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A Review on Security Constrained Economic Dispatch of Integrated Renewable Energy Systems

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Abstract

This paper presents a selective survey of papers, books, and reports that articulate recent trends of Security Constrained Economic Dispatch (SCED) of integrated renewable energy systems (IRES). The time-period under consideration is 2008 through 2020. This is done to provide an up-to-date review of the recent, major advancements in the SCED, and state-of-the-art since 2008. This helps identify further challenges needed in adopting smarter grids, and indicate ways to address these challenges. The study was conducted in three areas of interest that are relevant for articulating the recent trends of SCED. These areas are (i) SCED of power systems with IRES, (ii) SCED mathematical formulation and solution methods, and (iii) SCED challenges. The review results and research directions deduce that the state of the art research is not enough and needs special attention on following the path of artificial intelligence-based optimization.

Keywords: Security constraints, economic dispatch, economic dispatch challenges, renewable energy sources

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Nomenclature

ai = constant coefficient measure of losses
bi= constant coefficient representing fuel cost
Bij= active power loss coefficients
c = Weibull probability distribution factor
Ch = Hydropower generation cost
Ci = constant coefficient including salary and wages
Cs= solar power generation cost
Csp= solar power penalty cost
Csr= solar power reserve cost
Cw= wind power generation cost
Cwp= wind power penality cost
Cwr= wind power reserve cost
D_{RI} = ramp rate limit
$f(x)$ = function to be minimized
F_{Bth}= biomass and waste to energy generation cost
F_{Gth}= Geothermal power generation cost
fpw= wind power probability distribution function
$Fsth$= solar thermal power generation cost
Fth= thermal power generation cost
$g_l(x)$ = Inequality constraints
G= solar irradiance
$Gstd$= solar irradiance in a standard environment
$h_k(x)$ = Equality constraints
Hi= average head
K = Number of equality constraints
k= Weibull probability distribution factor
L= Number of inequality constraints
N_{cc}= Number of Credible contingencies
N_G= Number of generating units
NL = Number of security levels
$Npoz$ = Number of prohibited zones
ϕ = Credible contingencies
Phr= Hydropower output
$PBth$= biomass and waste to energy power output
P_D= Power demand
P_{Gth}= geothermal power output
P_{hgi} = Hydropower unit output
P_{imax}= maximum power generation limit
P_{imin}= minimum power generation limit
P_L = Power loss
Psg = solar power output
Psr= rated solar power output
$Psth$= solar thermal power output
Pth= thermal power output
Pwr= wind power output

Qi= discharge outflow
Rca= certain irradiance point set at 150 w/m2
Sl = Security level
Sl_{max} = maximum Security level
SRi= spinning reserve limit
SSR= maximum spinning reserve limit
Vi= cut in wind speed
Vo= cut out wind speed
Vr= rated wind speed
Vwt= forecasted wind speed
x i (1)= Security constraint
α = weight factors of unit costs between 0&1
ψ = penetration rate

1. Introduction

The importance of electricity in our daily lives is noticed when sudden blackouts occur. Moreover, sudden and uncontrolled power outages can threaten the socio-economic endeavours of electricity-addicted community. Considering the Ethiopian electric power network, which is a power system of integrated renewable energy systems, the supply of power interrupts every time it rains. The resulting blackouts impose substantial damage to Ethiopian production plants, service centers, and home appliances.

According to the blackout report of the Ethiopian electric power network from 2013 to 2016, 15 major blackouts were reported. Production plants and service centers were down for an average of four months a year. Natural incidents, equipment failure, and power mismatch collectively known as contingencies cause these sudden interruptions and blackouts. A contingency is an event, which removes one or more generators or transmission lines from the power system, increasing the stress on the remaining network [1]. One of the main challenging aspects of power system operation is that electrical energy is difficult to economically store in significant amounts. This aspect requires a continuous balance between generation and demand considering generation limits, security constraints, and contingencies i.e. Security Constrained Economic Dispatch (SCED). SCED is a process of allocating generation levels to generating units to entirely and economically supply the load while satisfying security constraints [2]-[3].

