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Optimal Power Flow Solution for Thermal-Wind-Solar Power Using L-SHADE

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ABSTRACT

In order for an electrical network to operate economically and efficiently, the generation from various sources must be optimally scheduled. With all important system characteristics, including generator outputs, the optimal power flow (OPF)problem is built and resolved to give best outcomes. The network might contain both conventional and non-conventional energy generators, such as wind and photovoltaic solar panels. Traditional optimal power flow (OPF) is known as complicated non-linear issuance with non-linear restriction. By integrating the irregular nature of both solar and wind energy, the complicated nature will be increased. In this paper, a method for determining the optimal power flow in a system that includes stochastic wind and solar generation as well as traditional thermal power sources is proposed. For intermittent renewable sources, the objective function takes into account reserve costs for overestimation and penalty costs for underestimation. Additionally, for some case studies, the emission factor is incorporated in the objectives. SHADE with linear population size reduction algorithm is used to solve the optimization problem. The superiority of feasible solutions constraints usable technique is merged on the L-SHADE algorithm to handle the problem's constraints. The algorithm that has been merged and created in this way produces optimal results that satisfy all network constraints.

Keywords:
Wind power, Carbon emission, Optimization, success history based differential adaption evolution, Linear Population Size Reduction, Constraint handling technique, superiority of feasible solution, Optimal power flow, Solar PV.

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NOMENCLATURE

Abbreviations

ISO	Independent system operator
L-SHADE	SHADE with Linear Population Size Reduction
OPF	Optimal power flow (OPF)
PDF	Probability density function
PV	Photovoltaic
SF	Superiority of feasible solutions
SHADE	Success history based adaptive differential evolution
TG	Thermal power generator
WG	Wind generator

Symbol

$P_{TG\text{u}}$	Output power produced by u-th steam generating unit
$P_{ws,\text{y}}$	power scheduled from y-th wind power generating unit
$P_{ss,\text{z}}$	Power scheduled from z-th wind power generating unit
$P_{wav,\text{y}}$	Power actually available from y-th wind power generating unit
$P_{sav,\text{z}}$	Power actually available from z-th solar power generating unit

Symbol

g_{y}	direct cost coefficient for y-th wind power generating unit
h_{z}	direct cost coefficient for z-th solar PV generating unit
$K_{Rw,\text{y}}$	reserve cost coefficient to over-estimate wind power from y-th generating unit
$K_{Pw,\text{y}}$	penalty cost coefficient to under-estimate wind power from y-th generating unit
$K_{Rs,\text{z}}$	reserve cost coefficient to over-estimate solar power from z-th generating unit
$K_{Ps,\text{z}}$	penalty cost coefficient to under-estimate solar power from z-th generating unit
$Ctax$	Carbon tax (\$/tonne)
G	solar irradiance (W/m^2)
$f_v(v)$	Probable wind speed (m/s)
$f_G(G)$	probability of incident solar irradiance (G W/m^2)
p_{wr}	rated power output from a wind turbine
P_{sr}	rated power output of the solar PV generating unit
c, k	Weibull PDF scale and shape parameters respectively
μ, σ	lognormal PDF mean and standard deviation respectively
P_{loss}	real power loss incurred in the given network
VD	cumulative voltage deviation in the given network

1. INTRODUCTION

Although around a half century ago, Optimal flow power concept has been an vital area in the field of power systems , The Optimal Power Flow (OPF) is used to solve the issues of fixing the appropriate operating levels to fulfil demand across a transmission network while reducing operating costs. This may be a challenging operation since electrical power flows from the physical characteristics of the system according to nonlinear functions. The primary purpose of OPF is to reduce cost of generations by utilizing optimal control variable settings that are active power of generator and generator bus voltages of the system. System constraint such as power flow balance, bus voltage, line capacity, generator capacity must be satisfied. The system's ideal operating state is indicated by the scheduled power generator, nonlinear power flow on the line, and bus voltage vector specified during the optimization method. A fossil-fuel-powered thermal power generator is included in the standard OPF problem. With the increased usage of wind power as well as solar-PV on the grid, OPF studies must account for the unpredictability of these solar and wind power.

