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RESEARCH ARTICLE ELECTRICAL POWER SYSTEMS

Concise Comparative Study of Economic Dispatch of Electrical Power Systems

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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, metaheuristic 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. For the proposed case study, Teaching-Learning-Based Optimization (TLBO) achieves the lowest total cost, outperforming Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) by 0.01% and 1.05%, respectively. It also exhibits markedly improved robustness, with reductions of 96.11% and 99.99% in the confidence interval, and 96.13% and 99.97% in the standard deviation, relative to PSO and GA.

دراسة مقارنة موجزة للتشغيل الاقتصادي لأنظمة القوى الكهربائية

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الكلمات المفتاحية

التشغيل الاقتصادي
شبكة الطاقة الكهربائية
طرق التحسين
الذكاء الاصطناعي
مصادر الطاقة المتجددة

الملخص

يُعد التشغيل الاقتصادي حاليًا أمرًا أساسيًا لتشغيل أنظمة القوي الكهربائية على مستوى العالم، بما في ذلك الشبكات الصغيرة غير المتصلة بالشبكة. ويضمن التشغيل الاقتصادي استقرار واستمرارية إمدادات نظام الطاقة الكهربائية مع الحفاظ على تكاليف التوليد عند أدنى مستوى ممكن. عادةً ما يكون تحديد حل عام للتشغيل الاقتصادي أمرًا معقدًا، حيث تختلف ظروف التشغيل من نظام طاقة إلى آخر. وقد تم توثيق العديد من الحلول للتشغيل الاقتصادي في الأدبيات التي تتضمن تقنيات الحساب التقليدية، والتحسينات الفوق-استدلالية، وتقنيات الذكاء الاصطناعي .هناك نقص في المراجعة العامة لهذه الأدبيات؛ حيث يمكن أن توجه هذه المراجعة الباحثين والمهندسين في مجال التشغيل الاقتصادي. تستعرض هذه المقالة التشغيل الاقتصادي بشكل شامل مع تحديد العوامل الأكثر بروزًا، بما في ذلك خسائر النقل والانبعاثات والطاقات المتجددة وقيود التشغيل. توضح المقالة بشكل أساسي الفجوة البحثية مع مقارنة الحلول المختلفة المبلغ عنها، بدءًا من التقنيات القياسية وصولًا إلى مناهج الذكاء الاصطناعي، بطريقة بسيطة وموجزة. تقدم المقالة عدة مقارنات لتوجيه وإرشاد القارئ المهتم بشكل مباشر .في دراسة الحالة المقترحة، حققت خوارزمية **TLBO** أقل تكلفة إجمالية، متفوقةً على خوارزميتي **PSO** و**GA** بنسبة 0.01% و1.05٪، على التوالي. كما تظهر تحسناً ملحوظاً في المتانة، مع انخفاض بنسبة 96.11٪ و99.99٪ في فاصل الثقة، و96.13٪ و99.97٪ في الانحراف المعياري، مقارنةً بـ **PSO** و **GA**.

Introduction

Fossil fuels like coal, natural gas, and oil have historically constituted the primary foundation of the energy sector [1–3]. However, this heavy reliance on fossil fuels has led to significant environmental consequences, as fossil fuel is the primary source of carbon dioxide (CO_2) emissions, which are the main contributor to global warming and climate change. The continued increase in CO_2 emissions has intensified global efforts to shift toward cleaner and more sustainable energy resources. In this context, modern power system operation, including ED, is no longer limited to fuel cost minimization but also incorporates environmental objectives such as emission reduction, supporting the transition toward low-carbon energy systems [4–6].

In response to these environmental challenges, there is a growing shift towards cleaner and more sustainable alternatives. Renewable Energy Sources (RES), including solar, wind, and geothermal power are becoming increasingly popular, while nuclear energy continues to play a significant role in many countries [1-3,7–15]. Additionally, biomass and

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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 [16-20].

Despite this progress, certain sectors—particularly transportation—remain heavily dependent on petroleum-based fuels, accounting for nearly 91% of their total energy consumption and contributing approximately 21% of global CO_2 emissions. Meanwhile, renewable energy deployment has expanded significantly, with global installed capacity surpassing 4,448 GW by the end of 2025, supported by rapid advancements in solar, wind, hydropower, and energy storage technologies. This increasing penetration of renewable energy, combined with conventional generation, has led to more complex and dynamic power system structures, thereby necessitating advanced operational strategies to ensure reliable, secure, and cost-effective system performance [21, 22].

Although renewable energy technologies such as solar PV and wind power are widely adopted in modern power systems due to their low operational emissions and contribution to sustainable development, they are not entirely free from environmental impacts. Their deployment may involve land-use requirements, potential ecosystem and biodiversity disturbances, noise effects, and environmental burdens associated with manufacturing and end-of-life processes. Nevertheless, these impacts are generally site-specific and can be effectively mitigated through proper planning and design considerations. Integrating RESs into power system operation introduces additional complexity due to their intermittent nature and environmental considerations, but it significantly enhances system sustainability by reducing overall fuel consumption and emission levels compared to conventional generation [23,24].

Electrical power systems recently have a variety of generation types/sources and a mix of conventional and RES [25]. 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 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 [7,8].

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 [7,8].