In the energy market context, the main objective of SCED is to minimize the power operation cost, while continuously respecting the operational constraints of the power system. Some methods have been used to solve this problem since its introduction, for example, iterative method, gradient-based techniques, interior points method, linear programming, and dynamic programming [3]. A substantial number of articles reported SCED in the perspective of Artificial intelligence [4], integrated renewable energy source, and post-disturbance corrective actions. F. Capitanescu et al [5] examine the recent trends towards stochastic search techniques and hybrid methods for OPF.

The other challenge is related to the intermittency renewables. With increasing emphasis on utilizing more renewable energy to mitigate climate change, the power industry is confronted with many new challenges [6].

A sudden change in a variable renewable source can cause a large surplus or lack of power output and subsequently affect the security of some power system networks with limited flexibility. The objective of this review is therefore to:

- Present papers, books, and reports published in the years 2008 through 2020 and finding ways to increase power system flexibility and security.
- Identify challenges posed to SCED reformulation due to the integrated renewable energy systems.
- Propos a hybrid computational intelligence based optimization method for SCED of integrated renewable energy sources.

Articulation of research gaps, providing an up-to-date review of the recent major advancements in the SCED state-of-the-art since 2008, identification of further challenging developments needed in the adoption of smarter grids, and indicating ways to address these challenges are also the novelty of this review.

2. Integrated Renewable Energy Systems

The contribution of renewable resources to the energy portfolio across the world has been steadily increasing over the past few years [7]. IRES is a system that harnesses two or more forms of locally available renewable energy resources to supply a variety of energy needs in a most efficient, cost-effective, and practical way, with the ultimate goal of amalgamating the advantages at the end-user [8]-[9]. The increasing level of uncertainties introduced by renewable energy sources (RESs) such as wind and solar energy made SCED complex. Traditional deterministic decision making in the electric power industry is gradually shifting towards stochastic decision making which explicitly takes into account the uncertainty in the power output of RES generators [10].

Integrating intermittent and non-dispatchable generators like wind and solar exhibit sub-hourly fluctuations [11]. This motivates the need for optimization at multiple timescales with a probability distribution function. Renewable energy resources are highly site-specific, stochastic, and evenly distributed around the world with little or no costs. They depend on the climatic conditions, geographical factors, and seasons of the site under consideration [10].

A substantial number of renewable integration studies have focused on optimization requirements of power systems with high renewable penetration such as wind [11] gas [12] natural gas [13] photovoltaic(PV) [14]. The most widely used and easily available renewable resources as inputs to IRES are biomass, hydro, solar, wind, and geothermal The figure below schematically describes IRES considered for this review.

