

Economic Dispatch for Hybrid Power System

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التشغيل الاقتصادي لنظام الطاقة الهجين

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Abstract:

The power grids are increasingly growing while involving different types of energy sources. The fossil fuels power plants are still account for most of the generation in the current power grids. The cost of fossil fuels, emission and/or losses are representing some operational constraints on the operation of the modern power system. Renewable Energy Sources (RESs) recently are considered for securing electricity demand in different power systems. However, these sources are subjected to climatological dependence and a high degree of uncertainty. Economic Dispatch (ED) is the key tool for running modern electrical power systems. It optimizes the energy cost while fulfilling the load requirements. ED considers different generation types including renewable sources. Moreover, ED techniques could be modified according to the operating scenarios and the imposed limitations. This article discusses comprehensively the evolution of ED from traditional techniques up to Artificial Intelligence (AI) methods. Moreover, the article analyzes the ED while integrating RESs. Moreover, different energy storage systems for mitigating the limitations of RESs are analyzed. The article concludes the significance of RESs in optimizing the operating costs achieving around 35% drop in the cost of energy. Moreover, RESs increase the margin of security and fulfill the sustainability requirement in the modern power systems.

Keywords: Economic Dispatch, Renewable, Energy, Sources, Meta-heuristic, Artificial Intelligence , Sustainability, Diversity.

المخلص:

تتوسع شبكات الطاقة الكهربائية بشكل متزايد، مع تنوع مصادر الطاقة المستخدمة. ولا تزال محطات توليد الطاقة التي تعمل بالوقود الأحفوري تُشكل الجزء الأكبر من إنتاج الطاقة في الشبكات الحالية. وتُمثل تكلفة الوقود الأحفوري والانبعاثات والمفاقد بعض القيود التشغيلية على تشغيل أنظمة الطاقة الحديثة. وقد تم مؤخراً النظر في مصادر الطاقة المتجددة لتلبية الطلب على الكهرباء في مختلف أنظمة الطاقة. ومع ذلك، فإن هذه المصادر تتأثر بالظروف المناخية وتتسم بدرجة عالية من عدم اليقين. ويُعد التشغيل الاقتصادي للطاقة الأداة الرئيسية لتشغيل أنظمة الطاقة الكهربائية الحديثة، حيث يُحسن تكلفة الطاقة مع تلبية متطلبات الأحمال. ويُأخذ التشغيل الاقتصادي للطاقة في الاعتبار أنواعاً مختلفة من مصادر التوليد، بما في ذلك مصادر الطاقة المتجددة. علاوة على ذلك، يُمكن تعديل تقنيات التشغيل الاقتصادي للطاقة وفقاً لسيناريوهات التشغيل والقيود المفروضة. وتناقش هذه المقالة بشكل شامل تطور التشغيل الاقتصادي للطاقة من التقنيات التقليدية وصولاً إلى

أساليب الذكاء الاصطناعي. كما تُحلل المقالة التشغيل الاقتصادي للطاقة عند دمج مصادر الطاقة المتجددة، بالإضافة إلى تحليل أنظمة تخزين الطاقة المختلفة للتخفيف من قيود مصادر الطاقة المتجددة. تؤكد المقالة على أهمية مصادر الطاقة المتجددة في تحسين تكاليف التشغيل، حيث تُحقق انخفاضًا بنحو 35% في تكلفة الطاقة. علاوة على ذلك، تُعزز مصادر الطاقة المتجددة هامش الأمان وتُلبي متطلبات الاستدامة في أنظمة الطاقة الحديثة.

الكلمات المفتاحية: التشغيل الاقتصادي، الطاقة المتجددة، مصادر الطاقة، الخوارزميات فوق الحدية، الذكاء الاصطناعي، الاستدامة، التنوع.

Introduction:

ED is one of the most fundamental optimization problems in power system operation. Its objective is to determine the optimal allocation of generation among committed units so that the total production cost is minimized while meeting system demand and operational constraints [1], [2]. The classical ED formulation considers a quadratic cost function for thermal generating units that includes constraints such as the power balance equation, generator capacity limits, and transmission loss modeling [3], [4]. Solving ED efficiently is vital for reducing operational costs and ensuring reliable grid performance [5].

Initially, ED was addressed using deterministic mathematical programming methods. The most widely used techniques include the lambda-iteration method, Lagrangian relaxation, and gradient-based approaches [5]. For convex cost functions and small systems, these approaches are efficient and guarantee global optima. More advanced deterministic methods, such as quadratic programming (QP), linear programming (LP), and interior-point methods, have been employed to handle larger systems and more complex formulations [6]. However, these classical methods encounter difficulties when dealing with non-convex cost curves, valve-point effects, and prohibited operating zones [7].