Extensive efforts have been undertaken by researchers to solve the problem of ED through various enhancement techniques [7,8]. 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 present a comparative review of ED methodologies 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.

Electrical power systems models

Standard power systems are widely used as benchmark models for evaluating ED techniques. Typically represented by IEEE bus systems, they provide a simplified and well-defined framework for validating and comparing various optimization algorithms. However, they do not fully reflect the complexity of practical power networks.

To overcome this limitation, real power systems are utilized to represent actual grid operations, where ED is applied in real-time for optimal generation and distribution. Although more realistic, their application is often constrained by limited data availability.

With the increasing complexity of modern grids, advanced power systems have emerged, incorporating intelligent algorithms and technologies to enhance economic efficiency, sustainability, and reliability under dynamic conditions.

In parallel, virtual power systems integrate Distributed Energy Resources (DERs), including renewable sources and Energy Storage Systems (ESSs), into unified frameworks that improve operational flexibility, reduce costs and emissions, and enhance system resilience.

Finally, hybrid power systems combine the realism of actual grids with the flexibility of Virtual Power Plants (VPPs), offering a comprehensive representation of modern networks. By supporting features such as bi-directional power flow, they further improve operational flexibility and economic performance.

Assumptions, limitations, and uncertainties associated with the study

It is assumed that all generating units are already installed and in operation. Therefore, capital investment costs (e.g., construction and installation costs) are not considered in the analysis. The study focuses solely on the short-term operational aspect of the system, where the objective is to optimally allocate generation based on fuel cost and emission cost functions. This assumption is consistent with the standard formulation of the ED problem, which addresses real-time or day-ahead scheduling rather than long-term planning.

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 [7].

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

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 [25,26]:

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

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

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 [9].

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

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.

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 (5-11), respectively [20,27–29].

$$F_W = C_{Dw}(P_{Wsch}) + C_{Sw}(P_{Wav} - P_{Wsch}) + C_{Rw}(P_{Wsch} - P_{Wav}) \tag{5}$$

$$C_{Dw} = k_{DW} \times P_{Wsch} \tag{6}$$

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

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

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

$$P_W = \begin{cases} P_{Wr} & v_{Wr} \le v_z \le v_{c-off} \\ P_{Wr} \left(\frac{v_z - v_{in}}{v_{Wr} - v_{in}} \right) & v_{in} < v_z < v_{Wr} \\ 0 & v_z \le v_{in} \ or \ v_z > v_{c-off} \end{cases} \tag{10}$$

$$v_z = v_0 \left(\frac{h_z}{h_0} \right)^{\propto} \tag{11}$$

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. v_{c-off} is the cut-off wind speeds, and v_z is the wind speed at the wind turbine hub height h_z. The term v_0 is the wind speed at a certain elevation (h_0) and α is the wind shear coefficient.

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 (12-17), respectively [15,30–32].

$$F_W = C_{DPV}(P_{PVsch}) + C_{SPV}(P_{PVav} - P_{PVsch}) + C_{RPV}(P_{PVsch} - P_{PVav}) \tag{12}$$

$$C_{DPV} = k_{DPV} \times P_{PVav} \tag{13}$$

$$C_{RPV}(P_{PVsch} - P_{PVav}) = k_{RPVij} \times f_s(P_{PVav,ij} < P_{PVsch,ij}) \times \left[E(P_{PVav,ij} < P_{PVsch,ij}) \right] \tag{14}$$

$$C_{RPV}(P_{PVsch} - P_{PVav}) = k_{RPVij} \times f_s(P_{PVav,ij} < P_{PVsch,ij}) \times \left[E(P_{PVav,ij} < P_{PVsch,ij}) \right] \tag{15}$$

$$P_{PV} = P_{STC}\left[1 + \beta_p (T_{cell} - T_{STC}) \right] \frac{H_t}{H_{STC}} \tag{16}$$

$$T_{cell} = T_\infty + 7.8 \times 10^{-2} H_t \tag{17}$$

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 $f_s(P_{PVav,ij} > P_{PVsch,ij})$ and $f_s(P_{PVav,ij} < P_{PVsch,ij})$ represent the probabilities of solar power surplus and deficit relative to the scheduled power, respectively. Moreover, $E(P_{PVav,ij} > P_{PVsch,ij}) - P_{PVsch,ij}$ and $E(P_{PVav,ij} < P_{PVsch,ij})$ denote the expected surplus and deficit of solar power with respect to the scheduled value, respectively. T_{STC} and T_{cell} are the cell's surface temperature at Standard Test Condition (STC) and under real operation conditions (°C), β_p is the power temperature coefficient (%/°C), and H_{STC} and H_t are the STC and real global solar irradiance incidents on the PV module surface.

