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REVIEW ARTICLE ELECTRICAL POWER SYSTEMS

Comprehensive and Concise Guide on Economic Dispatch of Electrical Power Systems Up to Artificial Intelligence Domain

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ABSTRACT
Economic Dispatch (ED) is currently essential for operating electrical power systems globally, including offline microgrids (MGs). ED ensures the stability and continuity of the electrical power system supply while keeping generating costs as low as possible. Identifying a generic solution for ED is usually complicated, as the operating conditions vary from one power system to another. Numerous solutions for ED have been documented in the literature involving conventional computation techniques, meta-heuristic optimizations, and Artificial Intelligence (AI) techniques. A general review of such literature is lacking; a review could guide the researchers and engineers in the field of ED. This article comprehensively reviews ED while identifying the most prominent parameters, including transmission losses, emissions, renewable energies, and operating constraints. The article basically clarifies the research gap while comparing the different reported solutions, starting from standard techniques up to AI approaches, in a simple and concise fashion. Several comparisons are provided in the article to direct and guide the interested reader straightforwardly.

دليل شامل وموجز حول التوزيع الاقتصادي للأحمال في أنظمة الطاقة الكهربائية، وصولاً إلى مجال الذكاء الاصطناعي

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الكلمات المفتاحية
التوزيع الاقتصادي للحمل
نظام الطاقة الكهربائية
طرق التحسين
الذكاء الاصطناعي
مصادر الطاقة المتجددة

الملخص
تُعد عملية التوزيع الاقتصادي للطاقة (Economic Dispatch - ED) عنصراً جوهرياً في تشغيل أنظمة الطاقة الكهربائية على مستوى العالم، بما في ذلك الشبكات المصغرة (MGs) المستقلة. تضمن هذه العملية استقرار واستمرارية إمدادات الطاقة الكهربائية مع الحفاظ على تكاليف التوليد عند أدنى مستوياتها الممكنة. ونظراً لاختلاف ظروف التشغيل من نظام طاقة لآخر، فإن التوصل إلى حل عام وموحد لهذه العملية يُعد أمراً معقداً؛ وقد وثّقت الأدبيات العلمية حلولاً عديدة تشمل تقنيات الحوسبة التقليدية، وخوارزميات التحسين الميتا-استدلالية (meta-heuristic)، وتقنيات الذكاء الاصطناعي (AI). ومع ذلك، تفتقر الساحة البحثية إلى مراجعة شاملة لهذه الأدبيات، وهي مراجعة من شأنها توجيه الباحثين والمهندسين العاملين في هذا المجال. تقدم هذه المقالة مراجعة شاملة لمفهوم التوزيع الاقتصادي للطاقة، مع تسليط الضوء على أبرز العوامل المؤثرة فيه، مثل فاقد النقل، والانبعاثات، ومصادر الطاقة المتجددة، وقيود التشغيل. كما توضح المقالة الفجوة البحثية القائمة وتجري مقارنة بين الحلول المختلفة المطروحة - بدءاً من التقنيات القياسية ووصولاً إلى أساليب الذكاء الاصطناعي - بأسلوب يتسم بالبساطة والإيجاز، مع تقديم عدة مقارنات تهدف إلى توجيه القارئ المهتم وإرشاده بشكل مباشر وواضح.

Introduction

Fossil fuels like coal, natural gas, and oil have historically constituted the primary foundation of the energy sector. However, there is a growing shift towards cleaner and more sustainable alternatives [1-11]. Renewable Energy Sources (RES), including solar [12-17], wind [18-22], and geothermal power [23-26] are becoming increasingly popular, while nuclear energy continues to play a significant role in many countries [27-29]. Additionally, biomass and waste-to-energy plants are being used to produce electricity, with the specific energy mix varying across countries and regions, depending on available resources and energy policies [30-35].

Electrical power systems recently have a variety of generation types/sources and a mix of conventional and RES. Running such systems requires elaborate management so that the power system achieves a high level of security and continuity while reducing costs. ED is an optimization process that distributes the required electricity load among

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available power generation units to minimize total generation costs. This process involves determining the most cost-efficient output level for each generator while considering various constraints, among which are capacity limits, and transmission line restrictions. Advanced optimization algorithms are used to assess each generator's cost, reflecting the additional cost of producing one extra unit of electricity. The primary objective is to reduce the whole cost of electricity generation [36,37].

Operating an electrical system without ED can lead to significant drawbacks. One of the main disadvantages is higher operating costs, as generators are not optimized to generate electricity with minimal possible cost. This inefficiency can result in increased fuel consumption, higher emissions, and reduced system performance. Additionally, without ED, certain generators may become overloaded, shortening their lifespan and raising maintenance costs. Moreover, the absence of ED could raise the possibility of power outages and reduce system reliability, as generators not be able to supply demand during peak periods efficiently.

Extensive efforts have been undertaken by researchers to solve the problem of ED through various enhancement techniques [36,37]. However, many studies concentrate solely on optimization methods without considering the essential component: the electrical power system itself, which should be improved through effective management. These studies often focus on hypothetical or standardized energy systems rather than applying their models to real-world systems. As a result, the research tends to address a limited scope of objective functions and constraints.

The contributions of the article could be;

- Presenting a comparative analysis of existing literature.
- The literature is classified into different categories, including modern and innovative classification types of ED, various electrical systems, objective functions, constraints, and other important factors.
- Providing a comprehensive guide for interested people in the field of ED for developing more elaborate solutions.

The remainder of this paper is organized as follows: Section 2 outlines the ED problem formulation. Section 3 classifies the ED for different electrical power systems for various optimization methods. Finally, Section 4 highlights the main conclusions of the study.

ED Problem Formulation

The ED aims to reduce overall generation costs while satisfying the system demand and adherence to various constraints. To solve ED problem, many factors must be taken into account before starting to ensure the success of the desired goal. This is dependent upon the viewpoint of the researchers and the information available. Fig. 1 illustrates the different factors influencing the economic employment problem, which will be addressed in detail.

Electrical and heat dispatch

The power systems used in ED are a network that includes various components such as generating units, transmission lines, and loads. There are many power systems used in ED, as presented in Fig. 2.

ED usually performs many functions, the most important of which is minimizing overall generation cost while meeting the system demand simultaneously, which ensures the most efficient power flow within the system. This considers the security constraints, such as:

1. Transmission line limits
2. Voltage stability
3. Emission limits
4. Combined Heat and Power (CHP) Dispatch

CHP is an important aspect not only in providing energy requirements, whether electricity or heat, but it is an operating system to optimize modern energy systems for many goals. The most notable of these is the provision of energy requirements and the reduction of total costs, emissions, and losses. This is realized by taking into account several restrictions, including energy balance, generation limits, and emissions limits. This is achieved through several advanced optimization algorithms that have already been mentioned. Below is some previous literature using a variety of optimization methods [36-41].

Objective functions

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

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

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

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 [42,43].

$$F_C = \sum_{i=1}^{N_g} a_i {Pg_i}^2 + b_i Pg_i + c_i \tag{1}$$

where F_C is the fuel cost (\$/h), Pg_i is the output power of unit i (MW), N_g is the number of units, $a_i, b_i,$ and c_i are the fuel cost coefficients.

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 [44-46]:

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

$$h_i = \frac{F_c(Pg_{i,max})}{E_c(Pg_{i,max})} = \frac{\left(a_i (Pg_{i,max})^2 + b_i Pg_{i,max} + c_i \right)}{\left(d_i (Pg_{i,max})^2 + e_i \, Pg_{i,max} + f_i \right)} \tag{3}$$

where h_i is the penalty factor, $d_i, e_i,$ and f_i are the emission cost coefficients of the unit, $Pg_{i,max}$ are the upper limits of power generated by unit i.