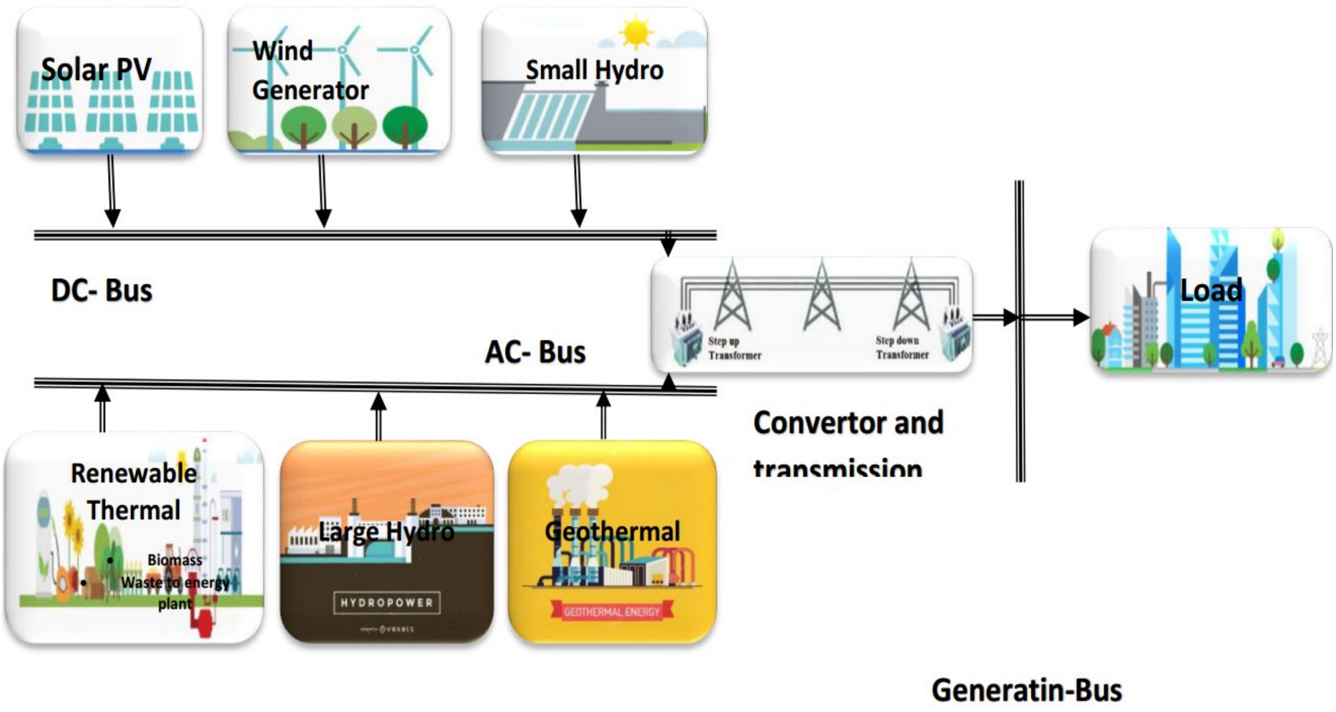

Figure 1. Proposed schematic diagram of IRES

Such a system can operate well in both stand-alone mode and when connected to a centralized grid. The prime significance of IRES is its focus to energize and electrify remote rural areas promoted by hybrid systems. This helps to achieve sustainable development and improve the basic living environment of rural masse [16]-[17]. This paper presents IRES comprising biomass, large and micro-hydro plants, solar PV, solar thermal, waste to energy plant, wind farm, and geothermal altogether with their problem formulation and constraint handling mechanisms that take into account credible contingencies.

3. SCED problem formulation

3.1. Problem formulation

Relations between generation cost and operation cost rely on power flow output and forecasted values [13]-[14]. Problem formulation starts with the optimization perspective of the SCED mathematical model. The general optimization problem form for SCED is therefore:

$$optimize f(x), x \in R^{n} \tag{1}$$

Subject to

$$h_k(x) = 0 \forall 1, 2 ... m \tag{2}$$

$$g_l(x) \leq 0 \forall 1, 2 ... L \tag{3}$$

In a practical power system, the SCED problem is non-linear and multi-objective due to operation constraints [12]. Objective function should minimize the non-detailed formulation of the SCED problem due to unnecessary assumptions that can lead to a limitation in the modeling of large-scale power systems. In light of this, multi-objective optimization is favored. The general form of multi-objective optimization is thus:

$$Optimize f(x) = (f_1(x), f_2(x), f_{Nobj}(x) \tag{4}$$

Subject to

$$g_i(x) = 0 \forall i = 1, 2 ... m$$

$$h_k(x) \leq 0 \forall k = 1, 2, ... K$$

$$x_i(1) \leq x_i \leq x_i(0) \tag{5}$$

The multi-objective optimization approach in the SCED context refers to minimizing generation cost and maximizing the security level of the operating system while considering a variable and intermittent generation [10]-[13]. This paper uses renewable resources as inputs to IRES such as biomass, hydro, solar, wind, and geothermal.

Each of these sources requires problem formulation, and constraint handling mechanisms as separate objective functions to construct a single multi-objective function detailed below [14].