The most difficult aspect of integrating wind and solar power into a network is their intermittent nature. Private operators own the costs of wind or PV solar. This private operator signed a memo with the grid operator/ independent system operator (ISO) to buy schedule power. However, since generations of these renewable energy sources are unknown, power generation is sometimes higher than planned power, which underestimates the quantity available. The expense of a penalty shall be borne by ISO in vain due to an excess power until utilised. In contrast, overestimates are instances when the power produced is less in comparison to the predicted power. In order to minimise the demand for electricity, ISO needs to retain spinning reserves, which raise the system running costs. Along with the costs of generating thermal power supplies, the objectives are specified in the direct costs, penalties and reserve costs of renewable sources. There is modification in IEEE-30 Bus System so that to assist wind generating units and solar PV plant with the reactive power support. The optimized cost (Rupees) of generation with the effects of changes in reserves and penalty costs on optimum load scheduling are analyzed. Thermal generators are emitting hazardous gases into the environment in terms of emissions, whereas renewable sources are not. Carbon taxes [1] are imposed in several countries proportionally with greenhouse gases emitted. The amount of carbon tax is combined with objective functions in some case studies to investigate the impact on generator scheduling.

L-SHADE is used for optimization problem which extends success-history based parameter adaptation technique (SHADE)with Linear Population Size Reduction (LPSR),that reduces the size of population according to a linear function. SHADE, the advanced variant of differential evolution (DE), using historical memory setting control parameters that succeed to assist in the choice of control parameters[2] in the future. This guarantees that multimodal, non-linear optimization problems are accurately and quickly converged to a global solution. L-SHADE combined with the most productive constraint holding process called the superiority of usable solutions (SF)[3].The penalty function method is used to examine constraint violations in most of the OPF literature. The way to choose penalty coefficients is critical in this approach. Excessive exploration of an infeasible area, slowing down process of getting proper solution, and prematurely converging to an infeasible solution are all consequences of a small penalty coefficient. A large penalty coefficient, rather may fail to properly explore unworthy areas, leading to infinite convergence[4]. The SF technique examines two solutions that can be feasible, infeasible, or a combination of the two. Based on the comparison process, the search directs to a feasible location. With a penalty function, there is very less chance of constraint violations if the penalty factors are chosen incorrectly, sometimes without the programmer's knowledge. However, by employing the proper constraint handling techniques, such probabilities can be eliminated.

This literature, on the other hand, is primarily concerned with real-time generator scheduling for economic operations, taking into account the various pricing strategies used by operator utilities and independent system operators (ISO).Reference [17] considers time-to-time (minutes) variations in reusable energy sources as the main objective. When it comes to economic load dispatch (ED), system constraints, particularly network parameter limitations are frequently neglected; however, network constraints must be followed at OPF. System constraints are mentioned in the literature [18], but the details about satisfying these constraints are not addressed explicitly. Furthermore, the voltage profiles throughout the network, as well as emissions, are usually not allocated ED problems, rather in OPF problems. In short, the optimum flow of power on network of thermal, solar PV and wind generators requires additional attention. The current research is focused on the optimal power flow problem, which includes detailed wind and solar power uncertainty modelling.

In general, optimal power flow(OPF) for thermal, wind, and solar PV sources in a

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connection requires additional effort. The optimal power flow problem are handled on the reference[21] by combining solar and wind energy into a system with a thermal generating unit. Basically, the minimization of generation cost is accomplished by employing a differential evolution-based method, namely SHADE, which stands for success history-based differential evolution. And it's paired with a powerful constraint-handling technique called superiority of feasible solution. The results obtained are really encouraging. The current study is focused on the optimal power flow problem using the same data as [21] , but to enhance the findings achieved in [21], LPSR (Linear Population Size Reduction) is combined with the SHADE algorithm.

