - \tilde{Ess}_{kt}^{dn}(\omega), \\ = [d_{kt}^{fr} + \varepsilon_{kt}^{d}] - \tilde{Dr}_{kt} - \tilde{l}_{kt}(\omega) - \tilde{PV}_{kt}(\omega).\end{aligned} \tag{40}$$

$$0 \leq \tilde{r}_{it}^{up}(\omega) \leq b_{it}(\omega) \cdot \hat{r}_{it}^{up}. \tag{41}$$

$$0 \leq \tilde{r}_{it}^{dn}(\omega) \leq (1 - b_{it}(\omega)) \cdot \hat{r}_{it}^{dn}. \tag{42}$$

$$0 \leq \tilde{l}_t(\omega) \leq l_t^{max}. \tag{43}$$

$$0 \leq \tilde{Dr}_t(\omega) \leq \hat{Dr}_t. \tag{44}$$

$$(\hat{Ess}_t, \tilde{Ess}_t^{up} \tilde{Ess}_t^{dn}) \in \mathcal{E}. \tag{45}$$

$$0 \leq \tilde{PV}_t(\omega) \leq PV_t^{max}. \tag{46}$$

$$\tilde{PV}_t^{curt}(\omega) = PV_t^{max} - \tilde{PV}_t(\omega). \tag{47}$$

Equation (40) shows the real time demand and supply balance constraints. Equations (41) and (42) present the ramp-up and ramp-down of the generator in real time; where ε^d is the load demand forecasted error in scenario ω.

2.5. Multiobjective Schedule

The UC state on the prior day and the actual PV power output are used in this multiobjective method. Equations (48) and (49) are operating costs (OC) of the day and the voltage stability index (VSI), respectively. In this research, voltage stability is taken into consideration as the second objective function to improve power system stability. The detail of the voltage stability index (VSI) used in this work is contained in [60]; it is called the critical boundary index (CBI), which is a direct estimate of the distance between the current operating point of the power system to the nearest voltage collapse point. CBI gives a satisfactory result for monitoring the stability of the power system with high penetration of PV and energy storage facilities.

$$\min F_1 = OC. \tag{48}$$

$$\max F_2 = VSI. \tag{49}$$

3. Overview of Algorithms for Solving UC Problem

There are several research works on deploying suitable optimization algorithms for solving UC problems; hence, different types of optimization algorithms have been implemented to get optimal UC solutions. A review of existing literature on the UC problem solution approach depicts that researchers have investigated various conventional, metaheuristic, and hybrid optimization algorithms. The major studied conventional methods include the Lagrangian relaxation (LR) method [61,62], and mixed-integer linear programming (MILP). Nowadays, the LR method is used along with different algorithms, which can be called hybrid methods for solving different types of UC problems. LR method and particle swarm optimization (PSO) are implemented to solve the cost minimization problem, which considered fuel and startup costs in [63]. LR is combined with a genetic algorithm (GA) to obtain satisfactory results for operational cost minimization UC problem in [64]. By implementing MILP, many UC problems involving ESSs have been solved with objective functions such as peak shaving [65], maximizing energy production by reducing curtailment [66], minimization of cost [67–71], minimization of emissions [72], and so on.

Besides the aforementioned conventional methods, various metaheuristic algorithms like Tabu search (TS) [73,74], GA [75], simulated annealing (SA) [76], evolutionary programming (EP) [77], PSO [78], nodal ant colony optimization (NACO) [79], multiagent modeling (MAM) [80], improved teaching–learning-based algorithm (TLBO) [81], binary fireworks algorithm (BFWA) [82], imperialist competitive algorithm (ICA) [83], parallel artificial bee colony (PABC) [84], Benders decomposition (BD) [85], binary fish swarm algorithm [86], binary whale optimization algorithm (BWOA) [87], and gravitational search algorithm (GSA) [88] have also been implemented to solve the UC problems. Typically, metaheuristic algorithms for solving UC problems search both local and global solutions. Some hybrid metaheuristic algorithms have also been efficiently used to solve UC problems. Hybrid algorithms normally give better optimal results. Some of the efficiently deployed hybrid metaheuristic algorithms in existing literature are the neural-network-based tabu search (NBTS) [89], GA and differential evolution (DE) [90], simulated annealing-based (EP) [91], PSO and EP [92], binary successive approach (BSA) and civilized swarm optimization (CSO) [93], and binary particle swarm optimization (BPSO) and PSO [94].