Hydro: To formulate an economic dispatch problem, the first objective function $f_1(x)$ can represent the objective function of hydropower generation plants [15]-[16]-[17].

$$\min f_1(x) = C_h \sum_{i=1}^{N_{hg}} P_{hgj}(t) \quad (6)$$

Where

$$P_{hgj}(t) = \sum_{t=1}^{24} \sum_{i=1}^{N_G} 0.00981 \eta_i H_{ij} Q_{ij} \quad (7)$$

Wind: the power for assumed wind speed is given by[18] [19][20]:

$$P_{wr} = \begin{Bmatrix} 0, for v_{wt} \le v_i and v_{out} \ge 0 \\ P_{wr}(\frac{v_{wt} - v_i}{v_r - v_i}), for v_i \le v_{wr} \le v_{out} \\ P_{wr}, for v_r \le v_{wt} \le v_{out} \end{Bmatrix} \quad (8)$$

In addition, its corresponding objective function ($f_2(x)$) that can be considered as a second objective function is:

$$f_2(x) = C_w \sum_{i=1}^{N_{WG}} P_{wgj}(t) + \sum_{t=1}^{24} \sum_{i=1}^{N_{WG}} C_R + C_P \quad (9)$$

C_R and C_P represent reserve cost and penalty cost coefficients of wind power generation respectively. The cost of renewable generation rises with reserve cost and penalty cost coefficients. The reserve cost coefficient helps to determine the debit that can be produced from the probability distribution function of variable wind speed.

The penalty cost coefficient helps to determine the debit that are produced from overestimation or underestimation of available wind speed [21]. The probability distribution function for the power output of variable wind in the range of *(vi ≤ v ≤ vr)* can be determined by:

$$f_{pw} = \frac{K_{rvi}}{P_{wc}} \left[\frac{1 + \frac{h_{Pw}(v_t)}{P_{wr}}}{C} \right]^{K-1} x e^{\left[\frac{h_{Pw}(v_t)}{P_{wr}}\right]K} \quad (10)$$

Where K and C are Weibull probability distribution factors

$$K = (\frac{\sigma}{v_m})^{-1.086} \quad (11)$$

$$C = \frac{V_m}{T(1 + \frac{1}{K})} \quad (12)$$

Solar PV: the solar power output that can be extracted from a given solar irradiance G is [10]-[21]:

$$P_{sg} j(t) = P_{sg}(G) = P_{sr} j(\frac{G^2}{G_{std} + R_{ca}}) \quad (13)$$

Where *for 0 <G< R ca:*

$$P_{sg} j(t) = \sum_{t=1}^{24} \sum_{i=1}^{N_{sg}} (C_R + C_P) \quad (14)$$

And its corresponding objective function ($f_3(x)$) is represented by:

$$f_3(x) = C_s \sum_{i=1}^{N_{sg}} P_{sg} j(t) + \sum_{t=1}^{24} \sum_{i=1}^{N_{sg}} C_R + C_P \quad (15)$$

C_R and C_P represent reserve cost and penalty cost coefficients of solar PV generation respectively. The reserve cost coefficient determines the debit produced from the probability distribution function of variable solar radiation.

The penalty cost coefficient helps to determine the debit that is produced from the overestimation or underestimation of solar irradiance. The probability distribution function for the power output of variable solar irradiance can also be determined using the Weibull probability distribution function [21]-[22]-[23].

Thermal: Despite the difference in their constraints, renewable energy systems adapted from thermal power plants have similar objective function [7]-[24]-[25]. REs adapted from thermal power plants considered in this study include geothermal power plants, solar thermal power plants, biomass, and waste to energy plants.

$$f_4(x) = C_{th} \sum_{i=1}^{N_{th}} P_{th} j(t) \left[\alpha_1 \sum_{i=1}^{N_{Gth}} F_{Gth} P_{Gth} + \alpha_2 \sum_{i=1}^{N_{Sth}} F_{Sth} P_{Sth} + \alpha_3 \sum_{i=1}^{N_{Bth}} F_{Bth} P_{Bth} \right] \quad (16)$$

Where

$$F_{th} = a_i P_{th}^2 + b_i P_{th} + c_i \quad (17)$$

$$F_{Gth} = a_i P_{Gth}^2 + b_i P_{Gth} + c_i \quad (18)$$

$$F_{Sth} = a_i P_{Sth}^2 + b_i P_{Sth} + c_i \quad (19)$$

$$F_{Bth} = a_i P_{Bth}^2 + b_i P_{Bth} + c_i \quad (20)$$

3.2. Constraint formulation

In power systems, continuously respected operation constraints and limits ensure the reliable and secure operation of the system.