Valve point effect

It refers to the phenomenon where the fuel cost of a unit increases non-linearly as the power output increases because of 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 [47-49].

$$F_{vpc} = \left| \alpha_i \sin\{\delta_i (Pg_{i,min} - Pg_i)\} \right| \tag{4}$$

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

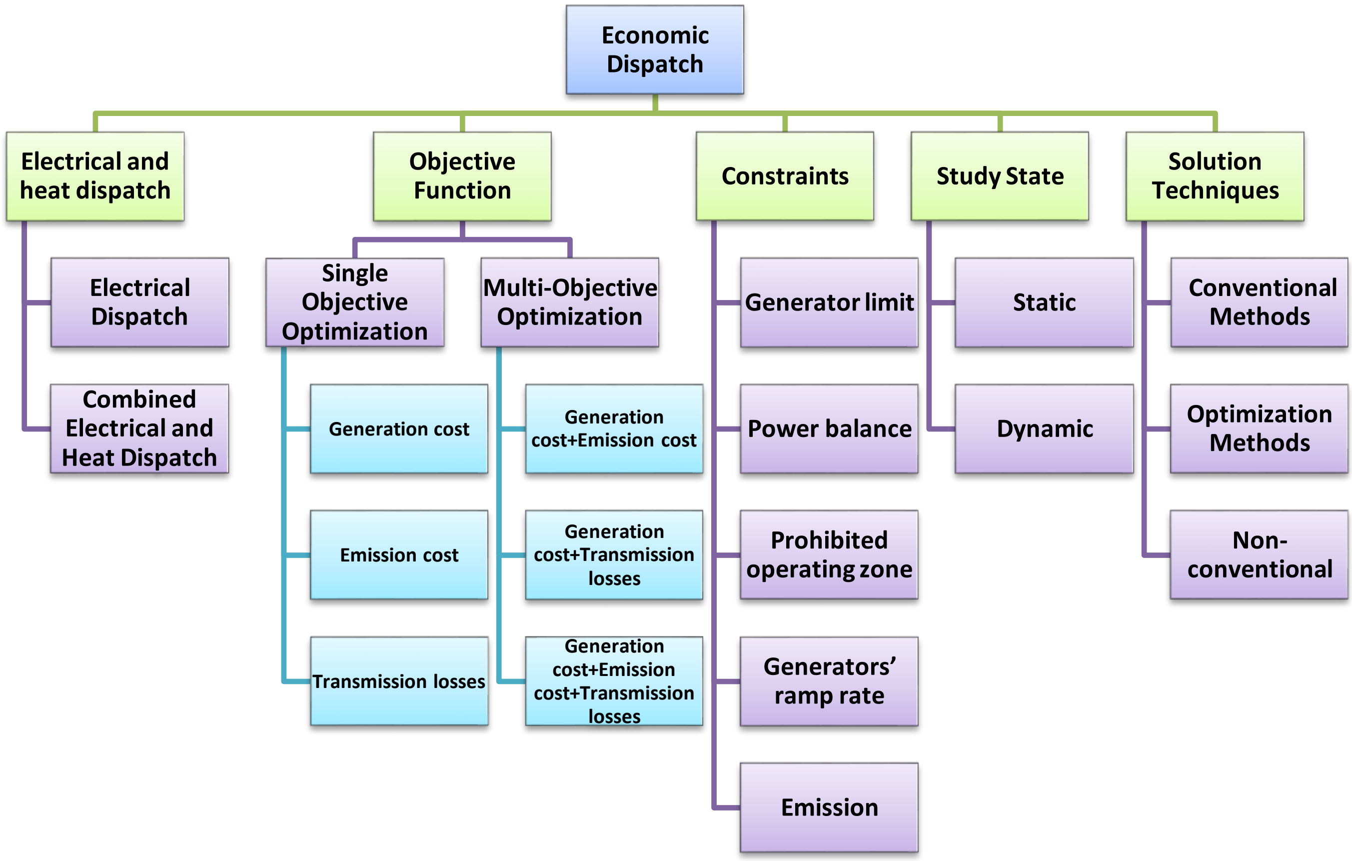

Figure 1: Classification of ED Formulation

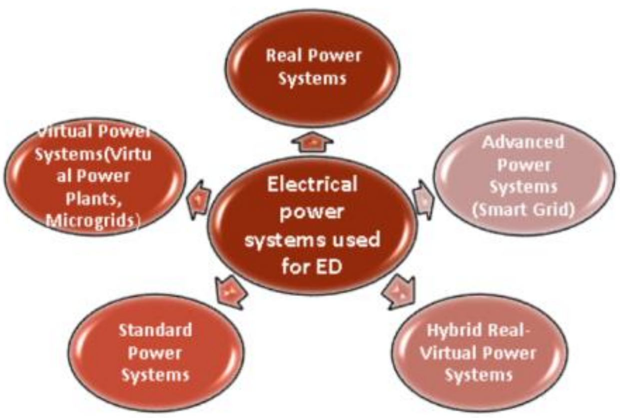

Figure 2: Schematic diagram of the electrical power systems used for ED

Wind Power

The wind power cost objective function aims to minimize the costs of wind-based electricity generation by optimizing the cost function F_w for each wind turbine, which is composed of three components: direct costs, underestimation penalties, and overestimation penalties, as defined in equations (5), (6), (7), and (8), respectively [50-54].

$$F_W = C_{DW}(P_{Wsch}) + C_{SW}(P_{Wav} - P_{Wsch}) + C_{RW}(P_{Wsch} - P_{Wav}) \quad (5)$$

$$C_{DW} = k_{DW} \times P_{Wsch} \quad (6)$$

$$C_{SW}(P_{Wav} - P_{Wsch}) = k_{SW} \times \int_{P_{Wsch}}^{P_{Wr}} (P_W - P_{Wsch}) f_w(P_W) dw \quad (7)$$

$$C_{RW}(P_{Wsch} - P_{Wav}) = k_{RW} \times \int_{0}^{P_{Wsch}} (P_{Wsch} - P_W) f_w(P_W) dw \quad (8)$$

$$f_w(P_W) = \left(\frac{k_s h v_{in}}{P_{wr,ij} c}\right) \left[\frac{\left(1 + \frac{hP_W}{P_{wr,ij}}\right) v_{in}^{k_s}}{c} \times \exp\left(-\frac{\left(1 + \frac{hP_W}{P_{wr,ij}}\right) v_{in}^{k_s}}{c}\right)\right] \quad (1)(9)$$

where P_w indicates the power output of the j^{th} wind turbine in region i, with cost, k_{DW}, k_{SW} and k_{RW} for direct, storage, and reserve costs, respectively. while k_s and c are the shape and scale parameters of the Weibull distribution, respectively. The term P_{wr} is the rated power of the wind turbine, and v_{in} represents the cut-in wind speed. The parameter h is a conversion constant used to relate wind speed to wind power. Together, these parameters define the probabilistic behavior of wind power generation under varying wind.

Photovoltaic (PV) power

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 (9), (10), and (11), respectively [55-61].

$$F_W = C_{DPV}(P_{PVsch}) + C_{SPV}(P_{PVav} - P_{PVsch}) + C_{RPV}(P_{PVsch} - P_{PVav}) \quad (10)$$

$$C_{DPV} = k_{DPV} \times P_{PVav} \quad (11)$$

$$C_{RPV}(P_{PVsch} - P_{PVav}) = k_{RPVij} \times f_s(P_{PVav,ij} < P_{PVsch,ij}) \times [E(P_{PVav,ij} < P_{PVsch,ij})] \times \quad (12)$$

$$C_{SPV}(P_{PVav}-P_{PVsch})=k_{SPVij}\times \left[E\left(P_{PVav,ij}>P_{PVsch,ij}\right)-P_{PVsch,ij}\right]\times f_s\left(P_{PVav,ij}>P_{PVsch,}\right. \tag{13}$$

where P_{PVij} denotes the power output of the j^{th} PV plant in region i, with cost coefficients k_{DPV}, k_{SPVij}, and k_{RPVij} for direct, penalty, and reserve costs, respectively. The terms $f_s\left(P_{PVav,ij}>P_{PVsch,ij}\right)$ and $f_s\left(P_{PVav,ij}<P_{PVsch,ij}\right)$ represent the probabilities of solar power surplus and deficit relative to the scheduled power, respectively. Moreover, $E\left(P_{PVav,ij}>P_{PVsch,ij}\right)-P_{PVsch,ij}$ and $E\left(P_{PVav,ij}<P_{PVsch,ij}\right)$ denote the expected surplus and deficit of solar power with respect to the scheduled value, respectively.

Startup cost and shutdown cost

Thermal power operating costs include fuel costs, startup costs, and shutdown costs. Typically, fuel costs are represented by a quadratic equation of the thermal power units' active output. Startup costs include 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 [37]:

$$f_{\text{fire}}(j,t)=u_{j,t}f_{\text{fuel}}(j,t)+u_{j,t}(1-u_{j,t-1})S_{j,t} \tag{14}$$

$$f_{\text{fuel}}(j,t)=\sum_{s=1}^{S}\left(a_jP_{j,t,s}^2+b_jP_{j,t,s}+c_j\right)\cdot\eta_s \tag{15}$$

$$S_{j,t}=\begin{cases}X_j^{\text{off}}\le T_j^{\text{cold}}+T_j^{\text{off}}, Sh_{j,t}\\ X_j^{\text{off}}>T_j^{\text{cold}}+T_j^{\text{off}}, Sc_{j,t}\end{cases} \tag{16}$$

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 unit j at period t, respectively.