4. ESS with UC Program

ESS can be operated by a system operator, or by an independent owner. Independently owned ESSs are operated as a vertically integrated facility with the utility, as opposed to that which is exclusively owned by the utility. From the investors' point of view, ESSs are to be operated to maximize their profit, and this captures the objective function of the UC problem. On the other hand, for vertically integrated ESS facilities, utility minimizes overall operating costs of the power system by using the ESSs. A comparison between total operating cost reduction with ESS and without ESS by considering different size UC model is shown in Table 1. ESSs can be operated in a few different ways as described below:

(a). **Energy arbitrage**: Buy energy (charge ESS) during the lower price and sell energy (discharge ESS) during the higher price [95–97].
(b). **Reserve provision of ESS**: Power shortages or frequency drops within a given period of time can be compensated by online energy storage, which may work as spinning reserve [98].
(c). **Co-optimization with renewable plants**: ESS helps to ensure optimal, stable, and profitable power delivery from a renewable generation like wind and PV by reducing renewable intermittency [99,100].
(d). **Load shifting**: ESS contributes to load shifting from peak to off-peak or load smoothing, which helps to make a profitable UC [100,101].

ESSs technology is not a totally new concept in power systems. The most famous and installed storage system is the battery energy storage system (BESS); however, pumped hydro storage (PSH) is becoming a more attractive option due to effective load-leveling attributes in many places. PSHs also have very good and efficient response time for ramp rate and frequency control of wind turbine [102]. Due to the uncertainty of renewable generations and load demand, utility needs to smooth generated power by using ESSs and proper energy management. Therefore, utility and independent ESS owners install various ESS technologies, which include PSH, compressed air energy storage (CAES), hydrogen storage with the fuel cell, flywheels, super-capacitor, thermal storage, superconducting magnetic energy storage (SMES), and different BESS technologies.

Table 1. A comparison of total operating cost without energy storage system (ESS) and with ESS [103].

No. of Units	Total Operating Cost		Comparative Net OC Benefit
	With ESS (WE)	Without ESS (WOE)	WE-WOE
10	555,908	563,668	−7760
20	1,107,733	1,124,453	−16,720
40	2,213,375	2,246,563	−33,188
60	3,329,062	3,367,153	−38,091
80	4,432,915	4,489,239	−56,324
100	5,531,812	5,608,888	−77,076

As earlier mentioned, ESS has significantly contributed to the reduction of the operation of fossil-fuel-based TGs by serving as an effective peak shaving mechanism. Typically, ESSs shift the load demand from peak to off-peak, which helps to achieve better optimal UC. Some of the additional constraints that are introduced for ESSs scheduling in UC programs are as follows:

(i) State of charge (SOC) for each storage

$$SOC_e^t = SOC_{t-1,e} + P_{t,e}^{ch} \times eff_e^{ch} - \frac{P^{dch}}{\eta_e^{dch}} \quad e \in [1, E], \ \ t \in [1, T]. \tag{50}$$

(ii) Up/down limits for SOC

$$SOC_e^{min} \leq SOC_{t,e} \leq SOC_e^{max} \quad e \in [1, E], \ \ t \in [1, T]. \tag{51}$$

(iii) Maximum charge constraint

$$P_{t,e}^{ch} \le Ch_e^{max} \times x_{t,e}^{ch} \quad e \in [1, E], \ \ t \in [1, T]. \tag{52}$$

(iv) Minimum charge constraint

$$P_{t,e}^{dch} \le dch_e^{max} \times x_{t,e}^{dch} \quad e \in [1, E], \ \ t \in [1, T]. \tag{53}$$

(v) Discharged power rating constraint

$$P_{t,e}^{dch} \le soc_e^{t-1} \times eff_e^{dch} \times X_{t,e}^{dch} \quad e \in [1, E], \ \ t \in [1, T]. \tag{54}$$