Dynamic programming (DP) has been used to solve ED problems that exhibit non-convexities or involve discrete decision variables [8]. While DP can find global solutions, it suffers from the "curse of dimensionality," which limits its application to large-scale systems. Other mathematical approaches, such as mixed-integer programming (MIP) and nonlinear programming (NLP), have also been utilized for ED with valve-point effects and prohibited zones [9]. Despite their robustness, these methods may require high computational resources and can be slow for real-time applications, making them less suitable for modern large-scale grids.

To overcome the limitations of conventional methods, metaheuristic algorithms have been extensively applied to ED. Genetic Algorithms (GA) [10], Particle Swarm Optimization (PSO) [11], Differential Evolution (DE) [12], Ant Colony Optimization (ACO) [21], Artificial Bee Colony (ABC) [13], Firefly Algorithm [14], Bat Algorithm [24], Grey Wolf Optimizer (GWO) [15], and Teaching–Learning–Based Optimization (TLBO) [16] are among the most prominent techniques. These algorithms are well suited for non-convex, nonlinear, and large-scale ED problems. Hybrid approaches that combine two or more metaheuristics, such as GA–PSO [17] or DE–PSO, have demonstrated faster convergence and improved solution quality.

Comparative analyses indicate that while deterministic methods remain efficient for convex and small-scale ED problems, metaheuristics excel in solving large-scale, nonlinear, and non-convex problems. Studies highlight that PSO and DE often outperform GA in terms of convergence speed and robustness [18]. Furthermore, hybrid metaheuristic algorithms provide an effective balance between exploration and exploitation, ensuring higher-quality solutions [19]. Current trends focus on multi-objective formulations of ED that address both economic cost and emissions, while ensuring computational efficiency and scalability for practical implementation. Despite significant progress, challenges remain in parameter tuning, ensuring global convergence, and reducing computational time for real-time dispatch [18-19].

Economic Dispatch: Methodology:

ED is classified into two categories: Static and Dynamic [3,5,20, 21-24].

Static vs. Dynamic ED:

- Static ED: This type of ED operates under the assumption of a steady-state power system, with the objective of determining the optimal power generation schedule for a single time interval.
- Dynamic ED: This ED method accounts for the power system's time-varying characteristics, including ramp rates, start-up and shut-down costs, and time-dependent constraints, to optimize generation over time.

objective functions:

The ED in general is currently solved as optimization problem. The optimal energy cost is obtained via minimizing the objective function. This type aims to minimize a single, overarching objective: the total cost of power generation [5,16,20, 21-24].

Single-Objective ED: This type aims to minimize a single objective function, usually the total cost of power generation.

Multi-Objective ED: This type optimizes several objective functions, such as minimizing generation cost, and reducing emissions.

Here are the detailed formulations of different objective functions used in ED problems:

1. Fuel Cost:

Minimizing fuel costs is a key objective, which involves reducing the total fuel expense for power generation at each generator, often modeled using a quadratic function [1].

$$F_C = \sum_{i=1}^N a_i(P_i)^2 + b_iP_i + c_i$$

Where F_C is the fuel cost of unit i (\$/MWh), P_i is the power output of unit i (MW), N is the number of units, $a_i, b_i,$ and c_i are the fuel cost coefficients of unit i .

2. Transmission Loss:

The goal of the transmission loss objective function is to optimize power transmission by minimizing energy losses in the system [2, 3, 5].

$$P_L = \sum_{i=1}^N \sum_{j=1}^N P_i B_{ij} P_j + \sum_{i=1}^N B_{oi} P_i + B_{oo}$$
(1)

Where P_L Total network loss of the system (MW), B_{ij}, B_{oi}, B_{oo} are the transmission loss formula coefficients.

3. Emission Cost:

The emission cost objective function aims to reduce the total cost of emissions from power generation at each generator, with the emission cost function defined as [8, 21-24]:

$$E_c = h_i * \left(\sum_{i=1}^N (d_i(P_i)^2 + e_i P_i + f_i) \right)$$
(2)

$$h_i = \frac{F_c(P_i^{Max})}{E_T(P_i^{Max})} = \frac{(a_i(P_i^{Max})^2 + b_i P_i^{Max} + c_i)}{(d_i(P_i^{Max})^2 + e_i P_i^{Max} + f_i)}$$
(3)

Where h_i is the penalty factor, $d_i, e_i,$ and f_i are the emission cost coefficients of the unit, P_i^{Max} are the upper limits of power generated by unit i .

4. Valve point effect:

The valve point effect refers to the phenomenon where the fuel cost of a generating unit increases non-linearly as the power output increases, due to the opening of valves in a multi-valve steam turbine. This creates a ripple effect in the generator's heat rate curve, resulting in a higher fuel cost [2, 5, 10].

$$Fvpc = |\alpha_i \sin\{\delta_i(P_i^{min} - P_i^t)\}|$$
(4)

The two parameters α_i and δ_i represent the valve point effect, and P_i^{min} are the upper limits of power generated by unit i .