The remaining part of the research work is organised on successive way. The mathematical representation is presented in Sections 2 and 3 include applicable constraints related to the OPF problem as well as modelling of uncertainties in wind power output and solar power. The briefing and implementation of the L-SHADE algorithm are presented in Section 4. Case studies and simulation results are discussed in Section 5, followed by conclusion in Section 6.

1. MATHEMATICAL MODELS-

Table1 summarises the essential parameters of the IEEE-30 bus network used in this research. Thermal, wind, and solar PV generators make up the customised network. Wind and solar PV power outputs are variable. The combination of all generator power output and all reserves must balance the variability of the power output. The overall cost of generation is thus made up of all generators' operating costs, penalty costs, and reserve costs, which will be discussed later.

Table 1: Description of IEEE-30 bus systems under study.

Items	Quantity	Details
No of Buses	30	[19]
No of Branches	41	[19]
No of thermal generators (TG1,TG2,TG3)	3	Buses: 1 (swing), 2 and 8
No of wind generators ($WG1$, $WG2$)	2	Buses: 5 and 11
No of solar PV unit (SPV)	1	Bus: 13
Control variables	11	Scheduled real power for 5 nos. generators: $TG2$, $TG3$,1, $WG2$ and SPV; bus voltages of all generator buses (6 nos.)
Connected load		283.4 MW, 126.2 MVAr
Load bus voltage range allowed	24	[0.95 – 1.05] p.u.

1.1. Cost model of thermal generating unit

The operation of thermal power plants necessitates the use of fossil fuels. The quadratic equation approximates the link between the cost of fuel ($/h) and generated electricity (MW):

$$C_{T0}(P_{TG}) = \sum_{u=1}^{N_{TG}} a_u + b_u P_{TGu} + c_u P_{TGu}^2 \quad (1)$$

Where a_u, b_u, c_u are the u-th thermal generator's cost coefficients that produces the production of P_{TGu} power. The number of total thermal generating units is $_{TG}$.

The valve point loading effect can be considered as additional realism and accurate cost function modelling. The fuel cost functions of thermal generating units having multi-valve steam turbines are more variable. Its valve point loading effect of multiple valves in steam turbines is represented by a function of sine wave, whose relative value is added to the fundamental cost($) function in equation (1). The producing cost of steam-thermal units ($/h) is calculated as follows:

$$C_{T0}(P_{TG}) = \sum_{u=1}^{N_{TG}} a_u + b_u P_{TGu} + c_u P_{TGu}^2 + \left| d_u \times \sin\left(e_u \times \left(P_{TGu}^{min} - P_{TGu}\right)\right)\right| \quad (2)$$

In which, valve point loading effect are considered as coefficients d_u and e_i.P_{TGu}^{min} would be the minimum generated power by the thermal unit when it is operating. Table 2 shows the overall cost in addition emission coefficients again for steam generating units involved in the computations.

Direct expenses associated with the z-th solar PV are similar to those associated with wind generating plants:

$$C_{s,z}(P_{ss,z}) = h_z P_{ss,z} \quad (4)$$

$P_{ss,z}$ becomes the scheduled power of same plant, and h_z would be the direct cost coefficient linked on the Solar PV plant.

1.2. Uncertainties in wind energy cost evaluation

When the actual electricity provided by wind farms is less than the predicted value, a scenario might occur. Overestimation is the term for this. In order to supply customers with uninterrupted supply, the system operator must maintain spinning reserves. The expense of running a backup generating unit to fulfil an overestimated quantity is referred to as a reserve cost [12].