(vi) Disables simultaneous charging and discharging

$$X_{t,e}^{ch} + X_{t,e}^{dch} \le 1 \quad e \in [1, E], \ \ t \in [1, T]. \tag{55}$$

(vii) Charge ramp-up

$$P_{t,e}^{ch} \le P_{e,t-1}^{ch} + P_{t,e}^{cru} \times X_{t,e}^{ch} \quad e \in [1, E], \ \ t \in [1, T]. \tag{56}$$

(viii) Charge ramp-down

$$P_{t,e}^{ch} \ge P_{e,t-1}^{ch} - P_{t,e}^{crd} \times X_{t,e}^{ch} \quad e \in [1, E], \ \ t \in [1, T]. \tag{57}$$

(ix) Discharge ramp-up

$$P_{t,e}^{dch} \le P_{e,t-1}^{dch} + P_{t,e}^{dru} \times X_{t,e}^{dch} \quad e \in [1, E], \ \ t \in [1, T]. \tag{58}$$

(x) Discharge ramp-down

$$P_{t,e}^{dch} \ge P_{e,t-1}^{dch} - P_{t,e}^{drd} \times X_{t,e}^{dch} \quad e \in [1, E], \ \ t \in [1, T]. \tag{59}$$

In Equation (51), maximum SOC SOC^{max} and SOC^{min} is not usually equal to 100% and 0%, respectively.

An example problem is drawn for understanding the contribution of ESSs in UC model. In this example, an ESS-rated 138 MW is considered along with 10 TG units. The objective function considers the minimization of cost, Equation (14), which includes the fuel cost, Equation (2), and start-up cost, Equation (3). The UC model considers several constraints such as spinning reserve constraint, Equation (4); OFF and ON time constraints, Equation (5)–(8); initial status of unit, Equation (9); load demand constraint, Equation (10); TG unit's power output constraint, Equation (11); generator ramp up and down constraint, as shown in Equations (12) and (13).

The UC problem considers a 138-MW ESS system with 1192-MWh capacity for leveling the load demand, and it considers ESSs constraints such as SOC constraint, Equation (50); maximum, and minimum limits, Equation (51); maximum charge constraint, Equation (52); minimum charge constraint, Equation (53); discharge power rating, Equation (54); disable simultaneous charging and discharging, Equation (55); charge ramp-up, Equation (56); charge ramp-down, Equation (57); discharge ramp-up, Equation (58); and discharge ramp-down, Equation (59). Figure 1 shows that the UC problem without considering the ESS system involves turning on all the 10 TG units, as shown in Figure 2, in order to meet the load demand. Figure 3 demonstrates the UC problem after considering ESS, and this results in only 7 TG units being turned on in order to meet the load demand after load shifting action of the ESS, as seen in Figure 4. It can be observed that there is a load shifting from the actual load profile due to the penetration of ESS optimal power output, and the UC outputs are obtained for the shifted load profile. Finally, ESS optimal power output (charging/discharging) and SOC are shown in Figures 5 and 6, respectively. This example problem is given only for demonstrating the optimal ESS contribution with the UC problem. Several types of research have proven this concept of load-leveling action of ESS in optimal UC implementation [104]. Most of the modeling used in the above example problem configurations and the parameters of the considered TG units are taken from Reference [104].

A review of some contributions of ESSs to power system operation considering UC problem is presented in Table 2.

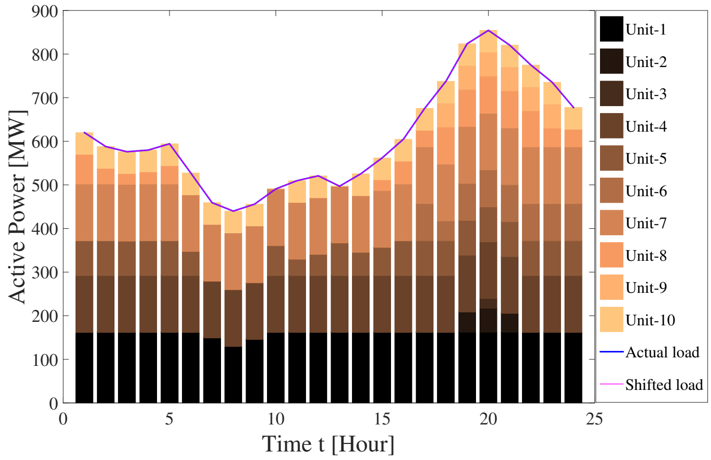

Figure 1. Unit commitment without considering ESS.