Multiple fuel options

Utilizing multiple fuel sources in different regions within their operational range increases the complexity of the cost function, introducing more non-differentiable points [49], resulting in

$$F_i(Pi)=\begin{cases}a_{i1}(Pg_i)^2+b_{i1}Pg_i+c_{i1}, Pg_{i,\min}\le Pg_i\le P_{\cdot}\\ a_{i2}(Pg_i)^2+b_{i2}Pg_i+c_{i2}, Pg_{i,1}\le Pg_i\le Pg\\ a_{i3}(Pg_i)^2+b_{i3}Pg_i+c_{i3}, Pg_{i,2}\le Pg_i\le P_{\cdot}\end{cases} \tag{17}$$

Constraints

Power balance

$$\sum_{i=1}^{N_g}Pg_i-P_L-P_D=0 \tag{18}$$

$$P_L=\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}Pg_iB_{ij}Pg_j+\sum_{i=1}^{N_g}B_{0i}Pg_i+B \tag{19}$$

where P_L is the network loss of the system (MW), $B_{ij}, B_{oi}B_{oo}$ are the transmission loss formula coefficients and P_D is the total system demand (MW).

Generator operating limits

$$Pg_{i,min}\le Pg_i\le Pg_{i,max}; i=1,\dots,N_g \tag{20}$$

Ramp rate limit

The output of a generator is not instantly adjustable, and this restriction governs how power output changes over time [62]. When power generation increases, it is represented as:

$$Pg_i(t)+Pg_i(t-1)\le \text{UR}_i \tag{21}$$

When power generation decreases, it is given as

$$Pg_i(t-1)-Pg_i(t)\ge DR_i \tag{22}$$

Now, the ED, with an up rate and down rate of power, is defined as

$$\begin{gathered}Pg_{min}=Max\left[\left(Pg_{i,min},Pg_i(t-1)-DR_i\right)\right]\\ Pg_{max}=Min\left[\left(Pg_{i,max},Pg_i(t-1)-UR_i\right)\right]\\ Pg_{i,min}\le Pg_i\le Pg_{i,max}\end{gathered} \tag{23}$$

where UR_i and DR_i indicate the upper and down ramp rate limits, respectively.

Prohibited Operating Zone (POZ)

The POZ defines the limits of a generator's active power output, which could 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 [62].

$$\begin{aligned}&Pg_{i,min}\le Pg_{i,t}\le P_{i,1}^{\text{lower}}\\ &P_{i,j-1}^{\text{upper}}\le Pg_{i,t}\le P_{i,j}^{\text{lower}};\ i=1,\dots,N_g;\ j=2,,\dots,n_i;\ t=1,\dots,24\\ &P_{i,n_i}^{\text{upper}}\le P_{gi}\le Pg_{i,max}\end{aligned} \tag{24}$$

The notation used to describe the 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.

Spinning reserve limits

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.

$$SR_i=min\left\{\left(Pg_{i,max}-Pg_i\right),SR_{i,max}\right\} \tag{25}$$

$$SR=\sum_{i=1}^{n\le N_g}SR_i \tag{26}$$

The spinning reserve is defined as follows: SR_i represents the 5-10% spinning reserve of unit i, measured in megawatts (MW), with $\text{SR}_{i,max}$ being its maximum capacity. The total spinning reserve, SR, is the cumulative contribution from all generating units that operate without any POZ.

Battery operation

Excessive battery charging and discharging can lead to premature aging, and the following constraints are imposed to mitigate this effect [63-66].

$$SOC_{min}\le SOC\ (t)\le SOC_{max} \tag{27}$$

$$P_{Cmin}\le P_{BS}(t)\le P_{Cmax} \tag{28}$$

$$P_{Dmin}\le -P_{BS}(t)\le P_{Dmax} \tag{29}$$

The battery storage system is characterized by its minimum and maximum State Of Charge (SOC) limits, denoted by SOC_{min} and SOC_{max}, respectively. P_{BS} is the battery power, where positive values indicate charging and negative values indicate discharging.

$P_{Cmin}, P_{Cmax}, P_{Dmin}$, and P_{Dmax} represent the limits of charging and discharging power.

Transmission line capacity

This constraint ensures that transmission lines are not loaded beyond their rated capacity, thereby preserving the stability and secure operation of the power system, as expressed below:

$$Pl_{min} \leq Pl \leq Pl_{max} \tag{30}$$

where Pl_{min} and $Pl_{\max}$ are the minimum and maximum line capacity [67].

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.

$$Em(t) \leq Em^{\max}(t) \tag{31}$$

where $Em^{\max}(t)$ is the maximum emission [68].

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 [37].

$$T_{up/down} \in \begin{cases} T_{j,t}^{up} \geq T_{j,on} \\ Tg_{j,t}^{down} \geq T_{j,off} \end{cases} \tag{32}$$

where $T_{j,on}$ and $T_{j,off}$ are the minimum operating time/down time of generator j.

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 [69].

$$Vn_{i,\min} < Vn_i < Vn_{i,\max} \text{ and } \delta n_{min} \leq \delta n_i \leq \delta n_{max} \tag{33}$$

where $Vn_{i,\min}$, δn_{min}, $Vn_{i,\max}$, and δn_{max} are the minimum and maximum limits.

Transformer tap setting

The transformer tap setting is constrained within the range:

$$0 \leq T \leq 1 \tag{34}$$

On the secondary side, the tap setting can defined within the range $0 \leq T \leq n_T$ where n_T represents the transformer turns ratio [69].

Regional Load Sharing Dispatch (RLSD)

RLSD is the exchange of available power among the diverse sources allocated in distinct areas. It can be expressed as follows:

$$\sum_{i=1}^{N_{\text{areas}}} P_{N_{i,\max}} \geq \sum_{i=1}^{N_B} P_{B_i} + \sum_{i=1}^{N_W} P_{W_i} + \sum_{i=1}^{N_{PV}} P_{PV_i} \tag{35}$$

where P_{PV}, P_B, and P_W denote the total available power from PV, biofuel, and wind resources based on system demand; P_N represents the power contribution from N regions corresponding to the generation sources [55].

Frequency Limits

Frequency limits are enforced to ensure that the system frequency remains within an acceptable range around its nominal value, as expressed below:

$$fg_{i,min} \leq fg_i \leq fg_{i,max} \tag{36}$$

where $fg_{i,min}$ and $fg_{i,max}$ denote the lower and upper frequency limits [70].

Reactive Power Constraints

For each generating unit, the reactive power Qg_i must remain within its specified operating limits:

$$Qg_{i,min} \leq Qg_i \leq Qg_{i,max} \tag{37}$$

where $Q_{i,\,min}$ and $Q_{i,\,max}$ indicate the lower and upper limits [69].

PV power

This constraint ensures that solar generation stays within available irradiance limits and above the minimum operating level, maintaining a realistic representation in the ED model.

$$P_{PV,min} \leq P_{PV} \leq P_{PV,max} \tag{38}$$

where $P_{PV,min}$ and $P_{PV,max}$ are the lower and upper PV limits [71].

Wind power

This constraint ensures that wind power dispatch stays within the actual operating limits of the turbines, avoiding any scheduling beyond their physical capacity.

$$P_{W,min} \leq P_W \leq P_{W,max} \tag{39}$$

where $P_{W,min}$ and $P_{W,max}$ denote the lower and upper wind limits [71].

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 for a single time interval.
- Dynamic ED: This ED method accounts for the power system's time-varying characteristics, including ramp rates, startup and shutdown costs, and time-dependent constraints, to optimize generation over time.

Optimization Techniques for ED

Several optimization techniques have been used in ED as shown in Fig. 3.

ED for electrical power systems

Standard power systems

Standard power systems are considered the most widely used systems to measure the effectiveness and existence of economic operating techniques. These systems are typically modeled as IEEE bus systems, which are standardized power system networks that consist of buses, generators, and transmission lines. A wide range of optimization algorithms has been employed to evaluate the ED of standard power systems. Still, due to the large literature and for greater ease and coordination, the literature will be divided based on the classification of the optimization methods used that were previously mentioned.