The y-th reserve cost for wind energy plants is defined as follows:

$$C_{Rw,y}\left(P_{ws,y} - P_{wav,y}\right) = k_{Rw,y}\left(P_{ws,y} - P_{wav,y}\right) = k_{Rw,y} \int_0^{P_{ws,y}} (P_{ws,y} - P_{wy}) f_w(P_{wy}) dp_{w,y} \quad (5)$$

Where, $K_{Rw,y}$ is a reserve cost coefficient for y-th wind power generating units, $P_{wav,y}$ is actual energy generated by the same plant. $f_w(P_{wy})$ is a function of wind power probability density for wind power plants y-th. In section 4.3.2, the probability determination of power output at different wind velocity is described.

In overestimation scenarios, on the other hand, sometimes in the network when the real power produced by wind farms exceeds the predicted value. In such instances, the production of renewable energy sources is underestimated. If the power surplus cannot be used by lowering the conventional generator's power output, it will be wasted. ISO must pay the penalty cost equal to the amount of the violation. Penalty cost for wind power plants y-th defined as:

$$C_{pw,y}\left(P_{wav,y} - P_{ws,y}\right) = k_{pw,y}\left(P_{wav,y} - P_{ws,y}\right) = k_{pw,y} \int_{P_{ws,y}}^{P_{wr,y}} (P_{w,y} - P_{wsy}) f_w(P_{wy}) dp_{w,y} \quad (6)$$

$P_{wr,y}$ is the nominal output power of the same farm, and $K_{pw,y}$ is the cost coefficient of the penalty for the wind power plant.

1.3. Uncertainties in solar energy cost evaluation

The solar PV plant, like the wind power plant, has an intermittent and unpredictable output. The approach for estimation (over/under) of solar energy is same as that of wind energy. However, because solar radiation pattern follows the lognormal PDF [20], as opposed to wind distribution, which follows the Weibull PDF, more information is included in section 3.

The cost of the reserve for the k-th solar PV is:

$$C_{Rs,z}\left(P_{ss,z} - P_{sav,z}\right) = k_{Rs,z}\left(P_{ss,z} - P_{sav,z}\right) = k_{Rs,z} * f_s\left(P_{sav,z} < P_{ss,z}\right) * \left[P_{ss,z} - E\left(P_{sav,z} < P_{ss,z}\right)\right] \quad (7)$$

Here, the reserve cost coefficient for the solar PV plant is $K_{Rs,z}$. The actual available power of the same plant is $P_{sav,z}$. E ($P_{sav,z}$<$P_{ss,z}$) is the expected solar PV power under $P_{ss,z}$ and $f_s(P_{sav,z}<P_{ss,z})$ is the probability of occurrence of solar energy shortage.

Cost of penalty for underestimating the k-th solar PV is:

$$C_{Ps,z}\left(P_{sav,z}-P_{ss,z}\right)=k_{Ps,z}\left(P_{sav,z}-P_{ss,z}\right)=k_{Ps,z}*f_s\left(P_{sav,z}>P_{ss,z}\right)*\left[E\left(P_{sav,z}>P_{ss,z}\right)-P_{ss,z}\right] \quad (8)$$

When, $K_{ps,z}$ is the coefficient of penalty relative to the solar PV plant, $f_s(P_{sav,z}>P_{ss,z})$ would be the probability among a solar power excess exceeding the amount of power scheduled ($P_{ss,z}$), E ($P_{sav,z}>P_{ss,z}$) is the solar photovoltaic expectation for power over $P_{ss,z}$.

Table2:Cost and emission coefficients of thermal generators for the system under study:

Generator	Bus	a	b	c	d	e	α	β	γ	ω	μ
TG1	1	0	2	0.00375	18	0.037	4.019	5.554	6.49	0.0002	6.667
TG2	2	0	1.75	0.0175	16	0.038	2.543	6.047	5.638	0.0005	3.333
TG3	8	0	3.25	0.00834	12	0.045	5.326	3.55	3.38	0.02	2

1.4. Objectives of optimization

All of the above-mentioned cost functions are incorporated into OPF's target. Emission costs are not factored into the first target. A second objective function is constructed to research the transition in generation scheduling when a carbon tax is implemented.