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 [20]:

$$f_{\text{fire}}(j,t) = u_{j,t} f_{\text{fuel}}(j,t) + u_{j,t}(1-u_{j,t-1})S_{j,t} \tag{18}$$

$$f_{\text{fuel}}(j,t) = \sum_{s=1}^{S} \left(a_j P_{j,t,s}^2 + b_j P_{j,t,s} + c_j\right) \cdot \eta_s \tag{19}$$

$$S_{j,t} = \begin{cases} X_j^{\text{off}} \leq T_j^{\text{cold}} + T_j^{\text{off}}, Sh_{j,t} \\ X_j^{\text{off}} > T_j^{\text{cold}} + T_j^{\text{off}}, Sc_{j,t} \end{cases} \tag{20}$$

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 [33], resulting in:

$$F_i(Pi) = \begin{cases} a_{i1}(Pg_i)^2 + b_{i1}Pg_i + c_{i1}, Pg_{i,\min} \leq Pg_i \leq Pg_{i,1} \\ a_{i2}(Pg_i)^2 + b_{i2}Pg_i + c_{i2}, Pg_{i,1} \leq Pg_i \leq Pg_{i,2} \\ a_{i3}(Pg_i)^2 + b_{i3}Pg_i + c_{i3}, Pg_{i,2} \leq Pg_i \leq Pg_{i,3} \end{cases} \tag{21}$$

Constraints

Power balance

$$\sum_{i=1}^{N_g} Pg_i - P_L - P_D = 0 \tag{22}$$

$$P_L = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} Pg_i B_{ij} Pg_j + \sum_{i=1}^{N_g} B_{0i} Pg_i + B_{00} \tag{23}$$

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) [8].

Generator operating limits

$$Pg_{i,min} \leq Pg_i \leq Pg_{i,max}; i = 1, \dots, N_g \tag{24}$$

Ramp rate limit

The output of a generator is not instantly adjustable, and this restriction governs how power output changes over time [34]. When power generation increases, it is represented as:

$$Pg_i(t) + Pg_i(t-1) \leq \text{UR}_i \tag{28}$$

When power generation decreases, it is given as

$$Pg_i(t-1) - Pg_i(t) \geq DR_i \tag{29}$$

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

$$\begin{gathered} Pg_{min} = Max\left[\left(Pg_{i,min}, Pg_i(t-1) - DR_i\right)\right] \\ Pg_{max} = Min\left[\left(Pg_{i,max}, Pg_i(t-1) - UR_i\right)\right] \\ Pg_{i,min} \leq Pg_i \leq Pg_{i,max} \end{gathered} \tag{30}$$

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 [34].

$$\begin{aligned} & Pg_{i,min} \leq Pg_{i,t} \leq P_{i,1}^{\text{lower}} \\ & P_{i,j-1}^{\text{upper}} \leq Pg_{i,t} \leq P_{i,j}^{\text{lower}}; \; i = 1, \dots, N_g; \; j = 2,3, \dots, n_i; \; t = 1,2, \dots, 24 \\ & P_{i,n_i}^{\text{upper}} \leq P_{gi} \leq Pg_{i,max} \end{aligned} \tag{31}$$

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.

$$SR_i = min\{(Pg_{i,max} - Pg_i), SR_{i,max}\} \tag{32}$$

$$SR = \sum_{i=1}^{n \leq N_g} SR_i \tag{33}$$

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 [9].

Battery operation

Excessive battery charging and discharging can lead to premature aging, and the following constraints are imposed to mitigate this effect [35-37].

$$SOC(t) = SoC(t-1).(1-\sigma) + \left(P_{sys}(t) - \frac{P_L(t)}{\eta_{inv}}\right) \times \eta_b \tag{34}$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{35}$$

$$P_{Cmin} \leq P_{BS}(t) \leq P_{Cmax} \tag{36}$$

$$P_{Dmin} \leq -P_{BS}(t) \leq P_{Dmax} \tag{37}$$

$$P_B = \frac{\max[SoC(t)]_{t=1,8760}}{DOD} \times CF_T \tag{38}$$

$$CF_T = 0.0004T^2 - 0.0246T + 1.3961 \tag{39}$$

where σ is self-consumption energy (1% per day), $P_L(t)$ is the load, $P_{sys}(t)$ input power from the RES, η_b and η_{inv} are the battery and inverter efficiencies. 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. CF_T is the temperature correction factor used to account for the effect of ambient temperature on battery performance. The term T represents the ambient temperature in °C. The Depth of Discharge (DOD) indicates the fraction of battery capacity that has been utilized relative to its maximum capacity and is a key factor affecting battery lifetime [14,20,35].

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:

$$Pl_{min} \leq Pl \leq Pl_{max} \tag{40}$$

where Pl_{min} and $Pl_{\max}$ are the minimum and maximum line capacity [38].

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.

$$Em(t) \leq Em^{\max}(t) \tag{41}$$

where $\text{E}m^{\max}(t)$ is the maximum emission [39].

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 [20].

$$T_{up/down} \in \begin{cases} T_{j,t}^{up} \geq T_{j,on} \\ Tg_{j,t}^{down} \geq T_{j,off} \end{cases} \tag{42}$$

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 [40].

$$Vn_{i,\min} < Vn_i < Vn_{i,\max} \text{ and } \delta n_{min} \leq \delta n_i \leq \delta n_{max} \tag{43}$$

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

Transformer tap setting

The transformer tap setting is constrained within the range:

$$0 \leq T \leq 1 \tag{44}$$

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 [40].

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:

$$\sum_{i=1}^{N_{\text{areas}}} P_{N_{i,\max}} \geq \sum_{i=1}^{N_B} P_{B_i} + \sum_{i=1}^{N_W} P_{W_i} + \sum_{i=1}^{N_{PV}} P_{PV_i} \tag{45}$$

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.[30].