Conventional optimization methods

A 3-unit and a 6-unit system are optimized using two novel techniques to enhance ED methods, with the objective of minimizing the fuel cost. The first technique efficiently allocates load demand across generating units, delivering

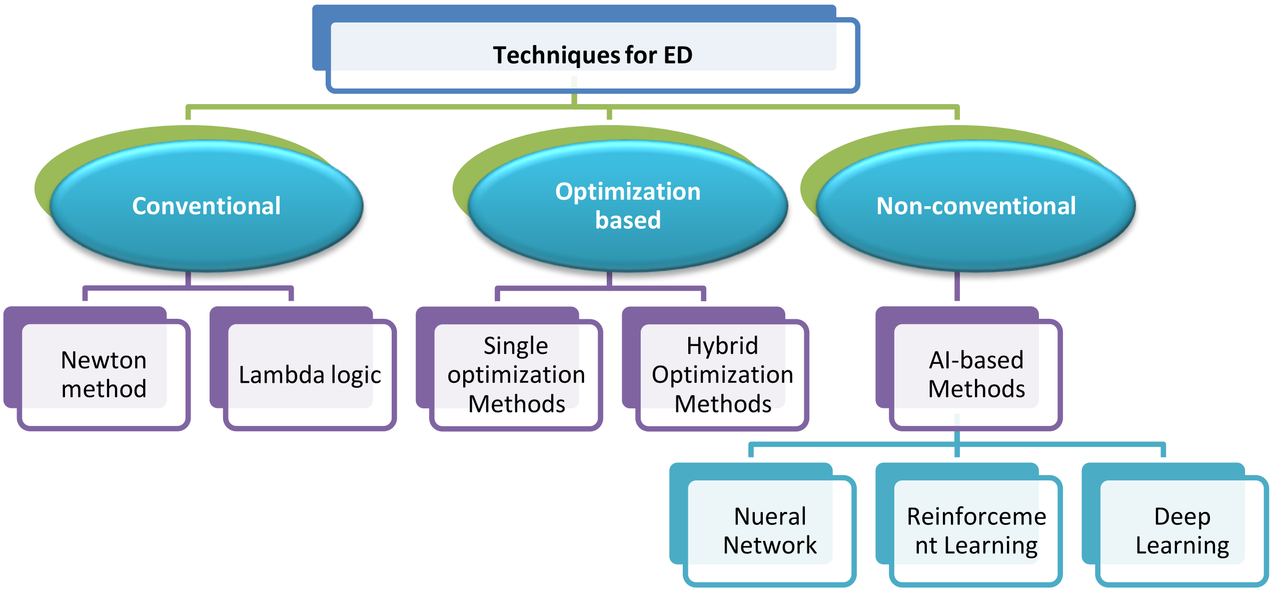

Figure 3: Classification of optimization techniques for ED

superior performance over conventional methods. The second technique approximates the non-convex cost function, allowing the application of gradient and Newton-based methods to solve ED problems with transmission losses. This approach has been proven to effectively reduce generation costs compared to other techniques.

The IEEE 39-bus system, consisting of 10 units, is optimized using a fully distributed ED strategy. The primary objective is to reduce the total generation cost, including thermal generator fuel costs, carbon trading expenses, and the costs of wind turbines. The proposed algorithm outperforms existing methods, excelling in both communication efficiency and faster convergence and enabling a fully distributed operational approach [72].

An efficient and robust approach optimizes a thermal unit system ranging from 6 to 240 units, aiming to reduce total generation costs while adhering to a range of operational constraints. The proposed algorithm delivers high-quality solutions with reduced computational effort, achieving highly optimal results for large-scale systems without experiencing convergence issues for convex functions. This effectiveness is demonstrated through numerical tests and comparative analysis across five different test cases [73].

A 6-unit system is optimized using a numerical algorithm for environmental ED, seeking to optimize the total cost, accounting for both fuel expenses and emissions allowances while adhering to load demand and emissions constraints. The proposed algorithm is shown to be far more economically efficient than traditional ED methods, particularly when factoring in the emissions trading system [74].

Table 1 presents a comprehensive summary of prior research, outlining key aspects such as the electrical power system, optimization techniques, and study state, as well as the objective functions and constraints. This provides a basis for an in-depth comparative analysis.

Optimization Methods

Single Optimization Methods

In the IEEE 39-bus system, a scenario-based ED model integrating wind power and an Energy Storage System (ESS) is applied using the Particle Swarm Optimization (PSO) technique to minimize the overall cost while stabilizing wind power fluctuations and reducing curtailment.

Table 1: Comprehensive summary of ED in standard power systems for conventional optimization methods

Ref.	Year	Test System	Method	Static or Dynamic	Objective Function					Constraints					
					F1	F2	F3	F4	F7	C1	C2	C3	C4	C5	C6
[36]	2013	3-6 units	Newton method	S	√		√		√	√	√	√	√		√
[72]	2024	39 bus	ADMM	S	√	√		√		√		√			
[73]	2009	6-15-20-40-80-120-160-240 units	Lambda logic	S	√					√	√	√	√	√	√
[74]	2024	6 units	Numerical algorithm	S	√	√				√		√			

* S denotes Static, and D denotes dynamic

* F1 denotes fuel cost, F2 denotes emission, F3 denotes valve point effect, F4 denotes wind cost, F5 denotes PV cost, F6 denotes start up + shutdown, and F7 denotes multi-fuel operation.

* C1 represents power balance without considering losses, while C2 accounts for power balance with losses. C3 refers to generation limits, C4 specifies ramp rate limits and C5 covers POZ. C6 sets reserve limits, and C7 governs battery operation. C8 concerns transmission line capacity, and C9 imposes emission constraints. C10 outlines minimum up/downtime requirements, and C11 deals with voltage constraints. C12 pertains to transformer tap settings, C13 to RLSD, C14 to frequency regulation limits, C15 to reactive power limits, C16 to PV power limits, and C17 to wind power limits.

A 6-unit and 10-unit systems are used to demonstrate an enhanced Artificial Bee Colony (ABC) technique for addressing the Dynamic Economic Emission Dispatch (DEED) problem. The DEED problem is a multi-objective optimization problem aimed at minimizing both total fuel and emissions costs simultaneously. The results indicate that the proposed optimizer surpasses ten other metaheuristic techniques [62].

In a thermal power plant with six generating units, a novel PSO algorithm is introduced to address the Economic Emission Dispatch (EED) problem. The main objective is to determine the optimal operation of the power plant that minimizes both generation costs and emissions. Results from the new PSO algorithm demonstrate superior performance than other optimization algorithms, proving its effectiveness in achieving minimal costs and emissions [44].

A thermal power plant with six generating units system is optimized using the PSO technique to optimize the power generation for each unit, aiming to minimize both fuel costs and emissions within the framework of the Economic Emission Load Dispatch (EELD) system; The results confirm a pronounced reduction in both the cost of generating power and the amount of emissions produced [75].

Three- and six-generator system models with multiple fuel options is examined, employing a PSO technique to minimize the generation cost while meeting constraints, including power balance and generator limits. The results demonstrate that this method is straightforward, efficient in identifying global solutions [76].

A 3-unit and a 6-unit system are utilized to assess the efficiency of PSO in solving EDP, which seeks to optimize the generation cost. The results indicate that PSO surpasses other evolutionary optimization methods, such as Cuckoo Search Optimization (CSO) and Genetic Algorithm (GA), in terms of achieving the lowest fuel costs and effectively managing complex constraints [69].

The IEEE 30-bus system is employed to optimize the Combined Economic and Emission Dispatch Problem (CEED) problem for thermal units using the PSO algorithm. This approach aims to reduce fuel costs and toxic gas emissions while adhering to load demands and system constraints [77].

A 13-unit, a 15-unit, and a 6-unit system are used to evaluate the Modified Particle Swarm Optimization (MPSO) algorithm, which addresses ED and EELD problems. The aim is to identify an effective method for enhancing power system operation and reducing costs. The results show that MPSO surpasses other optimization algorithms in both solution and computational efficiency [78].

A 3-unit system with multiple fuel options and a 6-unit system are utilized to assess the performance of GA in addressing the EDP. The objective is to minimize the total power generation cost. The results demonstrate that the GA is both effective in finding near-optimal solutions and computationally efficient [49].

The IEEE-9 bus system, which includes three generators, is analyzed using GA aimed at minimizing the fuel costs of the generating units. Constraints are managed through a penalty function. The results indicate that the GA effectively addresses the EDP for the power system [79].

The IEEE 30-bus electrical network is analyzed using a novel stochastic GA to tackle the EDP. The study aims is to minimize the fuel cost for all operational plants while ensuring that demand and losses are met [80].

The IEEE 30-bus transmission system is optimized using a novel micro-Genetic Algorithm (μ-GA) to minimize total generation costs while maintaining system constraints. The results demonstrate that μ-GA surpasses both Lagrange and standard GA methods in reducing generation costs and system losses [81].

For systems with 5, 10, and 15 generating units, an Improved Grey Wolf Optimization (IGWO) algorithm is presented to address the Dynamic Economic Dispatch (DED) problem. This improved version incorporates three enhancements over the original GWO: chaotic initialization, an improved convergence factor, and a dynamic weight factor for the location update formula. Results indicate that IGWO effectively reduces fuel costs, achieves faster convergence, and demonstrates superior global optimization capabilities compared to other algorithms [82].

The IEEE 30-bus system is optimized using a Multi-Objective Genetic Programming Evolutionary Algorithm (MOGPEA) to reduce both fuel and emissions costs while ensuring compliance with system constraints in the EED problem. The results revealed that MOGPEA is both efficient and competitive in addressing this issue [83].

The 5-unit IEEE system is optimized via the Whale Optimization Algorithm (WOA) to minimize both generation costs and emissions. The outcomes reveal that the proposed WOA outperforms other recently developed optimizers in solving the DEED problem [84].

A power system with 10 thermal units is optimized using the Teaching-Learning-Based Optimization (TLBO) algorithm to minimize the total generation cost, which incorporates both the fuel costs of thermal units and the expenses associated with charging Plug-in Electric Vehicles (PEVs). The study also explores the effects of PEVs on ED under various charging scenarios [70].