5. Wind Power Cost:

The wind power cost objective function aims to minimize the total cost of wind-based electricity generation by optimizing the cost function $f_{wij}(P_{wij})$ for each wind turbine in region i , which is composed of three components: direct costs, underestimation penalties, and overestimation penalties, as defined in equations (7), (8), (9), and (10), respectively [3, 5, 21-25].

$$f_{wij}(P_{wij}) = k_{wij} \times P_{wav,ij} + C_{pwij}(P_{wav,ij} - P_{wsh,ij}) + C_{wwij}(P_{wsh,ij} - P_{wav,ij})$$
(5)

$$C_{wwij}(P_{wav,ij} - P_{wsh,ij}) = k_{pwij} \times \int_{P_{w+1,ij}}^{P_{wr,ij}} (w_{ij} - P_{iwsh,ij}) f_{wij}(w_{ij}) dw_{ij}$$
(6)

$$C_{rwiij}(P_{wsh,ij} - P_{wav,ij}) = k_{rwiij} \times \int_0^{P_{wsh,yj}} (P_{iwsh,ij} - w_{ij}) f_{wij}(w_{ij}) dw_{ij}$$
(7)

With

$$f_{wij}(w_{ij}) = \left(\frac{k_s h v_{in}}{P_{wr,ij} c} \right) \left[\frac{\left(1 + \frac{h w_U}{P_{w,ij}}\right) v_{in}^{k_s}}{c} \times \exp\left(-\frac{\left(1 + \frac{h v_{il}}{P_{wr,ij}}\right) v_{in}^{k_g}}{c}\right) \right]$$
(8)

Where P_{wij} represents the power output of the j^{th} wind turbine in region i , with cost, k_{wij}, k_{pwij} and k_{rwiij} for direct, penalty, and reserve costs, respectively.

6. PV power cost:

The PV-based power cost function has three components: direct costs, penalty costs for reserve costs (C_{rsij}), and underestimation (C_{psij}), with a lognormal pdf characterizing solar power, as defined in equations (10), (11), and (12), respectively [5,9, 21-24].

$$f_{sij}(P_{sij}) = k_{sij} \times P_{sav,ij} + C_{psij}(P_{sav,ij} - P_{ssh,ij}) + C_{rsij}(P_{ssh,ij} - P_{sav,ij}) \quad (9)$$

$$C_{rsij}(P_{ssh,ij} - P_{sav,ij}) = f_s(P_{sav,ij} < P_{ssh,ij}) \times [E(P_{sav,ij} < P_{ssh,ij})] \times k_{rsij} \quad (10)$$

$$C_{psij}(P_{sav,ij} - P_{ssh,ij}) = k_{psij} \times [E(P_{sav,ij} > P_{ssh,ij}) - P_{ssh,ij}] \times f_s(P_{sav,ij} > P_{ssh,ij}) \quad (11)$$

Where P_{sij} represents the power output of the j^{th} PV plant in region i , with cost coefficients k_{sij} , k_{psij} , and k_{rsij} for direct, penalty, and reserve costs, respectively.

7. Startup cost, and shutdown cost:

Thermal power operating costs include fuel costs, startup costs, and shutdown costs. Fuel costs are usually represented by a quadratic function of the thermal power units' active output. Startup costs can be broken down into cold start and hot start costs, based on the downtime. Shutdown costs, although fixed, are typically negligible compared to startup costs and can be disregarded. The formulas for these costs are presented below [3, 10, 16, 21-24]:

$$f_{\text{fire}}(j, t) = u_{j,t} f_{\text{fuel}}(j, t) + u_{j,t}(1 - u_{j,t-1}) S_{j,t} \quad (12)$$

$$f_{\text{fuel}}(j, t) = \sum_{s=1}^S (a_j P_{j,t,s}^2 + b_j P_{j,t,s} + c_j) \cdot \eta_s \quad (13)$$

$$S_{j,t} = \begin{cases} X_j^{\text{off}} \leq T_j^{\text{cold}} + T_j^{\text{off}}, & Sh_{j,t} \\ X_j^{\text{off}} > T_j^{\text{cold}} + T_j^{\text{off}}, & Sc_{j,t} \end{cases} \quad (14)$$

where $f_{\text{fuel}}(j, t)$ is the fuel cost of generator j at period t , $S_{j,t}$ is the startup cost of generator j at period t , $Sh_{j,t}$ and $Sc_{j,t}$ are the hot start and cold start cost of generator j at period t , respectively.

8. Multiple fuel options:

The flexibility of generating units to use multiple fuel options in different regions within their operational range adds complexity to the cost function, introducing more non-differentiable points, resulting in.

$$F_i(P_i) = \begin{cases} a_{i1}(P_i)^2 + b_{i1}P_i + c_{i1} \\ a_{i2}(P_i)^2 + b_{i2}P_i + c_{i2} \\ a_{i3}(P_i)^2 + b_{i3}P_i + c_{i3} \end{cases} \quad (15)$$

Where F_i is the fuel cost of unit i (\$/MWh), P_i is the power output of unit i (MW), $a_i, b_i,$ and c_i are the fuel cost coefficients [10].