First objective:

Minimize –

$$F_1=C_T(P_{TG})+\sum_{y=1}^{N_{WG}}\left[C_{W,y}\left(P_{ws,y}\right)+C_{Rw,y}\left(P_{ws,y}-P_{wav,y}\right)+C_{Pw,y}\left(P_{wav,y}-P_{ws,y}\right)\right]+\sum_{z=1}^{N_{SG}}\left[C_{s,z}\left(P_{ss,z}\right)+C_{Rs,z}\left(P_{ss,z}-P_{sav,z}\right)+C_{Ps,z}\left(P_{sav,z}-P_{ss,z}\right)\right] \quad (11)$$

where N_{WG} , N_{SG} are the total number of wind generating units and solar PVs on mentioned network. Equations (2) to (8) are used to figure out the rest of the costs.

Second objective: Minimize –

$F_2 = F_1 + C_{tax}$E(12)

The aims of the OPF are constrained by framework equality and inequalities.

2. UNCERTAINTY MODEL AND STOCHASTIC WIND SOLAR EERGY-

For modelling the distribution of wind speed (PDF) [10-12] , the Weibull probability density function is generally accepted. The probability of wind speed v m/s is given by [21], using the Weibull PDF with scale factor (c) and shape factor (k) :

$$f_v(v)=\left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{(k-1)}e^{-(v/c)^k} for\ 0<v<\infty \quad (26)$$

The Weibull distribution's mean may be calculated as follows:

$$M_{wbl}=c*\Gamma(1+k^{-1}) \quad (27)$$

The gamma function (x) is represented as:

$$\Gamma(x) = \int_0^\infty e^{-t} t^{x-1} dt \quad (28)$$

In the study of IEEE-30 bus system, traditional generators in bus 5 & bus 11 are modified by wind generators. Values are selected in Weibull form (k) & scale (c) parameters are given in Table 4.3. We stick to these PDF specifications throughout, unless an unique case study specifies different. For wind farms the shape (k) & scale (c) parameters are carefully chosen so that the entire Weibull mean value is around ten. Furthermore, geographical locations are also taken into account while choosing PDF parameter values.

Wind power generating plants					**Solar PV plants**		
Windfarm#	*No. of turbines*	*Rated power,P_{wr}(Mega Watt)*	*Weibull PDF parameters*	*Weibullmean, M_{wbl}*	*Rated power,P_{sr}(Mega Watt)*	Lognormal PDF parameters	Lognormal mean,M_{lgn}
1 (bus5)	25	75	c=9 k=2	v=7.976 m/s	50 (bus 13)	μ=6 σ=0.6	G=483W/m^2
2 (bus11)	20	60	c=10 k=2	v=8.862 m/s			

Table 3:PDF parameters of wind power and solar PV plants:

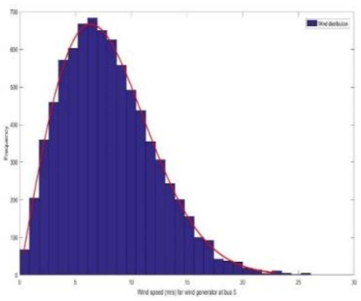

Fig. 1: Wind speed distribution for wind farm #1 at bus 5 (c = 9, k = 2)

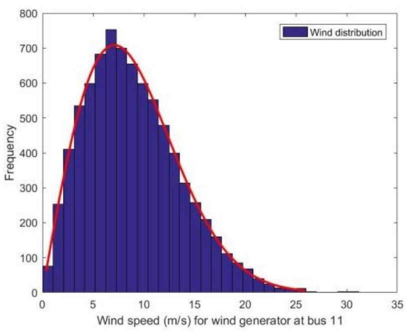

Fig. 2: Wind speed distribution for wind farm #2 at bus 11 (c = 10, k = 2)