Frequency Limits

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

$$fg_{i,min} \leq fg_i \leq fg_{i,max} \tag{46}$$

where $fg_{i,min}$ and $fg_{i,max}$ denote the lower and upper frequency limits [41].

Reactive Power Constraints

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

$$Qg_{i,min} \leq Qg_i \leq Qg_{i,max} \tag{47}$$

where $Q_{i,\min}$ and $Q_{i,\max}$ indicate the lower and upper limits [40].

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.

$$P_{PV,min} \leq P_{PV} \leq P_{PV,max} \tag{48}$$

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

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.

$$P_{W,min} \leq P_W \leq P_{W,max} \tag{49}$$

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

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

The ED problem has been addressed using a wide spectrum of solution techniques, ranging from traditional methods to metaheuristic approaches and, more recently, AI-based techniques. Traditional methods are known for their fast convergence and strong mathematical foundations; however, their performance is limited when handling nonlinear, non-convex, and highly constrained problems.

To address these challenges, metaheuristic algorithms have been widely adopted due to their flexibility and strong global search capabilities. Despite their effectiveness, they may suffer from high computational cost and sensitivity to parameter settings. Consequently, hybrid approaches have been developed to enhance performance by combining multiple techniques, albeit with increased complexity.

Recently, AI-based methods have gained attention due to their adaptive learning capabilities and effectiveness in handling uncertainty and multi-objective ED problems. Nevertheless, their success largely depends on data quality and proper model validation.

Comparative Review of ED Methodologies

Standard power systems

Conventional optimization methods

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 [42].

Optimization Methods

Single Optimization Methods

A power system with 10 thermal units is optimized using the 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 [41].

Hybrid Optimization Methods

Three systems, consisting of three, six, and ten units, are employed for the ED problem using a hybrid algorithm that combines the GA with the Artificial Bee Colony (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 [43].

AI-based Methods

The 30-bus and 118-bus IEEE systems are utilized to showcase the effectiveness of a novel approach for solving the multi-period Security-Constrained Economic Dispatch (SCED) model. This model integrates a Deep Learning (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 [44-47].

Virtual Power Systems

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 [48].

Optimization Methods

<u>Single Optimization Methods</u>

The Sustainable Power System (S-PS), comprising fuel-based units, PV units, and ESS is optimized through a comprehensive framework that integrates an Improved Salp Swarm Algorithm (ISSA) 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 [49].

<u>Hybrid Optimization Methods</u>

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 [50].

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 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 [51].

Advanced Power Systems

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 Combined Economic and Emission Dispatch Problem (CEED) problem. The results indicate that CISSA outperforms the other algorithms and that integrating RES significantly reduces both emissions and fuel consumption [52].

Real Power Systems

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. 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 [53].

Hybrid Power Systems

Conventional optimization Methods

In a provincial power grid and 39-bus systems, a novel approach based on 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 stations. The proposed ADP method is evaluated to two power systems, and the analysis confirms its efficiency in addressing the SED problem [54].

Optimization Methods

<u>Nature-Inspired Optimization Methods</u>

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 [55].

<u>Hybrid Optimization Methods</u>

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 ED problems and evaluated against other existing optimization techniques, and the simulation results indicate its effectiveness in solving complex ED problems [56].

AI-based Optimization Methods

Six units system is employed to demonstrate the effectiveness of a novel method for solving the non-convex Economic Emission Dispatch (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 [57].

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.

Case Study

As a representative and widely adopted benchmark, a case study based on the IEEE standard 39-bus, 10-unit system is

Table 1: Inclusive summary of ED studies with diverse systems and optimization methods.

Ref.	Test System	Method	Static or Dynamic	Objective Function							Constraints																
				F1	F2	F3	F4	F5	F6	F7	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
[42]	39 bus	ADMM	S	√	√		√				√		√														
[41]	10 units	TLBO	D	√							√		√	√							√			√	√		
[43]	3-6-10 units	ABC+GA	S	√		√					√	√	√														
[44]	30-118 bus	DNN	S	√							√		√					√									
[48]	MG	ADP	D	√			√	√			√		√				√	√			√				√	√	
[49]	S-PS	ISSA	D	√		√		√			√		√	√	√		√									√	
[50]	Pakistan	PSO+BA	D	√		√	√	√			√	√	√	√	√								√				
[51]	MG	DRL	D	√							√		√				√										
[52]	a smart grid	CISSA	D	√	√	√	√	√			√	√	√	√	√												√
[53]	HES	RL+NN	S	√			√	√			√		√				√										
[54]	provincial power grid +39 bus	ADP	S	√							√		√	√		√	√	√			√				√		√
[55]	6-10 units	FSSA	S	√	√	√				√	√	√	√					√	√					√			
[56]	15-10-40-140-280 units	MSPBO	S	√		√				√	√	√	√	√	√												
[57]	6 units	RNN	D	√	√	√					√		√														

* 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, and C4 specifies ramp rate limits. 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.