Constraints:

1. Power balance:

$$\sum_{i=1}^n P_i - P_L - P_D = 0 \quad (16)$$

Where P_D Total load demand of the system (MW) [1].

2. Generator operating limits:

$$P_{i,\min} \leq P_i \leq P_{i,\max}; i = 1, \dots, N \quad (17)$$

Where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum limits [1].

3. Ramp rate limit:

The output power of a generator is not instantly adjustable, and this restriction governs how power output changes over time [11].

When power generation increases, it is represented as:

$$P_i(t) + P_i(t-1) \leq UR_i \quad (18)$$

When power generation decreases, it is given as

$$P_i(t-1) - P_i(t) \geq DR_i \quad (19)$$

Now the economic load dispatch (ELD), with an up rate and down rate of power, **is defined as:**

$$\begin{aligned} P_{\min} &= \text{Max}[(P_i^{\min}, P_i(t-1) - DR_i)] \\ P_{\max} &= \text{Min}[(P_i^{\max}, P_i(t-1) + UR_i)] \\ P_{i,\min} &\leq P_i \leq P_{i,\max} \end{aligned} \quad (20)$$

Where UR_i and DR_i are the upper and down ramp rate limits, respectively.

4. Prohibited operating zone (POZ):

The prohibited operating zone defines the limits of a generator's active power output, which can be impacted by technical issues such as excessive shaft vibrations. Within these prohibited ranges, adjustments to the generator's power output are typically not permitted. The allowable operating range for the generator is specified in the following Equation [11, 21-24].

$$\begin{aligned} P_i^{\min} &\leq P_{i,t} \leq P_{i,1}^{\text{lower}} \\ P_{i,j-1}^{\text{upper}} &\leq P_{i,t} \leq P_{i,j}^{\text{lower}}; \quad i = 1, \dots, n; \quad j = 2, 3, \dots, n_i; \quad t = 1, 2, \dots, T \\ P_{i,n_i}^{\text{upper}} &\leq P_i \leq P_i^{\max}. \end{aligned} \quad (21)$$

The notation used to describe the Prohibited Operation Zones (POZs) is as follows: for the i^{th} unit, $P_{i,j-1}^{\text{upper}}$ and $P_{i,j}^{\text{lower}}$ represent the upper and lower boundaries, respectively, of the j^{th} POZ, where j ranges from 1 to n_i , the total number of POZs for unit i .

5. Branch power flow:

$$P_l^m \leq P_{l,t,s} \leq P_l^M \quad (22)$$

Where P_l^m , and P_l^M minimum/maximum power flow of the line [3].

6. Reverse limit constraints:

To ensure a reliable power supply, generators often operate below their maximum capacity, typically maintaining a 5-10% capacity reserve. This deliberate underutilization enhances the power system's emergency response capabilities. Furthermore, spinning reserve constraints are only applied to online units that operate within their allowable zones.

$$SR_i = \min\{(P_{i(\max)} - P_i), SR_{i(\max)}\} \quad (23)$$

$$SR = \sum_{i=1}^{n \leq n_g} SR_i \quad (24)$$

The spinning reserve is defined as follows: SR_i represents the spinning reserve of unit i , measured in megawatts (MW), with $SR_{i(\max)}$ being its maximum capacity. The total spinning reserve, SR , is the cumulative contribution from all generating units that operate without any POZ [2].

7. Battery operation:

Excessive charging and discharging of the battery can lead to premature aging, and the following constraints are imposed to mitigate this effect [21-24].

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max} \quad (25)$$

$$-P_{BS\max} \leq P_{BS}(t) \leq P_{BS\max} \quad (26)$$

$$SOC_{\text{end}} = SOC_{\text{start}} + \sum_{t=0}^{N-1} P_{BS}(t) \eta_C \Delta t = SOC_{\text{start}} \quad (27)$$

$$SOC_{\text{end}} = SOC_{\text{start}} + \sum_{t=0}^{N-1} \frac{P_{BS}(t)}{\eta_D} \Delta t = SOC_{\text{start}} \quad (28)$$

The battery storage system is characterized by its minimum and maximum state of charge (SOC) limits, denoted by SOC_{\min} and SOC_{\max} , respectively. Additionally, the system is defined by its maximum power capacity ($P_{BS\max}$), charging and discharging efficiencies (η_C , and η_D), and minimum and maximum power values ($P_{BS}(t)$). The initial and final SOCs of a cycle are represented by SOC_{start} and SOC_{end} , respectively [3].

8. Transmission line capacity:

Power flow between two grids is expressed as:

$$-P_{L\max} \leq P_{\text{Grid}} \leq P_{L\max} \quad (29)$$

Where $P_{L\max}$ is the maximum capacity [12, 21-24].