On the IEEE-30 bus system, bus 13, a solar Photovoltaic unit substitutes the traditional generator. Solar irradiance (G), which describes the lognormal PDF [20], is used to determine the unit's efficiency. The following probabilities apply to solar irradiance (G) after a lognormal PDF using mean μ with levelled deviation σ:

$$f_G(G) = \frac{1}{G\sigma\sqrt{2\pi}} exp\left\{\frac{-(lnx-\mu)^2}{2\sigma^2}\right\} \; for \; G > 0 \quad (29)$$

The lognormal distribution's mean is calculated as follows:

$$M_{lgn} = \exp\left(\mu + \frac{\sigma^2}{2}\right) \quad (30)$$

Fig.3 shows the frequency distribution & lognormal fitting of solar irradiance. Selected parameters for lognormal PDF are summarised under Table 3.

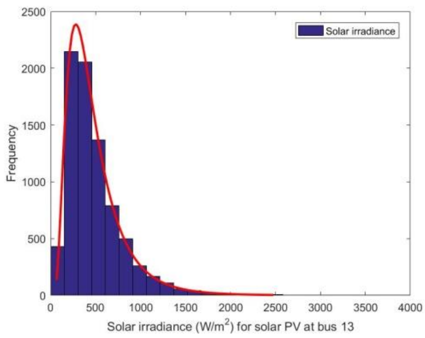

Fig. 3: Solar irradiance distribution for solar PV at bus 13 (μ = 6, σ = 0.6)

2.1. Model of wind and solar photovoltaic power

Wind power generating units connecting to bus 5 represents total production of the 25 no. of turbines in a power station, while wind power connected to bus 11 represents the production of a wind power station having 20 turbines. Each turbine has a 3 MW output. The wind velocity is used to calculate the amount of electricity generated by a wind turbine. By the function of wind velocity (v), the power output of a turbine can be designed as follows:

$$P_w(v) = \begin{cases} 0, & for \quad v < v_{in}\, and\; v > v_{out} \\ P_{wr}\left(\frac{v-v_{in}}{v_r-v_{in}}\right) & for\;\; v_{in} \le v \le v_r \\ P_{wr} & for\;\; v_r < v \;\le v_{out} \end{cases} \quad (31)$$

where v_{in}, v_r, and v_{out} are the turbine's cut-in, rated, and cut-out wind velocity, respectively. The wind turbines rated output power is p_{wr}. For a wind turbine with a capacity of 3 MW. V_{in} = 3 m/s, v_r = 16 m/s, and v_{out} = 25 m/s are the different speed values [21].
For solar PV, solar irradiance (G) to source conversion is provided by:

$$P_s(G) = \begin{cases} P_{sr}\left(\frac{G^2}{G_{std}R_c}\right) & for\; 0 < G < R_c \\ P_{sr}\left(\frac{G}{G_{std}}\right) & for\;\; G \ge R_c \end{cases} \quad (32)$$

in which G_{std} refers to the solar irradiance in a normal setting, which is set to 800 W/m^2. The irradiance point R_c is set to 120 W/m^2. P_{sr} denotes the solar PV unit's rated output capacity.

The histogram in Figure4 indicates the stochastic power production of a solar PV unit. Schedule power, as previously indicated, can be whatever quantity of electricity that the solar PV and ISO owner agree on. Cost($) of overestimation in equation (7) may be determined as follows (the suffix 'k' in equation (7) is eliminated for a one solar Generating unit):

$$C_{Rs}(P_{ss} - P_{sav}) = K_{Rs}(P_{ss} - P_{sav}) = k_{Rs}\sum_{n=1}^{N-}[P_{ss} - P_{sn-}] * f_{sn-} \quad (36)$$