Table 2: Statistical results of TLBO, PSO, and GA methods over 50 runs at 2000 MW for the 10-unit system

Method	Mean cost **($)**	SD	CI	CI Width	Execution time **(s)**
TLBO	149122.92	3.33E-01	[149122.83, 149123.02]	0.19	3.24
PSO	149133.97	8.61E+00	[149131.53, 149136.42]	4.89	2.35
GA	150704.76	1.08E+03	[150398.29, 151011.23]	612.95	1.79

incorporated to evaluate the performance of different optimization techniques for the ED problem [58]. In this study, three of the most commonly used metaheuristic algorithms—TLBO, PSO, and GA—are systematically compared [58–60]. The primary objective is to minimize the total generation cost as formulated in (1), subject to the operational constraints defined in (22), and (24). The comparison is conducted under a fixed load demand of 2000 MW, with each algorithm executed multiple independent runs to ensure statistical reliability. Performance assessment is not limited to the obtained optimal cost, but is further extended to include statistical indicators such as the Standard Deviation (SD) and Confidence Level (CI), providing a comprehensive evaluation of solution robustness, consistency, and convergence behavior. This comparative analysis offers deeper insight into the effectiveness and stability of these widely used optimization methods in solving practical ED problems. A statistical analysis is conducted to identify the most effective metaheuristic optimizer for the proposed systems among TLBO, PSO, and GA. Table 2 presents the performance metrics, including SD, CI analysis, and average execution time, based on 50 independent runs of each optimizer for the 10-unit systems.

Table 2 demonstrates that TLBO exhibits the highest stability and robustness, as reflected by the narrower CI. The total cost of TLBO is lower by 0.01% and 1.05% compared to PSO and GA, respectively. The CI of TLBO is lower by 96.11% and 99.99% compared to PSO and GA, respectively. In addition, TLBO achieved reductions of approximately 96.13% and 99.97% in SD relative to PSO and GA, indicating its consistent performance. However, TLBO requires longer computation time than PSO and GA, primarily due to the higher complexity of its search operations.

Conclusions

This article presents a comprehensive review of ED applications across various power systems, highlighting their role in enhancing reliability, improving security, and reducing emissions. It adopts a multi-perspective approach, covering system classifications, key ED parameters with clear formulations, and a wide range of solution methodologies, including conventional, metaheuristic, and AI-based techniques.

In addition, the study provides quantitative comparisons through well-structured tables, offering clear insights into the performance of different ED approaches across specific power system models. Accordingly, the article serves as a valuable and concise reference for researchers and engineers in the field. The main findings can be summarized as follows:

- 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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References

[1] A. Hafez, Y. Fathi, M. Hammdan, and S. Alsadi. "Technical and Economic Feasibility of Utility-Scale Solar Energy Conversion Systems in Saudi Arabia." *Iran. J. Sci. Technol. - Trans. Electr. Eng.*, vol. 44, no. 1, pp. 213–225, 2020. https://doi.org/10.1007/s40998-019-00233-3

[2] D. Albuzia, A. Ali, M. Mohmed, and A. Hafez. "Reliable and Robust Optimal Interleaved Boost Converter Interfacing PhotoVoltaic Generator." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 3, no. 2, pp. 192-201, 2025. https://doi.org/10.63318/waujpasv3i2_24

[3] H. El-Khozondar, M. Andeef, Y. Fathi, R. El-Khozondar, and H. Awad. "Feasibility of Concentrating Solar Power as a Solar Fuel for Electrical Power Stations: A Case Study of Ubari Gas-Power Station in Libya." *Wadi Alshatti Univ. J. Pure Appl. Sci.*, vol. 4, no. 1, pp. 56–69, 2026, https://doi.org/10.63318/waujpasv4i1_06

[4] Y. Nassar et al. "Estimation of CO2 emission within Libya's electricity generation sector." *Next Res.*, vol. 2, no. 3, p. 100567, 2025. https://doi.org/10.1016/j.nexres.2025.100567

[5] S. Alfathi, G. Miskeen, and W. Mremi, W. "Evaluation and Prediction Performance of Solar Panel and Wind Turbine Systems Using Simulation." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 4, no. 1, pp. 94-104, 2026. https://doi.org/10.63318/waujpasv4i1_10

[6] A. Youssef. "Nuclear Plants Trends for Development Planning in Egypt." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 4, no. 1, pp. 277-286, 2026. https://doi.org/10.63318/waujpasv4i1_29

[7] M Khaleel, et al. "Harnessing nuclear power for sustainable electricity generation and achieving zero emissions." *Energy Exploration & Exploitation*, vol. 43, no. 3, pp. 1126-1148, 2025. https://doi.org/10.1177/01445987251314504

[8] W. Gao, and Y. Lin. "Energy Dispatch for CCHP System in Summer Based on Deep Reinforcement Learning." *Entropy*, vol. 25, no. 3, 2023. https://doi.org/ 10.3390/e25030544

[9] M. Abouheaf, W. Lee, and F. Lewis. "Dynamic formulation and approximation methods to solve economic dispatch problems/" *IET Gener. Transm. Distrib.*, vol. 7, no. 8, pp. 866–873, 2013, https://doi.org/ 10.1049/iet-gtd.2012.0397

[10] N. Fathi et al. "Dynamic analysis and sizing optimization of a pumped hydroelectric storage-integrated hybrid PV/Wind system: A case study." *Energy Convers. Manag.*, vol. 229, p. 113744, 2021, https://doi.org/10.1016/j.enconman.2020.113744