9. Emission Constraints:

To mitigate air pollution, we can incorporate maximum emission constraints into our system. If these constraints are exceeded, a penalty fee will be imposed, proportional to the volume of excess emissions.

$$em(t) \leq em^{\max}(t) \quad (30)$$

Where $em^{\max}(t)$ is the maximum emission [13, 23].

10. Minimum up/down time:

Minimum up/down time refers to a set of constraints that ensure a generating unit is not started up or shut down too frequently. These constraints are essential to prevent excessive wear and tear on the unit, reduce maintenance costs, and minimize the risk of equipment failure [3, 21-24].

$$T_{\text{up/down}} = \begin{cases} X_{j,t}^{\text{on}} \geq T_j^{\text{on}} \\ X_{j,t}^{\text{off}} \geq T_j^{\text{off}} \end{cases} \quad (31)$$

Where T_j^{on} and T_j^{off} Minimum operating time/downtime of generator j.

11. Voltage constraints:

Optimal performance requires that phase angle and voltage values at each node remain within their specified limits, as even slight deviations can impact the generating unit's operation [14].

$$V_{\min} < V < V_{\max} \text{ and } \delta_{\min} \leq \delta \leq \delta_{\max} \quad (32)$$

Where V_{\min} , δ_{\min} , V_{\max} , and δ_{\max} are the minimum and maximum limits.

12. Transformer tap setting:

The transformer tap setting lies between 0 and 1.

$$0 \leq t \leq 1 \quad (33)$$

For the secondary side, the relation of the tap setting can be given as $0 \leq t \leq n$ where n is the turns ratio [14].

13. Regional load sharing dispatch (RLSD):

RLSD is characterized as the exchange of obtainable power among the various sources that may be allocated in different areas [21-24]. It can be calculated by the following equation.

$$\sum_{i=1}^{N_{\text{areas}}} P_{N_{i,\max}} \geq \sum_{i=1}^N P_{B_i} + \sum_{i=1}^N P_{W_i} + \sum_{i=1}^N P_{S_i} \quad (34)$$

where P_S , P_B , and P_W represent the available total power provided by PV, biofuel, and wind resources according to the power demand; P_N represents the power due to N areas according to the generation sources [9, 24].

14. Frequency Regulation Limits:

Frequency limits for the power system.

$$f_{i,\min} \leq f_i \leq f_{i,\max} \quad (35)$$

Where $f_{i,\min}$ and $f_{i,\max}$ are the minimum and maximum limits [15, 21-25].

15. Reactive Power Constraints:

Reactive power (Q) limits for each thermal unit:

$$Q_{i,\min} \leq Q_i \leq Q_{i,\max} \quad (36)$$

Where $Q_{i,\min}$ and $Q_{i,\max}$ are the minimum and maximum limits [14].

16. PV power:

$$P_{PV,\min} \leq P_{PV} \leq P_{PV,\max} \quad (37)$$

Where $P_{PV,\min}$ and $P_{PV,\max}$ are the minimum and maximum limits [16].

17. Wind power:

$$P_{WT,\min} \leq P_{WT} \leq P_{WT,\max} \quad (38)$$

Where $P_{WT,\min}$ and $P_{WT,\max}$ are the minimum and maximum limits [16].

Renewable Energy Sources for Sustainable Electric Supply:

Growth of Renewable Energy:

Renewable energy sources—such as solar, wind, hydro, geothermal, and biomass—are increasingly essential for resilient and environmentally responsible electric power supply. Unlike fossil fuels, these sources replenish naturally and emit little to no greenhouse gases during operation. Global renewable energy capacity has grown steadily over the past decade due to falling technology costs and supportive policies, Fig.1. This rapid expansion is vital for reducing dependence on carbon-intensive power plants while enhancing long-term energy security [26, 27].

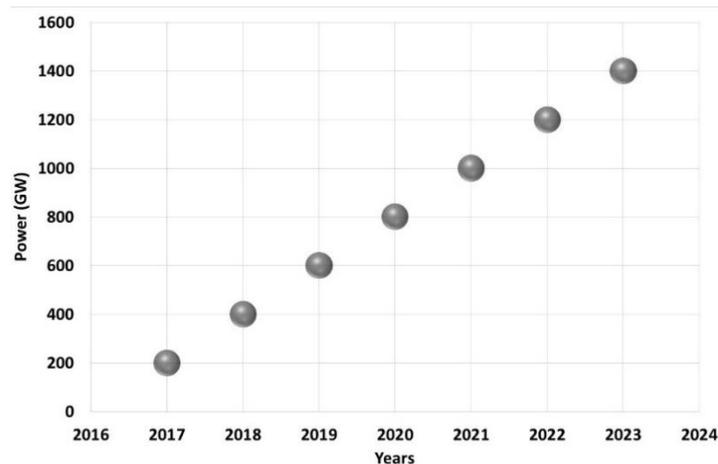


Fig.1: Power from RES globally

Fig.1 shows that the harvested energy from RESs increases annually by around 200GW. This reflects the world trend for converting into renewable sources to secure the demands of the energy [26,27].