1. Demand and generation balance:

Demand is equal to the sum of generation and power lost transporting it.

$$P_D + P_L = \sum_{i=1}^{N_{hgg}} P_{hg} + \sum_{i=1}^{N_{wg}} P_{wg} + \sum_{i=1}^{N_{sg}} P_{sg} + \sum_{i=1}^{N_{th}} P_{th} \quad (21)$$

2. Generation limits

$$P_i^{\min} \leq P_i \leq P_i^{\max} \tag{22}$$

$$P_{\min} \leq 0.00981\eta_i H_{ij} Q_{ij} \leq P_{\max} \tag{23}$$

$$0 \leq P_w j(t) \leq P_{wr} \tag{24}$$

$$0 \leq P_s j(t) \leq P_{sr} \tag{25}$$

$$0 \leq P_h j(t) \leq P_{hr} \tag{26}$$

3. Prohibited operating Zones

$$P_i^{\min} \leq P_i \leq P_i^{Lj} \forall j = 1, 2 \ldots N_{Poz} \tag{27}$$

$$P_i^{V_j - 1} \leq P_i \leq P_i^{lj} \tag{28}$$

$$P_i^{V_j - 1} \leq P_i \leq P_i^{\max} \tag{29}$$

4. Transmission constraints:

For transmission constraints, Kron's loss equation is considered as data for B coefficients are easily accessible and this eqaution is favored by most of the researchers cited in this review.

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{m} P_{gi} B_{ij} P_{gj} = B_{oo} + \sum_{i=1}^{n} B_{io} P_{gi} + \sum_{i=1}^{n}\sum_{j=1}^{m} P_{gi} B_{ij} P_{gj} \tag{30}$$

Where

$$B_{ij} = \frac{\cos(\theta_i - \theta_j) R_{ij}}{\cos\phi_i \cos\phi_j V_i V_J} \tag{31}$$

$$B_{oo} = \sum_{i=1}^{n}\sum_{j=1}^{m} P_{Di} B_{ij} P_{Dj} \tag{32}$$

$$B_{ij} = -\sum_{j=1}^{m}\left(B_{ij} + B_{ji}\right) \tag{33}$$

5. Security limits

$$S_1 \leq S_1^{\max} \forall l = 1, 2 \ldots N_L \tag{34}$$

$$\phi_j P(t) > o \forall j = 1, 2 \ldots N_C \tag{35}$$

6. Generator ramp rate limits

$$\max(P_i^{\min}, P_i^{t-1} - DR_i) \leq P_i(t) \leq \min(P_i^{\max}, P_i^{t-1} + DR_i) \tag{36}$$

7. Spinning reserve limits

$$\sum_{i=1}^{N_G} S_{Ri} \geq S_{Sr} \tag{37}$$

8. Water discharge and reservoir limits:

$$X_i^{\min} \leq X_i \leq X_i^{\max} \tag{38}$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \tag{39}$$

$$Q_i^{\min} \leq Q_{ij} \leq Q_j^{\max} \tag{40}$$

$$V_i^{\min} \leq V_{ij} \leq V_j^{\max} \tag{41}$$

$$V_{i,j+1} = V_{ij} - (Q_{ij} - q_i + S_{ij})\Delta t + \sum_{K \in K_j}\left(Q_{ij} + S_{kij} + I_j\right)\Delta t \tag{42}$$

9. Renewable energy penetration rate constraints

$$P_w j(t) + P_s j(t) + P_h j(t) + P_{th} j(t) \leq \Psi P_D \tag{43}$$

Constraint (9) considers thermal (biomass, solar thermal, geothermal), hydro, wind, and solar PV penetration ratios. Hasnae Bilil et al [26] formulated a multi-objective problem that allows optimization of both the annualized renewable energy cost and the system reliability defined as the renewable energy load disparity considering the lack of energy as well as the exceed weighted by a penalty factor.

The instability created by the integration of variable renewable energy sources made SCED a complex optimization problem [27]. Regarding wind energy penetration several methods have been used to solve this problem [3]-[14]. W. Zhang [7] generally gives a state of the art, recent developments, and future trends of power flow and examines the recent trend towards stochastic, or non-deterministic, search techniques, and hybrid methods for OPF.