[11] M. Mohamed, G. El-Saady, and A. Yousef. "Performance analysis of genetic algorithm and ant colony optimization dependent on PID controller for matrix converter." *ICEEM 2021 - 2nd IEEE Int. Conf. Electron. Eng.*, no. July, pp. 3–4, 2021/ https://doi.org/ 10.1109/ICEEM52022.2021.9480640

[12] H. Awad, Y. Fathi, A. Hafez, M. Sherbiny, and A. Ali. "Optimal design and economic feasibility of rooftop photovoltaic energy system for Assuit University, Egypt." *Ain Shams Eng. J.*, vol. 13, no. 3. 2022, https://doi.org/10.1016/j.asej.2021.09.026

[13] B. Ahmed, et al. "Optimal Design of Hybrid Renewable Energy System (PV/Wind/PHS) Under Multiple Constraints of Connection to the Electricity Grid: A Case Study." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 4, no 1, pp. 83-93, 2026. https://doi.org/10.63318/waujpasv4i1_09

[14] H. El-Khozondar et al. "Economic and Environmental Implications of Solar Energy Street Lighting in Urban Regions: A Case Study." *Wadi Alshatti Univ. J. Pure Appl. Sci.*, vol. 3, no. 1, pp. 142–151, 2025. https://doi.org/10.63318/waujpasv3i1_21

[15] E. Salim, A. Abubaker, B. Ahmed, and Y. Fathi. "A Brief Overview of Hybrid Renewable Energy Systems and Analysis of Integration of Isolated Hybrid PV Solar System with Pumped Hydropower Storage for Brack city – Libya." *Wadi Alshatti Univ. J. Pure Appl. Sci.*, vol. 3, no. 1, pp. 152–167, 2025, https://doi.org/ 10.63318/waujpasv3i1_22

[16] E. Salim, et al. "Performance Evaluation of a Standalone PV-Hydrogen Power System for Continuous Supply Reliability in Brack Al-Shatti." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 4, no. 1, pp. 362-376, 2026. https://doi.org/10.63318/waujpasv4i1_40

[17] I. Imbayah, et al. "Modeling A 600 MW Floating Photovoltaic System in Al-Khums city, Libya: Performance Analysis and Implementation Using PVSyst." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 4, no. 1, pp. 223-237, 2026. https://doi.org/10.63318/waujpasv4i1_24

[18] K. Amer, et al. "Economic-Environmental-Energetic (3E) analysis of Photovoltaic Solar Energy Systems: Case Study of Mechanical & Renewable Energy Engineering Departments at Wadi AlShatti University." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 3, no. 1, pp. 51-58, 2025. https://doi.org/10.63318/waujpasv3i1_09

[19] S. Mohammed, et al. "Exploring Promised Sites for Establishing Hydropower Energy Storage (PHES) Stations in Libya by Using the Geographic Information Systems (GIS)." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 3, no. 1, pp. 85-94, 2025. https://doi.org/10.63318/waujpasv3i1_13

[20] Y. Zeng, C. Li, H. Wang, and H. Wang, "Scenario-Set-Based Economic Dispatch of Power System with Wind Power and Energy Storage System," IEEE Access, vol. 8, pp. 109105–109119, 2020, https://doi.org/10.1109/ACCESS.2020.3001678

[21] Y. Fati, H. J. El-Khozondar, W. Salah, A. Alatrash, and M. Salem, "Technical and environmental cost benefit analysis of strategies towards a green economy in the electricity sector in

Libya." *Economics and Policy of Energy and Environment*, vol. 2, 2025, http://doi.org/10.3280/ EFE2025-002007

[22] A. Abduallah, N. Fathi, S. Mohammed, and M. Ghatus. "Integrating Electricity Sub-Grid with Pumped Hydropower Storage System for Grid Stability and Sustainability." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 3, no. 2, pp. 322-332, 2025. https://doi.org/10.63318/ waujpasv3i2_40

[23] M. Al-Maghalseh. "The Environmental Impact and Societal Conditions of PV Power Plants: A Case Study of Jericho Gate-Palestine Stat Of." *Wadi Alshatti Univ. J. Pure Appl. Sci.*, vol. 3, no. 2, pp. 16–31, 2025. https://doi.org/ 10.63318/waujpasv3i2_03

[24] M. Salem, et al. "Technical and environmental cost-benefit analysis of strategies towards a green economy in the electricity sector in Libya." *Economics and Policy of Energy and the Environment*, vol. 2, no. (2025/2), pp. 133-167, 2025. https://doi.org/10.3280/EFE2025-002007

[25] W. El-Osta, et al. "Financial Modeling of Social and Environmental Impacts of Wind Farm in Urban Zones : A Case Study of Zawia-Libya." *International J. of Energy and Environmental Engineering,* vol. 15, no. 4, 2024. https://doi.org/10.57647/ijeee.2024.1504.17

[26] N. Singh et al. "A New PSO Technique Used for the Optimization of Multiobjective Economic Emission Dispatch." *Electron.*, vol. 12, no. 13, pp. 1–13, 2023, https://doi.org/ 10.3390/electronics12132960