Variability, Uncertainty and Storage Systems:

RESs enjoys environmental compatibility, sustainability and versatility. However, their intermittency particularly solar and wind types present challenges for grid stability. Solar output varies with shading from wind and irradiance levels. Therefore, the solar harvested power varies throughout the day hours. The wind power, meanwhile, fluctuates with atmospheric conditions, which difficulties the integration of the output of these sources into the common supply. Elaborate and rather complicated techniques must be adopted for interfacing these RESs source. Moreover, to maintain a stable electric supply, grid operators increasingly rely on energy storage systems, flexible demand strategies, and advanced forecasting [28,29].

Energy storage systems used with renewable energy are versatile including:

- Pumped Hydro Storage (PHS),
- Compressed Air Energy Storage (CAES),
- Flywheel,
- Thermal Energy Storage,
- Electrochemical.

These types vary in size and application.

PHS is the most mature, widely used, and largest-capacity energy storage technology used for renewable energy integration into power systems. PHS operates by using surplus electricity, often from wind or solar, to pump water from a lower reservoir to a higher one, storing energy as gravitational potential. Then, when electricity demand rises, the stored water is retrieved through turbines to generate power. PHS systems typically achieve round-trip efficiencies of 70–85% [30] and are well suited for large-scale, long-duration storage, with individual plants commonly providing power capacities of several hundred megawatts to over 1 GW and energy storage durations from 6 to more than 20 hours [31]. Due to their long operational lifetimes, often exceeding 50 years, high reliability, and ability to provide grid services such as frequency regulation, load balancing, and reserve power, PHS facilities account for more than 90% of the installed energy storage capacity. Therefore, they are considered a cornerstone technology for stabilizing grids with high shares of renewable energy. They provide the required power for maintaining power stability under disturbance in similar fashion to the conventional power plants [30,31].

CAES is a large-scale energy storage technology well suited for integrating variable renewable energy sources such as wind and solar into power systems. CAES operates by using excess electricity to compress air and store it in underground caverns, depleted gas fields, or engineered tanks; then, when electricity is needed, the compressed air is released, heated, and expanded through turbines to generate power. Conventional CAES plants typically provide power capacities in the range of 100–500 MW with storage durations of several hours to days, making them suitable for long-duration energy shifting and grid reliability services. Advanced CAES concepts, such as adiabatic CAES, aim to improve round-trip efficiency, currently around 40–55% for conventional systems, by capturing and reusing compression heat, reducing fuel consumption and emissions. Due to their large storage capacity, long service life, and relatively low cost per kilowatt-hour at scale, CAES systems are considered a promising complement to batteries and PHS in future renewable-dominated energy systems [32,33].

Flywheel energy storage systems (FESS) are a promising mechanical energy storage technology increasingly studied for supporting renewable energy integration due to their high-power density, rapid response, long cycle life, and minimal environmental impact. In FESS, electrical energy is converted into kinetic energy by spinning a rotor at high speeds. This is often in a vacuum with magnetic bearings. The kinetic energy could be rapidly converted back to electricity once required. FESS are particularly suitable for frequency regulation, power smoothing, and short-duration balancing of intermittent wind and solar generation. The literature reported that modern FESS designs achieve high round-trip efficiencies and prolonged operational lifetimes, often exceeding 100,000 cycles, with low degradation compared to chemical batteries, and they could deliver large bursts of power on the order of megawatts [34,35]. However, FESS suffer from inherent energy capacity, which is generally lower than that of electrochemical or PHS. This limits them to short-term storage applications rather than long-duration energy shifting. The literature emphasizes ongoing advancements in rotor materials, magnetic bearing systems, and power electronics to further improve performance, system integration, and economic viability within renewable energy-rich grids [34,35].

Thermal Energy Storage (TES) is a pivotal technology for enhancing the reliability and dispatchability of renewable energy systems, especially solar and wind power. TES stores surplus heat for later use when generation is low or demand peaks. TES systems are broadly categorized into sensible heat storage (e.g., molten salts or heated solids), latent heat storage using phase change materials (PCMs), and thermochemical storage, each offering distinct advantages in energy density, temperature range, and application context. Sensible heat storage, widely used in concentrated solar power (CSP) plants, stores energy by raising the temperature of a medium like molten salt, enabling utility-scale energy retention and dispatchability; latent heat systems leverage the high energy absorption during a material's phase change to boost storage density, while thermochemical systems promise even higher storage potential through reversible chemical reactions [36]. The literature highlights that these TES technologies not only smooth the mismatch between intermittent renewable generation and energy demand but also significantly improve grid flexibility, reduce curtailment of renewable output, and support broader integration of low-carbon energy infrastructures [37].