A substantial number of SCED with respect to renewable integration studies have focused on optimization requirements of power systems with high renewable penetration such as wind [3] natural gas [7] photovoltaic (PV) [28]-[29].

4. SCED solution methods

Many approaches were established to optimize the economic dispatch of modern power systems with integrated renewable energy systems. Some proposed approaches do not pay much attention to the impacts of generation uncertainty, which affects the system security, and only consider renewable energy to serve the spot market in these methods.

Solution methodologies of SCED widely vary from simple analytical to highly complex and theoretically sophisticated computations according to different approaches in the objective function formulation. This section discusses the different solution methods studied so far by grouping them into three main categories.

4.1. Analytical methods

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Usually, refer to the approximate solution obtained by variations of linear programming techniques or gradient and quadratic based methods. Several authors have presented efficient algorithms in the applications of linear and nonlinear programming methods. Analytical methods include Gradient Methods, Newton's Method, Linear Programming Method, Quadratic Programming Method, and Interior Point Method [30].

Even though they have considerable drawbacks, analytical methods are efficient methods of determining local optimum of unconstrained ideal optimization problems. However, practically SCED problems are multi-objective, highly non-convex, and global optimization problems. To overcome these drawbacks intensive studies have been conducted on alternative computational intelligence methods.

4.2. Computational intelligence methods

For the last two decades, researches have been looking for an optimization method with better global optimum searching performance and fast convergence. This quest paved a way to the understanding of heuristic, or random search, optimization methods.

These methods are used for the solution of highly non-convex, global optimization problems. They have the advantage of finding global optimum much faster than analytical methods but their inability to guarantee convergence causes skepticism for some practical problems.

Many of these techniques have been applied to SCED problems, including Ant Colony Optimization (ACO)[31] [23], Artificial Neural Networks (ANN) [32]-[31]-[33] Bacterial Foraging Algorithms (BFA) [34], Chaos Optimization Algorithms (COA) [35], various Evolutionary Algorithms (EAs)[36]-[37], and Tabu Search (TS) [13].

Due to the drawbacks of deterministic criteria and unguaranteed convergence, hybrid methods, which model uncertainties, have been proposed to overcome these challenges.

4.3. Hybrid methods

Hybrid methods are a merger of two or more optimization algorithms to improve the overall performance of a single or multi-objective optimization problem. The main goal of developing hybrid methods is to achieve an improvement in terms of complexity and computational effort reduction on one hand, and increasing the accuracy and robustness of the solution on the other had.

With the increasing interest in hybrid optimization methods, substantial articles have been published. Hybrid methods including bacterial foraging optimization that is Nelder- Mead hybrid algorithm [38], improved harmonic search, and hybrid ACO-ABC HS algorithm [39] have clearly introduced an efficient and effective optimal solution to SCED problem.

Stephen Frank et al [34] have chronicled a bibliographic survey of papers with a perspective of non-deterministic hybrid methods for solving optimal power flow problems. Irina [40] proposed a novel heuristic optimization algorithm called GAAPI, a hybridization between a special class of Ant Colony Optimization and Genetic Algorithm, to solve a large and complex optimization problem. This review proposes optimization SCED for IRES using a robust GAHNN method, a Hybridization Hopfield neural network, and an improved genetic algorithm, which takes into account the intermittency of renewable energy sources and handles probable contingencies.

5. SCED Challenges and future work

SCED challenges identified in this paper are grouped into three main categories. Challenges concerning to IRES, challenges regarding handling constraints or contingencies and challenges respective to computational, and optimization problems are discussed below.

5.1. IRES challenges

With the increasing use of renewable generation, many approaches have been established to optimize modern power systems with integrated renewable energy systems. Some proposed approaches do not pay much attention to the impacts of generation uncertainty, which will affect system security, and renewable energy is only considered to serve the spot market in these methods.

Renewable energy resources are highly site-specific, stochastic, and they are highly dependent on the climatic conditions, geographical factors, and seasons of the site under consideration. The main challenging aspects of integrated renewable energy systems are variability, intermittency, uncertainty, and non-dispatch ability.