[27] A. Abdalla, et al. "Estimation of Dynamic Wind Shear Coefficient to Characterize Best Fit of Wind Speed Profiles under Different Conditions of Atmospheric Stability and Terrains for the Assessment of Height-Dependent Wind Energy in Libya." *Appl. Sol. Energy*, vol. 59, no. 3, pp. 343–359, 2023. https://doi.org/ 10.3103/S0003701X23600212

[28] M. Elnaggar, et al. "Assessing the Techno-enviro-economic viability of wind farms to address electricity shortages and Foster sustainability in Palestine." *Results Eng.*, vol. 24, no. October, p. 103111, 2024. https://doi.org/10.1016/j.rineng. 2024.103111

[29] A. Elmabruk, M. Salem, M. Khaleel, A. Mansour. "Prediction of Wind Energy Potential in Tajoura and Mislata Cities." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 3, no. 2, pp. 125-131, 2025. https://doi.org/10.63318/ waujpasv3i2_17

[30] M. Ellahi, G. Abbas, G. Satrya, M. Usman, and J. Gu. "A Modified Hybrid Particle Swarm Optimization With Bat Algorithm Parameter Inspired Acceleration Coefficients for Solving Eco-Friendly and Economic Dispatch Problems." *IEEE Access*, vol. 9, pp. 82169–82187, 2021, https://doi.org/ 10.1109/ACCESS.2021.3085819

[31] Alkhazmi, et al. "Design and Analysis of PV Solar Street Lighting systems in Remote Areas: A Case Study." Wadi Alshatti University Journal of Pure and Applied Sciences, vol. 4, no. 1, pp. 1-14, 2026. https://doi.org/10.63318/ waujpasv4i1_01

[32] A. Aqila, et al. "Design of Hybrid Renewable Energy System (PV/Wind/Battery) Under Real Climatic and Operational Conditions to Meet Full Load of the Residential Sector: A Case Study of a House in Samno Village– Southern Region of Libya." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 3, no. 1, pp. 168-181, 2025. https://doi.org/10.63318/waujpasv3i1_23

[33] P. Olulope, A. Ekiti, O. Amusan, B. Adebanji, and A. Ekiti. "Application of genetic algorithm in solving economic dispatch with multiple fuel options." *International Journal of Applied Science and Research*, no. April, pp. 257-270, 2024. https://www.researchgate.net/ publication/379726981

[34] I. Marouani, A. Boudjemline, T. Guesmi, and H. Abdallah. "A Modified Artificial Bee Colony for the Non-Smooth Dynamic Economic/Environmental Dispatch." *Eng. Technol. Appl. Sci.* Res., vol. 8, no. 5, pp. 3321–3328, 2018, https://doi.org/ 10.48084/etasr.2098

[35] M. Abuqila, Y. Nassar, and M. Nyasapoh, "Estimation of the Storage Capacity of Electric Vehicle Batteries under Real Weather and Drive mode Conditions: A Case Study," Wadi Alshatti Univ. J. Pure Appl. Sci., vol. 3, no. 1, p. 59, 2025, https://doi.org/ 10.63318/waujpasv3i1_10

[36] M. Albardawil, et al. "DC off-grid PV system to supply electricity to 50 boats at Gaza seaport." in *2023 8th International Engineering Conference on Renewable Energy & Sustainability (ieCRES)*, 2023: IEEE, pp. 1-5. https://doi.org/10.1109/ieCRES57315.2023.10209467

[37] I. Latiwash, et al. "Performance Analysis and Sizing Optimization of Utility-Scale PV/Battery Storage System for Urban Zones." *University of Zawia Journal of Engineering Sciences and Technology*, vol. 3, no. 2, pp. 261–275, 2025. https://orcid.org/0009-0001-8521-8177

[38] P. Biswas, P. Suganthan, B. Qu, and G. Amaratunga. "Multiobjective economic-environmental power dispatch with stochastic wind-solar-small hydro power." *Energy*, vol. 150, pp. 1039–1057, 2018/ https://doi.org/10.1016/j.energy.2018. 03.002

[39] H. Ryu and M. Kim. "Combined economic emission dispatch with environment-based demand response using wu-abc algorithm." *Energies*, vol. 13, no. 23, 2020. https://doi.org/ 10.3390/en13236450

[40] S. Tiwari, N. Pal, M. Ansari, D. Yadav, and N. Singh. "Economic Load Dispatch Using PSO." Lect. Notes Networks Syst., vol. 106, no. July 2021, pp. 51–64, 2020. https://doi.org/ 10.1007/978-981-15-2329-8_6

[41] T. Khobaragade, and K. T. Chaturvedi. "Enhanced Economic Load Dispatch by Teaching–Learning-Based Optimization (TLBO) on Thermal Units: A Comparative Study with Different Plug-in Electric Vehicle (PEV) Charging Strategies." *Energies*, vol. 16, no. 19, 2023. https://doi.org/10.3390/ en16196933

[42] Y. Zhang, and M. Ni. "Fully Distributed Economic Dispatch with Random Wind Power Using Parallel and Finite-Step Consensus-Based ADMM." *Electronics*, vol. 13, no. 8, p. 1437, 2024. https://doi.org/ 10.3390/electronics13081437

[43] B. Naama. "Solving the Economic Dispatch by New Hybrid Algorithm." *Preprint*, 2024. 10.21203/rs.3.rs-4154846/v1