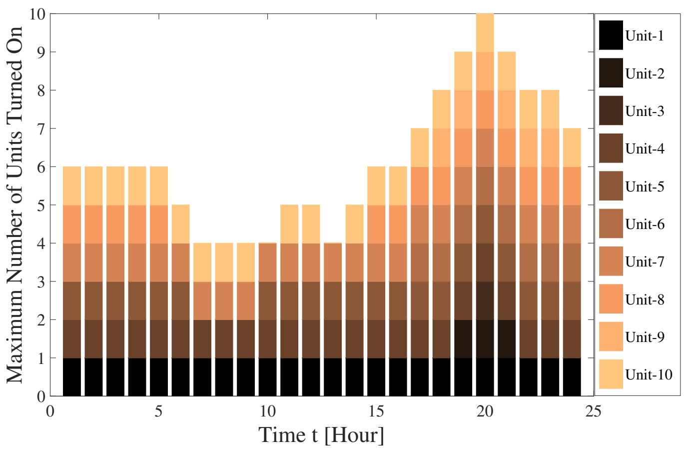

Figure 2. Number of thermal generation (TG) units turned on without considering ESS.

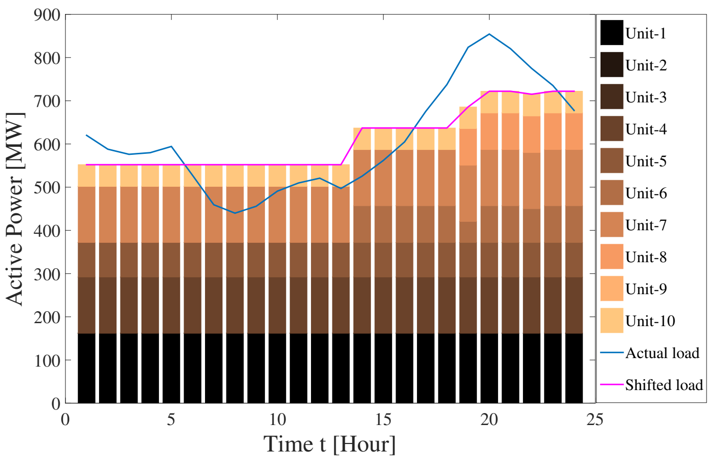

Figure 3. Unit commitment considering ESS.

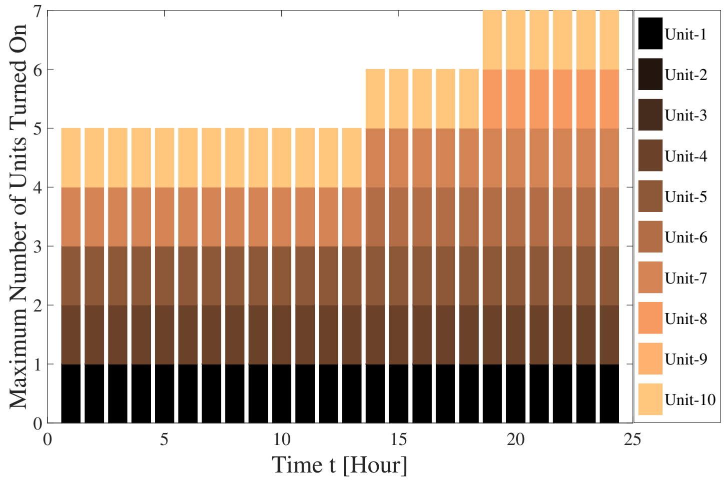

Figure 4. Number of TG units turned on considering ESS.