5.2. Constraints handling challenges

In a real power system, the SCED problem is a non-linear and multi-objective problem due to power-system operation constraints. SCED is classified into two different types: preventive SCED (PSCED) and corrective SCED (CSCED). In post contingency states, PSCED does not consider the rescheduling of control variables. On the other hand, CSCED can correct rescheduling within a certain limit to satisfy more contingency scenarios.

Although PSCED can secure the system against all contingencies, the strategy is viewed as conservative in that it leads to a higher operational cost [5]. Approaches of increasing the security level of a power system in post contingency state have been reported. Wang et al [13] clearly chronicled the advantages and application of the probabilistic N-1 security criterion. P. Kaplunovich and

K. Turitsyn [23] deployed a method for fast selection of N-2 contingencies of online security assessment.

Considering, European transmission network composed of 13,000 busses and 20,000 branches, there will be 13,000 voltage constraints and 20,000 flow constraints. For N-1 security of 20,000 contingencies we must consider 20,000 x (13,000 + 20,000) = 660 million inequality constraints.

However, not all contingencies create limit violations. Some contingencies have only a local effect. The problem with the N-1 security criterion is it does not ensure a consistent level of risk. Probabilistic security analysis which considers system operation at a given risk level is proposed to alleviate these challenges [41].

In connection with handling contingencies, recent advances have been made along two major avenues: (i). Contingency filtering (CF) techniques [42]-[43] to effectively reduce the problem size and (ii). Decomposition and parallel algorithms [3]-[44] to obtain approximate global solutions efficiently. Generally, the main constraint handling challenges posed to SCED include the higher cost of preventative dispatch, non-predictability of contingencies, and higher fluctuation of variable generation.

5.3. Optimization and computational challenges

In a practical power system, the SCED problem is a non-linear and multi-objective problem due to power system operational constraints.

Apart from the size, non-linearity, and non-convexity of the SCED problem for IRES is a highly challenging problem. Considering the above equations of SCED, optimization problems with such number of equality, and inequality constraints, face considerable computational challenges.

Other challenges in connection with optimization and computation of SCED are difficulties with the stochastic nature of objective functions. Due to this, most multi-objective functions consume immense computation time. All these challenges require figuring out a way of analyzing varying operating conditions under multiple and intermittent contingency scenarios to ensure no sudden cascade failures from overloading and disasters occur. The following table presents papers and reports reviewed in this paper with respect to the type of optimization tools used, the type of objective function, and the type of test system or case study they used.

Table 1. Literature Survey/Review Summary

Ref.	Optimization Type	Objective function	Case study
[2]	MOSCED-LP, QP, NFP, NCLFP, GA	Minimize the cost of generation, Minimize cost of power loss and Maximize security level	IEEE 5, 30 Bus systems
[28]	MOSMPC SCED-OCD	Optimize the operating cost and Optimize security level	Modified WECC 9-bus test system
[29]	MOSCOPF, HPSO-APO	Minimize total production cost, Minimize active power loss and Maximize security level	IEEE 30 bus system, Practical Indian 75 Bus system
[30]	MOSCED	Minimize deviation of transactions and Minimize operating cost of generation	IEEE 24 Bus system
[7]	SCED, GAMS, SNOPT	Minimize production cost and Maximize security level	IEEE 30 Bus system
[31]	MO SCED-EA,HOMER, MATLAB	Minimize the cost of electricity Maximize utilization of resources	IEEE test systems
[8]	MO RELD-(NSGA-II)	Optimize annualized cost and Optimize renewable energy load disparity	Belgium's electricity transmission system
[5]	SCED-IRESIO	Optimize operating cost and Optimize security level	IEEE 39 Bus system
[32]	SCED-SDP ACF-SDP	Maximize security level(Identify feasible post contingency operating point)	IEEE 30, 57 and 118 Bus systems
[33]	MRSCED-IBD, GAMS, CPLEX	Maximize security level and Minimize operating cost	IEEE 30, 57 and 118 Bus systems
[34]	MOSCELD-MATLAB and CPLEX	Minimize operating cost	IEEE 30 Bus system, Finish Transmission system
[25]	CSCOPF, MCSCOP, ICF	Minimize operating cost Maximize security level	IEEE 300 Bus system, Chinese 543-bus power grid system
[4]	SC-SCED, CPLEX ,API	minimize the base-case ED cost and maximize security level	Polish 2383-bus system
[35]	LMP SCED-GA	Minimize bus LMP and Minimize total fuel cost	IEEE 14 Bus system, Indian 75 Bus system New England 39 Bus system
[36]	ELD, CSO	Minimize total fuel cost	3-Generating Units, 6 Generating Units
[37]	PED, IIA MU	Minimize total operating cost	5- Unit system 15-Unit system
[21]	MO SCED-HGAAPI	Minimize cost of generation and Maximize security level	Cyprus Power System