[44] M. Osman, et al. "A comparative Analysis on Stacked Hybrid Intelligence: A Multi-Paradigm Machine Learning Framework for Robust Phishing URL Detection." *Comprehensive Journal of Science*, vol. 10, no. 39, pp. 1037-1062, 2026. https://doi.org/10.65405/gcfgsj10

[45] L. Dalla, O. Karal, M. EL-Sseid, and A. Alsharif. "An IoT-Enabled, THD-Based Fault Detection and Predictive Maintenance Framework for Solar PV Systems in Harsh Climates: Integrating DFT and Machine Learning for Enhanced Performance and Resilience." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 4, no. 1, pp. 41-55, 2026. https://doi.org/10.63318/waujpasv4i1_05

[46] F. El-Batta, et al. " AI-Based Monitoring of Solar Panels in Desert Environments: Distinguishing Dust Accumulation for Fault Detection." *Wadi Alshatti University Journal of Pure and Applied Sciences*, vol. 4, no. 1, 340-353, 2026. https://doi.org/10.63318/waujpasv4i1_38

[47] A Ahmed, et al. "AI-Powered Energy Forecasting: A Next-Gen Approach for Smart Grids and Sustainable Power Systems." *Eurasian Journal of Theoretical and Applied Sciences*, vol. 1, no. 2, pp. 1-15, 2025. https://doi.org/10.32213/w4zdxg34

[48] H. Shuai, J. Fang, X. Ai, Y. Tang, J. Wen, and H. He. "Stochastic optimization of economic dispatch for microgrid based on approximate dynamic programming." *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 2440–2452, 2019. https://doi.org/ 10.1109/TSG.2018.2798039

[49] K. Mahmoud, M. Abdel-Nasser, E. Mustafa, and Z. M. Ali. "Improved salp-swarm optimizer and accurate forecasting model for dynamic economic dispatch in sustainable power systems." *Sustain.*, vol. 12, no. 2, pp. 1–21, 2020. https://doi.org/ 10.3390/su12020576

[50] M. Ellahi, and G. Abbas. "A Hybrid Metaheuristic Approach for the Solution of Renewables-Incorporated Economic Dispatch Problems." *IEEE Access*, vol. 8, pp. 127608–127621, 2020, https://doi.org/ 10.1109/ACCESS.2020.3008570

[51] F. Lin, C. Chang, Y. Huang, and T. Su. "A Deep Reinforcement Learning Method for Economic Power Dispatch of Microgrid in OPAL-RT Environment." *Technologies*, vol. 11, no. 4, 2023. https://doi.org/10.3390/ technologies11040096

[52] M. Azeem, et al. "Combined Economic Emission Dispatch in Presence of Renewable Energy Resources Using CISSA in a Smart Grid Environment." *Electron.*, vol. 12, no. 3, 2023. https://doi.org/ 10.3390/electronics12030715

[53] H. Farh. "Neural Network Algorithm with Reinforcement Learning for Microgrid Techno-Economic Optimization." *Mathematics*, vol. 12, no. 2, 2024. https://doi.org/ 10.3390/math12020280

[54] S. Lin, G. Fan, G. Jian, and M. Liu. "Stochastic economic dispatch of power system with multiple wind farms and pumped-storage hydro stations using approximate dynamic programming." IET Renew. *Power Gener.*, vol. 14, no. 13, pp. 2507–2516, 2020. https://doi.org/ 10.1049/iet-rpg.2019.1282

[55] V. Sakthivel, and P. Sathya. "Single and multi-area multi-fuel economic dispatch using a fuzzified squirrel search algorithm." *Prot. Control Mod. Power Syst.*, vol. 6, no. 1, 2021. https://doi.org/ 10.1186/s41601-021-00188-w

[56] S. Basu, and M. Basu. "Modified Student Psychology Based Optimization Algorithm for Economic Dispatch Problems." *Appl. Artif. Intell.*, vol. 35, no. 15, pp. 1508–1528, 2021. https://doi.org/ 10.1080/08839514.2021.1985050

[57] J. Wang, X. He, J. Huang, and G. Chen. "Recurrent Neural Network for Nonconvex Economic Emission Dispatch." *J. Mod. Power Syst. Clean Energy*, vol. 9, no. 1, pp. 46–55, 2021. https://doi.org/ 10.35833/MPCE.2018.000889

[58] T. Optimizer, M. Mohamed, A. Yousef, and A. Hafez. "Optimized Dynamic Economic Dispatch incorporating Dynamic Generation Capacity Using Generator operating limits constraints." *15th International Conference on Electrical Engineering (ICEENG)*, 2025. 10.1109/ICEENG64546.2025. 11031333

[59] M. Mohamed, A. Yousef, and A. Hafez. "Results in Engineering Risk management strategies for fuel shortages in economic dispatch with multiple fuel options using walrus algorithm." *Results Eng.*, vol. 27, no. April, p. 106427, 2025. https://doi.org/ 10.1016/j.rineng.2025.106427

[60] M. Mohamed, A. Yousef, and A. Hafez. "Efficient and innovative dynamic power system economic dispatch for fuel shortages via walrus and artificial gorilla troops optimizer." *Eng. Res. Express*, vol. 7, no. 3, 2025. https://doi.org/ 10.1088/2631-8695/ade7f6.