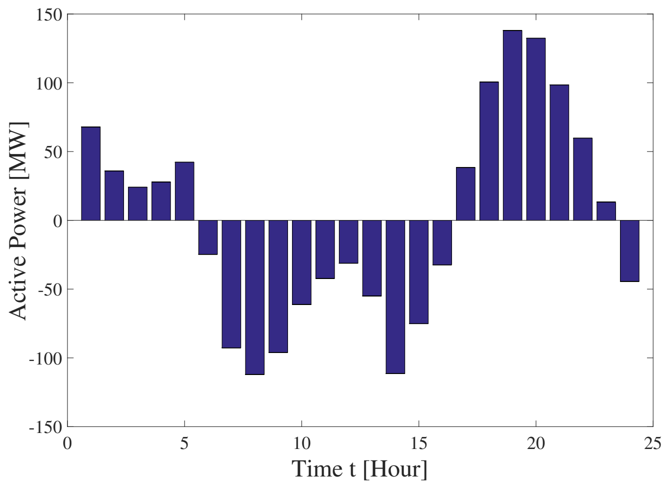

Figure 5. Optimal charging and discharging dynamics of ESS.

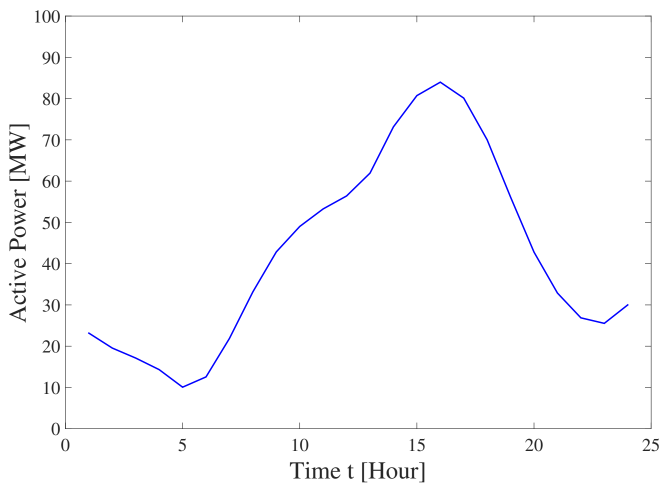

Figure 6. Optimal state of charge (SOC) of ESS.

Table 2. ESS contribution in unit commitment (UC) with references.

References	ESS Constraints	ESS Type	Objective	Power System	Summary
[105]	Equation (51), Equation (52)	Battery	Minimization of costs: including fuel cost of TGs, nuclear generators, start up and shut down cost, and peak shaving cost.	IEEE RTS-24 bus system, which includes 10 TGs, two WTGs, two nuclear power plats and two ESS stations.	Propose research, nuclear power plants mainly work for peak shaving, and ESS mitigate the renewable fluctuations and makes schedules more flexible which help the UC program for reducing the operation of TG unit and system cost
[106]	Equation (A1), Equation (A2), Equation (A3), Equation (A4), Equation (A5)	Pumped storage hydro (PSH)	Minimization of scheduling costs with high wind penetration	Power system consists of 16 TG units, 4 PSH units, and 3 wind turbine generators (WTGs)	Constant start-up costs and ramps of the TG units for measuring the contribution of PSH to reduce the scheduling costs of power system with high WTG penetration.
[107]	Equation (A1), Equation (A2), Equation (A3), Equation (A4), Equation (A5), Equation (A6), Equation (A7)	Pumped storage hydro (PSH)	Minimizing operational cost which includes fuel cost of TGs, and start-up and shut-down cost of both TGs and PSH units.	IEEE-9 bus system, the PEGASE 89-bus system and the Shenzhen city grid including the 110-kV network.	Security-constrained UC program with PSH, which was able to reduce the fuel costs of TGs and total operational cost of the system.
[108]	Equation (50), Equation (51), Equation (52), Equation (53), Equation (54), Equation (55), Equation (56), Equation (57), Equation (58), Equation (59)	PSH, Compressed air, Battery (lead acid and lithium-ion)	Minimization of total operational cost, which includes fuel cost, start-up cost, shut-down cost, and load shedding cost	IEEE 24-bus reliability test system (RTS) with three types of ESSs and TG units.	ESSs in the proposed methodology for UC problem contributed to the leveling of the load, which help to reduce the operation time of expensive TGs units, thus the total operational cost was reduced.
[109]	Equation (A9), Equation (A10), Equation (A11), Equation (A12), Equation (A13)	Superconducting magnetic energy storage (SMES)	Minimizing operational cost, which includes fuel cost of TGs and start-up and shut-down cost	IEEE ten-unit test system with SMES	SMES contributes to level the load, which leads to peak load decrease and off-peak load increase. This reduces the number of start-up of TGs and consequently, the usage of fossil fuel and cost of production was reduced.
[110]	Equation (A14), Equation (A15), Equation (A16), Equation (A17), Equation (A18), Equation (A19), Equation (A20), Equation (A21), Equation (A22), Equation (A23), Equation (A24), Equation (A25)	Hydrogen storage system (HSS) [111]	Mainly minimizing fuel and start-up costs of TG units, cost of HSS in both generation and storage mode, and DR cost	Proposed model has been tested on a 6-bus system. Model consists of TG units, WTG, and HSS considering DR	The proposed research considers three cases: case 1 does not consider HSS and DR and it needs all TG units to be turned on, case 2 considers HSS that contributes to leveling the load and needs only two units turned on, and case 3 reduces the operation time of TG unit 3. From case 1 to case 3, the operation cost was gradually reduced.