A power system with 10 units is optimized using the TLBO algorithm to simultaneously minimize both total costs and harmful gas emissions. The simulation results demonstrate that TLBO outperforms other metaheuristic optimizers, such as PSO, IBFA, and NSGA-II, in identifying the optimal generation for the dynamic economic environmental dispatch problem [85].

The five-unit generation system is optimized using a novel meta-heuristic algorithm known as Ant Lion Optimization (ALO) to optimize the power output schedule for the online generating units. This approach aims to concurrently minimize both operating costs and emissions while ensuring that the load demand is fully satisfied. The proposed method is also compared with other optimizers, demonstrating superior performance [86].

The IEEE 30-Bus system is optimized using a novel technique called Multiverse Optimization (MVO). The objective is to optimize the output power to meet the demand at the lowest possible cost by minimizing the total generation cost. In this study, The effectiveness of MVO is compared with Evolutionary Programming (EP), showcasing its effectiveness in addressing the EDP [87].

The IEEE 30-bus system, with three and six generating units, is optimized using an Improved Yellow Saddle Goat Fish Algorithm (IYSGA). The primary objective is to reduce the mismatch between the generated power and the demanded load while reducing costs, resulting in a more economical and robust solution for the EDP. The proposed IYSGA outperforms other algorithms in both cost efficiency and accuracy, achieving the lowest cost while meeting the load demand with zero error, offering a practical and effective solution for real-world applications [88].

The modified IEEE 30-bus system, incorporating natural gas units and variable RES, is optimized using two algorithms: Multi-Objective Harris Hawks Optimization (MOHHO) and the Multi-Objective Flower Pollination Algorithm (MOFPA). The goal is to minimize both emissions and fuel costs while adhering to system constraints. The results indicate that the MOHHO algorithm surpasses MOFPA in terms of convergence and the uniform distribution of solutions [71].

Power systems with 3, 5, 6, 10, 13, 15, 20, 38, and 40 generating units are optimized using the Slime Mould Algorithm (SMA). This approach is designed to achieve the minimum possible total fuel cost of the power system, while ensuring that the load demand is fully met and all operational system constraints are strictly satisfied, effectively addressing the non-convex EDP. When compared to other established optimizers, the proposed SMA exhibits enhanced performance in providing a cost-effective and efficient solution [89].

A system with 6 and 10 generating units is optimized using the Gradient-Based Optimizer (GBO) algorithm. The aim is to achieve the minimum level of total production costs while complying with system constraints. The proposed GBO algorithm is evaluated across various ED problem scenarios, and the results demonstrate that it outperforms other benchmark algorithms [90].

Six test systems, consisting of 3, 6, 20, 40, 110, and 160-unit systems, were utilized to evaluate the performance of a novel Cauchy-Gaussian Quantum-Behaved Bat Algorithm (CGQBA) for solving the EDP. The CGQBA operators optimize total cost while satisfying system constraints of the system. Simulation results demonstrate that CGQBA is highly effective and outperforms other algorithms in addressing the EDP [91].

A detailed overview of previous research is provided in Table 2, covering the electrical power system, optimization techniques, study conditions, and both objective functions and constraints, allowing for a inclusive comparative analysis.

Table 2: Inclusive summary of ED in standard power systems for nature-inspired optimization methods.

Ref.	Year	Test System	Method	Static or Dynamic	Objective Function							Constraints													
					F1	F2	F3	F4	F5	F6	F7	C1	C2	C3	C4	C5	C6	C7	C10	C11	C12	C14	C15	C16	C17
[37]	2020	39 bus	PSO	D	√			√		√		√		√	√		√	√	√						
[62]	2018	6-10 units	ABC	S	√	√	√					√	√	√	√	√									
[44]	2023	6 units	PSO	S	√	√						√		√											
[75]	2022	6 units	PSO	S	√	√						√		√											
[76]	2021	3-6 units	PSO	S	√							√	√	√											
[69]	2020	3-6 units	PSO	S	√							√	√	√	√					√	√		√		
[77]	2012	30-bus 6- units	PSO	S	√	√						√	√	√											
[78]	2023	6-13-15 units	MPSO	S	√	√	√					√		√	√										
[76]	2024	3-6 units	GA	S	√						√	√	√	√											
[79]	2020	3 units	GA	S	√							√		√											
[80]	2014	30 bus	GA	S	√							√	√	√											
[81]	2022	30 bus	μ-GA	S	√							√	√	√											
[82]	2024	5-10-15 units	IGWO	D	√		√					√	√	√	√										
[83]	2020	30-bus 6- units	MOGPEA	S	√	√	√					√	√	√											
[84]	2021	5 units	WOA	D	√	√	√					√	√	√	√										
[70]	2023	10 units	TLBO	D	√							√		√	√					√		√	√		
[85]	2020	10 units	TLBO	D	√	√	√					√	√	√	√	√									
[86]	2020	5 units	ALO	D	√	√	√					√	√	√	√	√									
[87]	2020	30 bus	MVO	S	√							√	√	√											
[88]	2024	30-bus 3 and 6 units	IYSGA	S	√		√					√		√											
[71]	2020	30 bus	MOHHO	S	√	√	√	√	√			√		√		√				√			√	√	√
[89]	2022	3-5-6-10-13-15-20-38-40 units	SMA	S	√							√	√	√	√	√									
[90]	2021	6-10 units	GBO	S	√	√	√					√	√	√											
[91]	2021	3-, 6-, 20-, 40-, 110-160-units	CGQBA	S	√		√				√	√	√	√	√	√									

Hybrid Optimization Methods

Three systems, consisting of three, six, and ten units, are employed for the EDP using a hybrid algorithm that combines the GA with the ABC method. The objective is to minimize fuel costs. The proposed GA/ABC hybrid algorithm demonstrates superior performance and more stable convergence compared to both the standalone GA and ABC algorithms [92].

The IEEE-118 power system is utilized to optimize the EDP using a novel hybrid algorithm that combines ALOA with a Fuzzy Logic Controller (FLC). The goal is to minimize fuel costs while adhering to system constraints. Results indicate that the FLC-ALOA approach is faster and yields better outcomes compared to conventional ALOA and PSO-ALOA methods [93].

A system comprising 6, 10, 26, and 40 units, which includes thermal, hybrid, and RES, is used to evaluate a Modified Hybrid Particle Swarm Optimization with Bat Algorithm parameter-inspired Acceleration Coefficients (MHPSO-BAAC). This evaluation is conducted both with and without the constriction factor. The MHPSO-BAAC algorithm aims to enhance the solution of the EDP by enhancing the recently proposed Hybrid PSO and Bat Algorithm (HPSOBA). Results demonstrate that MHPSO-BAAC surpasses other metaheuristic algorithms in fuel cost reduction, rapid convergence, and computational efficiency [55].

Four test cases featuring 5, 10, and 30 generating units are utilized to evaluate the efficacy of a hybrid algorithm. This algorithm combines PSO and Termite Colony Optimization (TCO) to address the DED problem, aiming to establish the optimal generation schedule for committed power units to meet predicted load demands over a specified time period while minimizing operating costs and adhering to various system constraints. The analysis indicate that the HPSTCO algorithm is both reliable and robust, delivering superior solutions compared to other methods [94].

A ten-unit system is used to assess the capability of five AI techniques: Differential Evolution (DE), PSO, EP, GA, and Simulated Annealing (SA). The objective is to obtain the optimal hourly generation schedule that minimizes the total production cost of committed units while satisfying various constraints. The results demonstrate that DE surpasses the other techniques, offering superior cost and CPU time performance. This highlights the effectiveness of DE in achieving optimal solutions with a favorable balance between cost and computational efficiency [95].

The performance of the new algorithm is assessed using a three-unit system and the six-unit IEEE 30-bus system. This algorithm integrates PSO with an Adaptive Neuro-Fuzzy Inference System (ANFIS) to determine the optimal power output of generating units. Its primary objective is to minimize total fuel costs while adhering to system constraints. The results show that the PSO-ANFIS algorithm surpasses traditional methods, such as the lambda iteration and standard PSO, in solving the ED problem effectively [96].

The 39-bus IEEE system, consisting of 10 generators, is optimized using a hybrid Firefly Algorithm (FA) and GA to minimize fuel costs and pollution emissions through a novel approach that incorporates loss indices, voltage stability, and pollution factors. This method demonstrates superior performance in reducing both fuel costs and emissions compared with other algorithms [97].

The performance of the IEEE 118-bus 14-unit system is optimized using an FA combined with a fuzzy approach to determine the optimal balance between generation cost and emissions while fulfilling load demand and operational constraints. The goal is to solve the Combined Economic-Emission Load Dispatch (CEELD) problem. The results confirm that FA significantly reduces both costs and emissions in comparison with other methods, making it a viable alternative for solving optimization problems [98].