Electrochemical energy storage systems are central to modern renewable energy deployment because they convert electrical energy into chemical energy and back with high efficiency, which enables reliable grid operation despite the variability of sources like solar and wind. The lithium-ion batteries dominate both commercial and research landscapes due to their high energy density, long cycle life, and efficient charge/discharge behavior, making them suitable for applications ranging from grid-scale storage to distributed renewable installations; state-of-the-art lithium-ion cells can achieve energy densities of 150–300 Wh/kg and round-trip efficiencies near 90–95 %. The research continues into advanced chemistries and solid-state designs to improve safety and longevity [38]. The literature reported that the redox flow batteries (RFBs) as a compelling alternative for large-scale, long-duration storage: by decoupling power and energy capacity through separate electrolyte tanks. RFBs offer flexible scalability and extended storage durations beyond 4–6 hours, although they typically have lower energy densities and somewhat higher fixed costs than lithium-ion systems [39].

The literature emphasizes that performance, reliability, and sustainability of electrochemical systems hinge on electrode materials, electrolytes, and interfaces, with developments in solid-state electrolytes, sodium-based batteries, and interface engineering promising improved safety, reduced reliance on critical metals, and enhanced capacity retention [40]. Furthermore, advanced battery management systems (BMS) using AI and predictive control are shown to optimize charging, state-of-health monitoring, and thermal performance, which are critical for maintaining efficiency and extending operational life in grid applications. Such integrative research highlights the dynamic evolution of electrochemical storage technologies as they adapt to the demands of renewable energy systems [41,42].

Different parameters are considered in determining the most appropriate energy storage systems such as: power, energy capacity, application whether mobile or stationary, other requirements as frequency regulation and etc. Short-duration, high-power services such as frequency regulation typically use batteries or flywheels with durations of seconds to a few hours. Long-duration energy shifting as storing solar energy for nighttime in mega scale projects prefers PHS, CAES, or emerging long-duration battery technologies, with capacities reaching gigawatt-hours. More comparison between different energy storage systems for renewable energy sources is given in Table 1.

Table (1): Energy storage systems for renewable energy sources

Technology	Typical Power Capacity	Storage Duration	Round-Trip Efficiency	Key Advantages	Main Limitations	Typical Applications
Pumped Hydro Storage (PHS)	100 MW – >1 GW	6–20+ hours	70–85%	Mature, high reliability, long life, bulk energy shifting	Geographic constraints, high capital cost, environmental impact	Grid-scale energy shifting, load balancing
Compressed Air Energy Storage (CAES)	100–500 MW	Hours–days	40–55% (conventional), up to 70% (adiabatic)	Large-scale, long-duration storage, flexible siting	Lower efficiency may need fuel for reheating, complex infrastructure	Grid energy shifting, renewable integration
Flywheel Energy Storage	kW – MW	Seconds–minutes	85–95%	Fast response, high power density, very long cycle life	Low energy capacity, short-duration only	Frequency regulation, power smoothing, voltage support
Thermal Energy Storage (TES)	MW – GW (thermal)	Hours–days	60–90% (depends on system)	Low cost per kWh, long duration, suitable for heat-intensive applications	Often application-specific, conversion losses to electricity	Concentrated solar power, industrial heat applications, building heating/cooling
Electrochemical Storage (Batteries)	kW – 100s MW	Minutes–hours (flow batteries: longer)	85–95%	High efficiency, modular, flexible, fast response	Degradation over cycles, cost, material availability	Residential storage, grid balancing, renewable integration

Future Trendsetter for a Fully Renewable Electric Supply:

A sustainable electric supply mandates the integration of diverse renewable resources, expanding transmission networks, and adopting smart-grid technologies. Currently, the multiple renewable sources such as solar, wind, and hydro mixes result in more reliable supply. These resources complement each other across seasons and weather patterns [41,42]. Long-term decarbonization strategies also emphasize electrification of transportation and heating, which increases electricity demand but enables deeper emissions reductions when powered by renewables. The current research efforts are directed for developing renewable-dominant power systems that support both economic growth and climate resilience, while solving problems as climate dependency, intermittency, stability and other related challenges. Fig. 2 shows the share of RESs in electricity production worldwide.