5. Conclusions

This paper has summarized a broad research area that is related to UC modeling with ESSs integration. Some models and methodologies of UC are drawn from reviewing several recent research articles. In this review work, some important ESSs-incorporated UC mathematical models with constraints are clearly elucidated and demonstrated. Additionally, some of the proven algorithms found in the existing literature for solving various types of UC problems are reviewed. Moreover, the various constraints considered for integrating ESSs in the UC model, as obtained from different research works, are collected and summarized for different types of ESSs. In references, as mentioned earlier, most of the research work with integrating ESS in the UC model either aim tominimize the cost or maximize the profit. An illustrative example of the UC problem with and without ESS inclusion is solved and analyzed using figures to give a better understanding of ESSs contribution to UC modeling and solution approach. Conclusively, this review article summarizes the contribution of various types of ESSs in UC with reference to existing works of literature. Mostly, ESSs contribution in the UC model involves injecting power during the peak period and consuming the surplus power during the off-peak period; that means ESSs reduce the gap between peak and off-peak periods, which is essential for achieving optimal UC. Some essential and unique ESSs model constraints for optimal UC are also stated in Appendix A.

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Appendix A

Appendix A.1. PSH Constraint

PSH constraints are given below:

$$pl_t \le ut_t(ps - ph_t^{min}) \quad t \in [1, T]. \tag{A1}$$

$$ut_t + up_t \le 1. \tag{A2}$$

$$ypt_t \ge \big(ut_t - up_t\big) - \big(ut(t-1) - up(t-1)\big) \quad t \in [1, T]. \tag{A3}$$

$$V_t = v(t-1) + 3600 \times \big(up_t \times qp - ut_t \times q_t^{min} - rt \times pl_t\big) \quad t \in [1, T]. \tag{A4}$$

$$v\big(t \in [1, T]\big) = v_0. \tag{A5}$$

$$oms \begin{cases} Z_t^{ge} + Z_t^{gu} + 1 \le 1 & t \in [1, T-1], \\ Z_t^{ge} + Z_t^{gu} + 2 \le 1 & t \in [1, T-2], \\ Z_t^{gu} + Z_t^{ge} + 1 \le 1 & t \in [1, T-1], \\ Z_t^{gu} + Z_t^{ge} + 2 \le 1 & t \in [1, T-2]. \end{cases} \tag{A6}$$

$$SRGM \begin{cases} 0 \le R_t^{guu} \le ph_t^{max} - ph_t^g, \\ 0 \le R_t^{gdd} \le ph_t^g. \end{cases} \tag{A7}$$

$$SRPM \begin{cases} 0 \le R_t^{guu} \le -ph_t^g, \\ 0 \le R_t^{gdd} \le ph_t^g - ph_t^{max}. \end{cases} \tag{A8}$$

Appendix A.2. SMES Constraints

(i) Charging/discharging constraint

$$-SM_{max}^{ch} \le SM_t^e \le -SM_{min}^{dch} \quad e \in [1, E], \ t \in [1, T]. \tag{A9}$$