A 3-generator system and a 6-generator system, the latter based on the IEEE 30-bus system, are optimized using the ALOA and BA to minimize total costs while satisfying system demand and adhering to system constraints. The results demonstrate that both ALOA and BA are highly effective in solving the EDP, achieving optimal or near-optimal solutions and outperforming competing algorithms such as PSO, GA, WOA, CSA, and FFA [99].

In a system with three generator units, the goal is to minimize total generation costs while satisfying the load demand and transmission line losses. This study proposes a solution to the ED problem using the Lambda Iteration method and the Back-Propagation Neural Network (BPNN) technique. A comparison of the two methods shows that the Neural Network (NN) approach delivers quicker and more accurate results than the lambda iteration method [100].

For a 30-bus system, the objective is to determine the optimal generation levels that minimize total generation costs and transmission line losses for a given load. This paper presents ED studies using two approaches: a classical method (the gradient method) and a NN method. A comparison of the outcomes shows that the NN approach is more efficient than the classical gradient method [101].

In the IEEE 24-bus system, the objective is to minimize the total cost of the interconnected power system by efficiently distributing active power generation across grid buses. This study present a method for addressing the Economic Dispatch Problem (EDP) using both traditional and neural network-based approaches. A comparison of the two shows that the NN method is superior in terms of speed and reliability, making it the preferred choice for ED optimization [102].

Two systems, one with five units and another with 10 units, are optimized using a hybrid algorithm that combines Mixed Integer Linear Programming (MILP) and the Interior Point Method (IPM). This integrated MILP-IPM method is designed to address the DED problem more effectively by utilizing the strengths of both techniques. The proposed technique was tested and validated through simulations, which confirmed its efficiency and robustness. The results indicate that the MILP-IPM surpasses other methods, particularly in handling transmission losses [103].

In a 15-generator system, a hybrid approach combining the Hill Climbing and Gravitational Search Algorithm (HCGSA) is applied to address the ED problem. This method aims to minimize the total operating cost while meeting load demand. The proposed HCGSA technique was tested on a standard benchmark problem and the 15-generator system, with results showing its effectiveness in reducing operating costs compared to the basic GSA [104].

A modified IEEE 30-bus test system, consisting of three thermal units, one wind generator, one PV unit, and a combined solar PV and small-hydro unit with 11 control variables, is optimized using a proposed method to identify Pareto optimal solutions. The prime objective is to minimize both generation cost and emissions. The objective function is designed to address the multi-objective economic-environmental dispatch problem, accounting for the stochastic nature of wind, PV, and small-hydro power generation [67].

Table 3 summarizes earlier research efforts, presenting key details on the electrical power system, optimization approaches, study parameters, and objective functions and constraints, enabling a robust comparative analysis.

Table 3: Comprehensive summary of ED in standard power systems for hybrid optimization methods

Ref.	Year	Test System	Method	Static or Dynamic	Objective Function					Constraints										
					F1	F2	F3	F4	F5	C1	C2	C3	C4	C5	C6	C8	C10	C11	C13	C15
[92]	2024	3-6-10 units	ABC+GA	S	√		√			√	√	√								
[93]	2023	118 bus	FLC-ALOA	S	√					√	√	√								
[55]	2021	6-10-26-40 units	MHPSO-BAAC	S+D	√	√	√	√	√	√	√	√	√	√			√		√	
[94]	2020	5-10-30 units	PSO +TCO	D	√		√			√	√	√	√	√						
[95]	2019	10 units	PSO+GA+SA+DE	D	√		√			√	√	√	√							
[96]	2018	3-6 units	PSO-ANFIS	S	√					√	√	√								
[97]	2022	39 bus	FA-GA	S	√	√	√			√	√	√	√	√				√		
[98]	2019	118 bus	FA with fuzzy	S	√	√	√			√	√	√								
[99]	2022	3-6 units	ALOA+ BA	S	√					√	√	√								
[100]	2016	3 units	classical methods +NN	S	√					√	√	√								√
[101]	2013	30 bus	classical methods +NN	D	√					√	√	√								
[102]	2012	24 bus	classical methods +NN	S	√					√	√	√								
[103]	2017	5-10 units	MILP-IPM	D	√		√			√	√	√	√		√					
[104]	2021	15 units	HCGSA	S	√		√			√	√	√								
[67]	2018	Modified 30 bus	MOEA/D-SF and SMODE-SF	S	√	√	√	√	√	√		√		√		√		√		√

AI-based Methods

The 30-bus IEEE system, along with 10-generator and 20-generator systems, is optimized using Reinforcement Learning (RL) techniques. Specifically, three RL algorithm variants are applied to the ED problem. The proposed methods outperform existing methods by effectively managing complexities like transmission losses and showing strong performance across various test systems [105].

The IEEE 6-bus system is optimized using an RL algorithm, specifically Q-learning, to reduce total costs while satisfying the laod demand and power constraints. The proposed algorithm outperforms traditional methods in both efficiency and accuracy in computation. It also effectively handles complexities such as transmission losses and non-convex fuel cost functions, with simulations demonstrating its robustness across various load demands [106].

The IEEE 30-bus system is optimized to minimize fuel costs while satisfying load demand and power system constraints using an NN-based Lambda iterative optimization method. The results illustrate the capability of the approach in delivering precise dispatch solutions across a diverse range of load demands at minimal total cost while also analyzing the system's total power losses [107].

For systems with 3 and 10 generator units, the primary objective is to determine the optimal ED of power plants by minimizing total fuel costs. BPNNs are employed to achieve this goal and are compared to the conventional Lambda iteration method. The results show that the NN method is more accurate and efficient, particularly in terms of reducing execution time [108].

For the IEEE 30-bus, IEEE 118-bus, and a real-world utility 661-bus system, the objective is to enhance the computational efficiency of the Security-Constrained Economic Dispatch (SCED) problem in smart grids. This study proposes a Deep Learning (DL) algorithim using Stacked Denoising Autoencoders (SDAEs) to identify active constraints, thereby decreasing the number of iterations needed to solve the SCED problem and speeding up computation times. Additionally, a fast parameter-tuning strategy for SDAEs based on transfer learning is introduced. Numerical tests show that the presented method improves computational efficiency while ensuring accuracy [109].

The 30-bus and 118-bus IEEE systems are utilized to showcase the effectiveness of a novel approach for solving the multi-period SCED model. This model integrates a DL technique with an existing iterative solution process by embedding a Deep Neural Network (DNN) into the computational framework to pre-identify active constraints. The objective is to significantly reduce computational costs and accelerate SCED calculations. Simulation experiments demonstrate that the developed method can efficiently solve the multi-period SCED model in no more than two iterations [110].

The ED problem of a 9-generating unit system is solved using an ANN trained with the Levenberg-Marquardt Back-Propagation (LMBP) algorithm. The objective is to minimize total costs. The LMBP algorithm trains the ANN using data generated by the Lambda iteration method. Once trained, the ANN predicts the optimal power output for each generator based on the load demand, delivering more rapid and accurate results compared to traditional methods like lambda iteration [111].

A modified IEEE 34-bus system is optimized using a distributed randomized gradient-free algorithm, specifically designed to solve the non-convex ED problem of a Virtual Power Plant (VPP) consisting of distributed generators, RES, and ESS. The method seeks to identify the optimal power of each Distributed Energy Resources (DER) within the VPP to minimize total generation costs while adhering to system constraints. The objective is to maximize the VPP's total income by optimizing its ED. The proposed algorithm effectively addresses the non-convex ED problem of the

VPP, offering performance comparable to centralized algorithms while improving scalability and reducing communication costs [112].

A modified IEEE 33-bus system, incorporating PV and wind power generation, is optimized using a G-LSTM method to optimize the accuracy of electricity price prediction and address the ED problem within the distribution network. The results were compared to other models, and the predicted electricity prices were applied as the selling prices for the distribution system. This approach achieved greater forecasting accuracy and more efficient ED in the distribution network [113].

A complete summary of prior studies is outlined in Table 4, showcasing the electrical power systems, optimization methods, study states, and the relevant objective functions and constraints, supporting a detailed comparative analysis.

Table 4: Comprehensive summary of ED in standard power systems for AI-based optimization methods.

Ref.	Year	Test System	Method	Static or Dynamic	Objective Function			Constraints								
					F1	F3	F7	C1	C2	C3	C4	C5	C7	C8	C16	C17
[105]	2011	3-6-10-20 units	RL	S	√			√		√						
[106]	2008	6 bus	RL	S	√			√	√	√						
[107]	2019	30 bus	NN	S	√			√	√	√						
[108]	2007	3-10 units	NN	S	√			√		√						
[109]	2020	30-118-661 bus	DL	S	√			√		√				√		
[110]	2021	30-118 bus	DNN	S	√			√		√				√		
[111]	2018	9 units	NN	D	√			√		√	√					
[112]	2017	34 bus	DRGF	S	√	√	√	√		√		√	√		√	√
[113]	2019	33 bus	G-LSTM	D	√			√		√	√			√		

Virtual Power Systems

Virtual power systems are regarded as a promising solution for optimizing the operation of modern energy systems. These systems combine DER, including RES, traditional energy generation, and ESS, to create a virtual energy network. This approach enables the evaluation of economic performance and allows for more efficient and flexible management of power generation resources. As a result, it reduces operation costs and emissions, increases the use of RES, and boosts grid reliability and resilience.