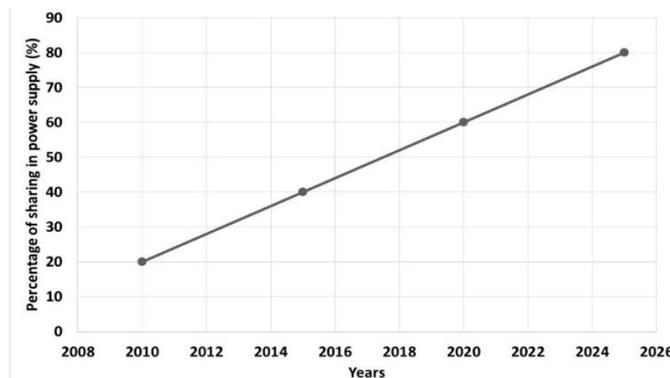


Fig. 2: Percentage share of RESs in global electrical power supply

Fig.2 shows that the share of RESs in electricity production worldwide is increased by around 300% in one decade. This is clear proof on the merits of RESs and their compatibility with environment. This share of RESs is anticipated to reach around 80% by 2026. However, this high sharing percentage require the ability of renewable energy systems in not only fulfilling the load but solving the integration problems as well.

Graphs for Renewable Energy Sources integrated in Economic Dispatch:

The increasing penetration of RES, such as wind and solar power, has significantly altered the traditional formulation of the ED problem. Unlike conventional thermal units with predictable generation characteristics, RESs introduce intermittency, variability, and uncertainty into the system, making the dispatch process more complex [20]. To address these challenges, stochastic optimization techniques have been widely applied, where uncertainties in renewable generation are modeled using probability distributions or scenario-based methods. Robust optimization approaches have also gained traction, providing solutions that remain feasible under worst-case realizations of uncertain parameters [43, 44]. Moreover, chance-constrained programming has been adopted to balance operational reliability with economic efficiency, allowing operators to manage renewable variability while minimizing cost.

In addition to stochastic and robust frameworks, heuristic and hybrid optimization techniques have been increasingly used to solve RES-integrated ED problems. Metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) have demonstrated strong performance in handling the nonlinear, non-convex nature of renewable-integrated dispatch [22].

Hybrid approaches that combine forecasting models with optimization algorithms further improve reliability by incorporating short-term predictions of wind and solar outputs. Recent studies also explore machine learning-based methods, including reinforcement learning and deep learning, to enhance the adaptability of ED frameworks under high-RES penetration. These advancements underline the importance of advanced optimization techniques to ensure cost-effectiveness, reliability, and sustainability in modern power systems with increasing renewable integration [43-50].

ED/DED for different power systems incorporating RESs are reported in the literature. The RESs resulted in cutting the energy cost while fulfilling the load requirements. Moreover, they reduce pollution via cutting the emissions of greenhouse gases. However, ED/DED is only interested in the running costs, emissions and losses. ED/DED is not considering capital, infrastructure and replacements costs while solving for the minimal energy cost [43-50]. In the following an example of ED for a 500MW load in a system with and without RESs are shown in Table 2. This power system has two sources of RESs; these are solar and wind [21-24].

Table (2): ED with and without RESs for 500MW load [21-24]

	Without RES	With RES
Fossil Fuels	500MW	300MW
Wind	0	120MW
Solar	0	80MW
CO ₂ Emissions (kg/hr)	4,500	2,100
Spinning Reserve Required (MW)	40MW	70MW
Renewable Penetration (%)	-	40%
Cost of Energy (CoE) (kWh/\$)	0.024	0.01056

Table 2 shows that incorporating RESs resulted in significant reduction in the energy cost, around 35%. The RESs in the system under consideration could achieve around 40% penetration. However, the spinning energy reserve is increased by around 75%. It jumps from 40MW into 70MW, which is attributed to weak ability of RESs in maintaining power system stability following disturbance such as faults and abnormal operating conditions.

Conclusion:

This article discusses the strategy of ED, which minimizes the cost of energy in the power system while adhering with the constraints as power balance, losses, emissions. The ED/DED is currently integral part in running and controlling modern power systems. The ED/DED is solved as constraint optimization problem. Therefore, numerous optimization techniques are evolved and being applied for ED/DED. The most recent trend for solving ED/DED is using AI, AI combined with meta-heuristic optimization and other evolved solvers.

Globally a move toward RESs for generating electricity is reported. This is attributed to the deficiencies of fossil fuels alternatives and the salient features of the RESs. However, RESs suffer from uncertainty and climatological dependence. This mandates the application of suitable storing and interfacing circuits/topologies/technologies.

Recently ED/DED is considering the integration of RESs and their storage systems when determining the optimal cost of energy for given load requirements. This achieves tremendous cut in the cost of the energy while increasing supply security and reliability. However, ED/DED could not be used alone for evaluating renewable energy projects. Since ED/DED considers only running cost, while the capital cost of RESs projects is not considered. Therefore, there is a need for developing a new technique, which while optimizing the energy cost considering the capital, maintenance, replacement costs.

The following conclusion could be drawn from the article:

- ED/DED is key tool for running a modern power system.
- RESs have to be deployed for fulfilling either partially or fully the requirements of the loads.
- Efficient, reliable and robust energy storage systems are required to boost the operational limits of RESs.
- ED/DED while incorporating RESs results in significant reduction operational energy costs, while boosting the supply continuity.

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