(ii) Storage capacity variation constraint

$$\Delta STC_t^e \begin{cases} \Delta t, SM_t^e / eff_{dch} & \text{if } EM_t^e > 0, \\ 0 & \text{if } EM_t^e = 0, \\ eff_{ch} \times \Delta t, SM_t^e & \text{if } EM_t^e < 0, \\ \quad e \in [1, E], \ \ t \in [1, T]. \end{cases} \tag{A10}$$

(iii) Storage capacity of SMES at the end of time

$$STC_t^e = STC_{t-1}^e - \Delta STC_t^e \quad e \in [1, E], \ \ t \in [1, T]. \tag{A11}$$

(iv) Storage capacity constraint

$$STC_{min}^e \leq STC_t^e \leq STC_{max}^e \quad e \in [1, E], \ \ t \in [1, T]. \tag{A12}$$

(v) Capacity balance constraint

$$STC_0^e = STC_T^e \quad e \in [1, E], \ \ t \in [1, T]. \tag{A13}$$

Appendix A.3. Hydrogen Storage System (HSS)

(i) HS can operate in generation, storage, or idling modes

$$I_{e,t}^{H2P} + I_{e,t}^{P2H} \leq 1 \quad e \in [1, E], \ \ t \in [1, T]. \tag{A14}$$

(ii) Generated and stored hydrogen has a maximum and minimum limit

$$P_{e,min}^{P2H} I_{e,t}^{P2H} \leq P_{e,t}^{P2H} \leq P_{e,max}^{P2H} I_{e,t}^{P2H} \quad e \in [1, E], \ \ t \in [1, T]. \tag{A15}$$

$$P_{e,min}^{H2P} I_{e,t}^{H2P} \leq P_{e,t}^{H2P} \leq P_{e,max}^{H2P} I_{e,t}^{H2P} \quad e \in [1, E], \ \ t \in [1, T]. \tag{A16}$$

(iii) HSS in both production and storage modes constraints

$$R_{e,t}^{o,H2P} + R_{e,t}^{S,H2P} + R_{e,t}^{RU,H2P} \leq I_{e,t}^{H2P} \min \left\{ RU_e^{H2P}, P_{e,max}^{H2P} - P_{e,t}^{H2P} \right\}. \tag{A17}$$

$$R_{e,t}^{RD,H2P} \leq I_{e,t}^{H2P} \min \left\{ RD_e^{H2P}, P_{e,t}^{H2P} - P_{e,min}^{H2P} \right\}. \tag{A18}$$

$$R_{e,t}^{o,P2H} + R_{e,t}^{S,P2H} + R_{e,t}^{RU,P2H} \leq I_{e,t}^{P2H} \min \left\{ RD_e^{P2H}, P_{e,t}^{P2H} - P_{e,min}^{P2H} \right\}. \tag{A19}$$

$$R_{e,t}^{RD,P2H} \leq I_{e,t}^{P2H} \min \left\{ RU_e^{P2H}, P_{e,max}^{P2H} - P_{e,t}^{P2H} \right\}. \tag{A20}$$

(iv) Amount of hydrogen stored from each HSS unit e at t time

$$A_{e,t} = A_{e,t-1} \eta_e^{P2H} P_{e,t}^{H2P} - \frac{P_{e,t}^{H2P}}{\eta_e^{H2P}} + M_{e,t} \quad e \in [1, E], \ \ t \in [1, T]. \tag{A21}$$

(v) HSS minimum and maximum capacity limits

$$A_e^{min} \leq A_{e,t} \leq A_e^{max} \quad e \in [1, E], \ \ t \in [1, T]. \tag{A22}$$

(vi) HSS initial capacity limits

$$A^{e,o} = A_{e,in} \quad e \in [1, E], \ \ t \in [1, T]. \tag{A23}$$

(vii) HSS initial value and final value

$$A^{e,o} = A_{e,NT} \quad e \in [1, E], \;\; t \in [1, T]. \tag{A24}$$

(viii) HSS supply limit to other production

$$0 \leq M_{e,t} \leq M_{e,max} \quad e \in [1, E], \;\; t \in [1, T]. \tag{A25}$$

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