Conventional optimization Methods

In an MG system with multiple DER, including wind turbines, PV panels, gas generators, fuel cells, and energy storage devices, an Approximate Dynamic Programming (ADP) method is proposed for ED. The ADP-based ED (ADPED) algorithm is designed to improve the operation of the MG, considering uncertainties such as fluctuating renewable generation, electricity prices, and power demand. The main objective is to reduce the operational cost over the optimization period, while accounting for factors such as fuel costs, operation and maintenance expenses, electricity purchases from the grid, and penalties for Renewable Energy (RE) curtailment and load shedding. The algorithm allows the MG to operate efficiently while connected to the main grid, with the flexibility to buy or sell electricity as needed [114].

In an MG system, two distributed dynamic optimization algorithms based on distributed incremental cost consensus are proposed to address ED problems. These methods optimize generator power output by leveraging the deviation between demand and generation, aiming to find the best solution to ED problems while accounting for generation constraints. The proposed algorithms are proven to converge at a geometric rate, and simulation results confirm their accuracy, effectiveness, efficiency, and scalability in solving ED problems [115].

Optimization Methods

Single Optimization Methods

A grid-connected MG system comprising three Diesel Generators (DG), a 30 MW wind farm, and a 40 MW PV system is analyzed. The approach employs a Weighted-Update Artificial Bee Colony (WU-ABC) algorithm to adjust the emission penalty factor. The objective is to solve the CEED problem by minimizing total costs while adhering to the maximum emission constraint. The results indicate that WU-ABC method outperforms other techniques in terms of both cost and computational efficiency, successfully meeting the emission limits while reducing operating expenses [13].

A hybrid renewable energy microgrid comprising solar, wind, a diesel engine, a fuel cell, and a battery storage system is employed to investigate the integration of Electric Vehicles (EVs) and the implementation of Vehicle-to-Grid (V2G) technology. The key objective is to minimize total costs, reduce pollutants, and lower carbon emissions under both grid-connected and islanded operating modes. To optimize system performance, two algorithms PSO and ABC are utilized. The findings indicate that the ABC algorithm outperforms PSO in terms of cost, carbon emission reduction, and computational efficiency [116].

The Multi-Area Power System (MA-PS), comprising thermal and wind power units, is optimized using the Salp Swarm Algorithm (SSA) to minimize total operating costs while meeting all operational constraints. The objective is to validate the effectiveness of the SSA in addressing the Multi-Area Economic Dispatch (MAED) problem, particularly in the context of stochastic wind power [117].

The Sustainable Power System (S-PS), comprising fuel-based units, PV units, and ESS, is optimized through a comprehensive framework that integrates an improved SSA with DL-based forecasting models. The primary aim is directed toward minimizing fuel consumption costs for the generating units while addressing practical constraints, including generation limits, ramp-rate restrictions, and power mismatch constraints [118].

An MG system, comprising three thermal power units along with solar and wind-powered generation units, is optimized using an Improved Mayfly Optimization Algorithm (IMA) to minimize total operating costs while reducing emission levels. The results reveal that IMA consistently outperforms other optimizers, such as PSO, GA, and GWO, in terms of lowering overall generation costs [119].

MGs are optimized using a Memory-Based Gravitational Search Algorithm (MBGSA) to minimize total generation costs while meeting load demand. MBGSA, an enhanced version of the traditional GSA that leverages memory to retain the best solution from previous iterations, is applied to solve the ED problem in an MG system comprising a CHP station, three DGs, and two PV plants. The main objective is to reduce the total cost of DER generation. The results indicate that MBGSA outperforms other metaheuristic methods including GSA, ABC, PSO, and GA in terms of cost minimization [120].

Hybrid Optimization Methods

A Multi-Energy Virtual Power Plant (ME-VPP) system is utilized to investigate the formulation of a bi-objective optimization problem utilizes the Multi-Objective Particle Swarm Optimization (MOPSO) method, aiming to reduce Economic Costs (EC) while improving power quality. A case study of Hongfeng Eco-town in Southwestern China reveals that two operational strategies,"improvisational"and "foresighted," which incorporate LSTM-based wind predictions, show varying performance. The "foresighted" strategy demonstrates superior Pareto dominance throughout the day, as tested on the IEEE 118-bus system [121].

A hybrid metaheuristic approach is proposed to solve ED Problems involving RESs, including wind, solar PV, and biofuel-based power systems, using a 6-40-26-12 unit system. The goal focuses on minimizing the dispatch cost of the power system while satisfying equality and inequality constraints. The authors formulate objective functions for various scenarios, including an all-RES power system, a hybrid power system with thermal units, and a fully thermal power system, all under specified constraints. The proposed algorithm is evaluated on a case study involving RESs in the southern region of Pakistan and is compared with other existing methods [122].

In a Hydrothermal Power System (H-PS), the primary objective is to minimize fuel costs while maximizing power generation. This study introduces a hybrid approach combining ANN and the Lambda iteration method for addressing anomalous short-term ED. The ANN with Back-Propagation (ANN-BP) is employed to forecast electricity demand during national holidays, while the Lambda iteration method calculates the optimal power for each unit. The results validate the capability of the hybrid approach to efficiently minimize operational costs [123].

An MG system is optimized through a hybrid algorithm that synergistically integrates the strengths of GWO, Sine Cosine Algorithm (SCA), and Crow Search Algorithm (CSA). This approach focuses on minimizing total costs while meeting multiple constraints. The main goal is to manage the Environment-Constrained Economic Dispatch (ECED) problem in an MG connected to the grid. The proposed MGWOSCACSA algorithm is tested on a low-voltage MG featuring various DERs such as fuel cells, wind turbines, and a microturbine. The outcomes demonstrate that it significantly reduces both generation and emissions costs compared to other methods [124].

AI-based Optimization Methods

An MG system's optimization is accomplished using a Deep Reinforcement Learning (DRL) approach merged with a Long Short-Term Memory (LSTM) network, referred to as the Deep Deterministic Policy Gradient (DDPG) with the LSTM method. The objective is to reduce costs while satisfying demand and constraints. This method is evaluated in a real-time environment using OPAL-RT and compared against experience-based energy management system, Newton-PSO, and Deep Q-learning Network (DQN) methods. Results show that it outperforms these alternatives in terms of fuel cost reduction, power balance, and load forecasting accuracy [125].

Table 5 presents an extensive overview of previous research, detailing the system, optimization methods, study contexts, and objective functions with their constraints, allowing for a thorough comparative analysis.

Table 5: Detailed summary of ED in virtual power systems

Ref.	Year	Test System	Method	Static or Dynamic	Objective Function					Constraints											
					F1	F2	F3	F4	F5	C1	C2	C3	C4	C5	C7	C8	C9	C11	C13	C15	C16
[114]	2019	MG	ADP	D	√			√	√	√		√			√	√		√		√	√
[115]	2020	MG	ICC	S	√					√		√									
[68]	2020	MG	WU-ABC	D	√	√	√	√	√	√		√				√	√				
[116]	2020	MG	ABC	D	√	√				√		√	√		√	√	√				
[117]	2020	MA-PS	SSA	S	√		√	√		√		√	√	√		√					
[118]	2020	S-PS	ISSA	D	√		√		√	√		√	√	√	√						√
[119]	2022	MG	IMA	D	√	√		√	√	√		√									
[120]	2021	MG	MBGSA	D	√					√		√									
[121]	2019	ME-VPP	DL+PSO	D	√	√				√	√	√	√		√	√		√			
[122]	2020	Pakistan	PSO+BA	D	√		√	√	√	√	√	√	√	√					√		
[123]	2020	H-PS	lambda-iteration and NN	S	√					√	√	√									
[124]	2022	MG	MGWOSCACSA	D	√	√		√		√		√									
[125]	2023	MG	DRL	D	√					√		√			√						

Advanced Power Systems

These systems employ advanced technologies and algorithms to distribute generation adjustments among generator units, optimizing economic efficiency within the area. Their sustainability and reliability are enhanced, especially with the integration of ED.

In a smart grid incorporating RES, a new Chaotic Salp Swarm Algorithm (CISSA) is used to optimize operations by minimizing both fuel and emission costs from thermal power plants while meeting load demands. The objective is to manage the CEED problem. The results indicate that CISSA outperforms the other algorithms and that integrating RES significantly reduces both emissions and fuel consumption [126].

A summary of prior research work is presented in Table 6, which includes the power systems, optimization techniques, study states, as well as objective functions and constraints, aiding in a detailed comparative analysis.