5.4. Future work

Figuring out a way of solving this multi-objective optimization problem that considers variable loads & intermittent generation is a challenge that requires substantial attention during the integration of renewables.

As a future work, hybrid computational intelligence based optimization of SCED for IRES with predictive control and post contingency corrective actions is proposed. This could alleviate the challenges related to the intermittency and unpredictability of renewable energy sources.

Besides using physical power systems, applying computationally intelligent and self-adaptive optimization tools of SCED for renewable microgrids, smart grids, and hybrid energy systems is also suggested. As long as the power system is renewables fuelled, advanced SCED mathematical formulation can result in a promising optimal solution.

Enhanced genetic algorithms are the best solution methods of obtaining a global optimum solution of multi-objective SCED given their efficient, and parallel computing features. Hybrid options can also be taken to increase the convergence problem of genetic algorithms

6. Discussions and research directions

Researchers and graduate scholars can use this review to help them understand the state of the art and identify the research direction of SCED. In this review, papers on power systems with higher penetration of renewable energy and relevant multi-objective stochastic optimization problem are discussed. The total number of publications related to this review and their trend is depicted in the figures below.

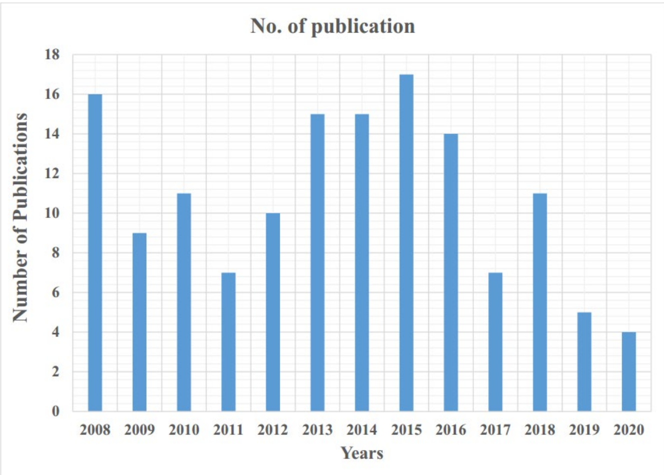

Figure 2. State of the Art of SCED publications

In one decade, more than 50 papers of SCED for IRES have been reported. It has been tried to include as many descriptions of the contents as possible in order to show the important and unique aspects of each paper. This review is not directed at evaluating and comparing relative performances of the existing algorithms but at presenting a clear picture of the state of the art of SCED. It is obvious from the survey that, SCED of a power system with IRES and corresponding ways of addressing their challenges are important areas of future research.

Considering post-disturbance corrective actions, formulating an intelligent searching algorithm with fast convergence, and taking into account the intermittency of all recently innovated renewable energy systems, figuring out a way of optimal dispatch is the future t research area of SCED of IRES. Most of the recent algorithms are tested on IEEE test systems and real-time power system networks.

7. Conclusions

This paper presents a survey of papers, books, and reports, which articulate the recent trends, and aspects of Security Constrained Economic Dispatch (SCED) of IRES. The period under consideration is 2008 through 2018. This is done to provide an up-to-date review of the recent major advancements in the SCED of IRES state-of-the-art since 2008, identify further challenging developments needed in adoption smarter grids, and indicate ways to address these challenges.

The study has been conducted in three categories of perspectives and areas of interest that are very important and relevant for articulating the recent trends of SCED. The novelty of this review lies in the articulation of research gaps, providing an up-to-date review of the recent major advancements in the SCED of IRES state-of-the-art since 2008, identification of further challenging developments needed in the adoption of smarter grids, and indicating ways to address these challenges altogether with their recommendation.

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