Table 6: Comprehensive synopsis of ED in advanced power systems.

Ref.	Year	Test System	Method	Static or Dynamic	Objective Function					Constraints					
					F1	F2	F3	F4	F5	C1	C2	C3	C4	C5	C17
[126]	2023	a smart grid	CISSA	D	√	√	√	√	√	√	√	√	√	√	√

Real Power Systems

Real systems are actual power grid systems that use the ED technique to optimize power generation and distribution in real-time. The ED here is considered the most feasible, but one of the disadvantages of these systems is the difficulty of obtaining system information.

For a Hybrid Energy System (HES) designed for a remote locations in Saudi Arabia, the objective is to minimize the annual system cost, improve system reliability, and maximize the Renewable Energy Fraction (REF). This paper explores the techno-economic optimization of the HES, which includes solar photovoltaic panels, wind turbines, diesel generator, and batteries. It introduces a new optimization method, the Reinforcement Learning Neural Network Algorithm (RLNNA), which outperforms five conventional metaheuristic algorithms in terms of convergence speed, ability to achieve global solutions, and economic efficiency. RLNNA offers a promising approach for optimizing HES configurations in remote areas, excelling in both economic and reliability aspects [127].

Table 7 provides a concise summary of earlier research, specifying the electrical power system, optimization strategies, study conditions, and objective functions alongside constraints, which supports a detailed comparative analysis.

Table 8: Extensive summary of ED in real power systems.

Ref.	Year	Test System	Method	Static or Dynamic	Objective Function			Constraints		
					F1	F4	F5	C1	C3	C7
[127]	2024	HES	RL+NN	S	√	√	√	√	√	√

Hybrid Power Systems

Hybrid power systems represent an innovative approach that combines the strengths of real energy systems and Virtual Power Plants (VPPs) to enhance the performance of energy networks. These systems provide a more accurate representation of real-world power systems by integrating multiple constraints, including bi-directional power flow between active distribution systems and VPPs. By utilizing the advantages of both real and virtual power systems, Hybrid Real-Virtual Power Systems can increase operational flexibility and reduce costs.

Conventional optimization Methods

Modified IEEE-34 and IEEE-123 bus test VPP systems are optimized using a Distributed Primal-Dual Sub-gradient Method (DPDSM). This study aims to investigate the distributed ED of VPPs and schedule DERs effectively. The proposed DPDSM is evaluated against the traditional centralized dispatch technique, and the results indicate that it achieves higher economic profits and improved system robustness [128].

In a provincial power grid and 39-bus systems, a novel approach based on Approximate Dynamic Programming (ADP) is introduced to solve the Stochastic Economic Dispatch (SED) problem. The primary goal is to achieve near-optimal solutions for the SED problem, which involves optimizing the operation of power systems with wind farms and Pumped-Storage Hydro (PSH) stations. The proposed ADP method is evaluated to two power systems, and the analysis confirms its efficiency in addressing the SED problem [129].

Optimization Methods

Nature-Inspired Optimization Methods

A 6-10 units system is optimized utilizing a Fuzzified Squirrel Search Algorithm (FSSA), aiming to minimize the fuel cost and pollutant emissions while complying with various constraints. The goal is to find the optimal solution for the Single-Area Multi-Fuel Economic Dispatch (SAMFED) and Multi-Area Multi-Fuel Economic Dispatch (MAMFED) problems. The results indicate that it outperforms other heuristic algorithms in terms of solution quality, convergence speed, and computational efficiency [130].

Hybrid Optimization Methods

A power system comprising 3, 6, 13, 15, 40, and 140 units, including both RES and thermal power plants, is used to test a novel Quasi-Oppositional Population-based Global Particle Swarm Optimizer with Inertial Weights (QPGPSO-w). This algorithm is specifically designed to address environmental EDPs by minimizing power generation costs while adhering to various constraints. The results confirm that QPGPSO-w outperforms competing methods in achieving cost-effective and environmentally conscious power generation [131].

Test systems consisting of 6, 10, 15, and 140 units are utilized to evaluate the performance of a hybrid approach. This approach combines the Imperialist Competitive Algorithm (ICA) and PSO methods to optimally solve the non-convex EDP, with the objective of minimizing the fuel cost in all areas while meeting all imposed system constraints. The results indicate the effectiveness of the proposed approach and confirm its suitability for addressing the EDP in large-scale power systems [132].

A 15-10-40-140-280 units system is optimized using a Modified Student Psychology-Based Optimization (MSPBO) algorithm. The proposed MSPBO algorithm is tested on five different EDPs and evaluated against other existing optimization techniques, and the simulation results indicate its effectiveness in solving complex EDPs [133].

A practical power plant consisting of 10 generating units and the IEEE system with 13 units are optimized using a new hybrid Cultural Algorithm (CA) combined with SA and Tabu Search (TS), with the aim of achieving minimum fuel costs and emissions while meeting demand. The results demonstrate that the proposed optimization algorithm achieves significant improvements in both fuel cost and emissions, thereby outperforming other algorithms [134].

A modified IEEE 39-bus system and a realistic 1009-bus power system are optimized using a Nested Sparse grid-based Stochastic Collocation Method (NS-SCM). The goal is to solve SED problems with high penetration of RES. The proposed NS-SCM simplifies the scenario-based optimization model, achieving better accuracy and computational efficiency than other methods, such as the Monte Carlo simulation and the sparse grid-based stochastic collocation method, as demonstrated through the test results [135].

AI-based Optimization Methods

Six units system is employed to demonstrate the effectiveness of a novel method for solving the non-convex EED. The method utilizes a Recurrent Neural Network (RNN) algorithm aiming to minimize the total cost. The results demonstrate that the RNN algorithm is capable of achieving more accurate and precise solution with a lower total cost compared to PSO [136].

A comprehensive overview of past research is compiled in Table 8, featuring the electrical power system, optimization techniques, study settings, and the objective functions and constraints, allowing for an in-depth comparative analysis.

Table 9: Detailed synopsis of ED in hybrid power systems.

Ref.	Year	Test System	Method	Static or Dynamic	Objective Function						Constraints													
					F1	F2	F3	F4	F5	F7	C1	C2	C3	C4	C5	C6	C7	C8	C9	C1	C1	C1	C1	C1
[128]	2017	modified IEEE-34 and IEEE-123 bus test VPP systems	DPDSM	S	√						√	√	√					√						
[129]	2020	provincial power grid +39 bus	ADP	S	√						√		√	√		√	√	√		√			√	√
[130]	2021	6-10 units	FSSA	S	√	√	√			√	√	√	√					√	√			√		
[131]	2023	power plants located in different regions	QPGPSO-ω	D	√	√		√	√		√		√								√			
[132]	2020	6-10-15-140 units	ICA-PSO	S	√		√			√	√	√	√	√	√									
[133]	2021	15-10-40-140-280 units	MSPBO	S	√		√			√	√	√	√	√	√									
[134]	2018	10-13 units	CA+SA+TS	S	√	√					√	√	√											
[135]	2019	39-1006 bus	NS-SCM	D	√			√	√		√		√					√	√					√
[136]	2021	6 units	RNN	D	√	√	√				√		√											

Conclusions

The article offers a comprehensive analysis and review of various electrical power systems where ED has been applied to enhance reliability, improve security, and reduce emissions. This is presented through detailed tables and figures. Unlike previous reviews, this article addresses ED from multiple perspectives in a simple, concise, and clear manner. As a result, it can serve as a valuable reference for researchers and engineers in the area of ED. The article also provides a quantitative comparison of different studies on specific power systems and their associated factors. It begins by classifying the various power systems discussed in ED literature and then identifies key ED parameters, presenting them with clear and straightforward equations. Furthermore, the article reviews different solution methodologies, including conventional approaches, meta-heuristic optimization techniques, and AI-based methods. The inclusion of concise tables that compare the performance of various ED solvers for specific power systems adds clarity. The article yields the following key conclusions:

- ED is currently elementary for running an electrical power system,
- ED is not constrained to conventional power grids; it could be applied to smart grids and microgrids as well.
- Most research is directed toward utilizing optimization methods for solving ED; however, less is directed toward developing simple and reliable models for the power system, objective functions, and constraints.
- Most reported researchers are for standard and virtual power systems; however, fewer are reported for actual/real power systems.

The following aspects for further in-depth research:

- Reducing reliance on simple, direct ED with one objective function and moving toward a more complex objective function and constraints.
- Remember that the primary focus is the electrical power system and its components, which define the objective function and the associated constraints. Optimization algorithms are merely tools used to achieve the desired outcome, not the ultimate goal.
- When using a modern optimization method for a specific power system, we recommend comparison with other optimization methods within the same system and consistent the operating conditions to help complete the practical research efficiently.
- It is necessary to look for realistic electrical power systems as much as possible in order to maximize the feasibility of the research.

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