From the left-half plane of P_{ss} in the histogram, P_{sn-} is usable power which is lesser from schedule power P_{ss}. P_{sn}'s relative frequency of occurrence is given by f_{sn-}. N- is the quantity of discrete bins on P_{ss}'s left half, or the number of pairs (P_{sn-}, f_{sn-}) provided for the PDF. To some degree, increasing the number of segments improves the precision of the results. Problem arises in my analysis, a total number of 30 segments (N) yields relatively precise findings.
In the same way, the cost of underestimation in equation (8) can be estimated as follows [21]:

$$C_{Ps}(P_{sav} - P_{ss}) = K_{Ps}(P_{sav} - P_{ss}) = k_{Ps}\sum_{n=1}^{N+}[P_{sn+} - P_{ss}] * f_{sn+} \quad (37)$$

On the right-half plane of P_{ss} in the histogram, P_{sn+} is the usable power greater than the scheduled power P_{ss}. P_{sn+} occurs with f_{sn+} frequency. N+ is the number of discrete bins created for the PDF on the right-side of P_{ss}, or on the other hand the total number of pairs (P_{sn+},f_{sn+}).

3. ALGORITHM AND APPLICATION OF OPTIMIZATION-

Storn and Price proposed Differential Evolution (DE) in 1996 as a stochastic, metaheuristis optimization technique where its separates in a population develop and improvise their efficiency employing probabilistic data like recombination and mutation. The DE efficiency is shown to be influenced by crossover rate (CR), scaling factor (F), the mutation/crossover strategies and population size (Np) are used. Adaptive mechanisms which improves several control parameters throughout the search process have been discussed by several experts. SHADE, favourable outcome history based differential evolution is a history based data adaption technique uses previously stored data to guide the selection. The L-SHADE method [22] is used in the study described here. L-SHADE stands for SHADE having linear population size cutting that cuts the population size over time to obtain greater convergence. The modified L-SHADE algorithm is combined with the superiority of feasible solution (SF) constraint handling technique. Below is a brief description of both algorithms, accompanied by a discussion of the integration strategy.

$$T_I(x) = \begin{cases} max\{g_u(x), 0\} & u = 1 \ldots..p \\ max\{|h_u(x)| - \delta, 0\} & u = p+1, \ldots..,m \end{cases} \quad (45)$$

where δ is the equality limit tolerance parameter. As a result, the aim is to minimise the fitness function f(x) thus the best solution satisfies all $T_I(x)$ inequality constraints. For an unfeasible individual, the general constraint violation is the weighted mean from the constraints, which is expressed as:

$$v(x) = \frac{\sum_{u=1}^{m} w_u [T_I(x)]}{\sum_{u=1}^{m} w_u} \quad (46)$$

$T_{max,}$ is defined as the maximum violation of constraint $T(x)$ obtained till now, and w_u(= $1/T_{max,u}$) is a weight parameter. Here, w_i is set to $1/T_{max,}$. Details can be referred in [3],[21].

Table 4: L-SHADE algorithm

L-SHADE-SF	
Input	• Dimension of problem, d (d = 11) • Population Size, Np (Np = 100 considered) • Maximum number of functions that are evaluated as a stopping criterion, max_nfes • xmin and xmax are the minimum and maximum values of d-decision variables in vector form. • $x_{max} = [x_{max}^1, \ldots, x_{max}^d]$ and $x_{min} = [x_{min}^1, \ldots, x_{min}^d]$
Initialization	• Set t = 0 for the generation counter and nfes = 0 for the function evaluation counter. • Set SHADE parameters as follows: H = 5, memory (M) size, μF = 0.5, and μCR = 0.5. • POP: Generate a population of Np individuals with a uniform distribution between [xmax, xmin].
Evaluation	• For each individual $x_i \forall i \in \{1, \ldots.., Np\}$ of POP ,use eqs. (44) to (46) to evaluate the objective function, constraint function, and constraint violation. • Increase the nfes,function evaluation counter by Np. • Implement the LPSR population reduction scheme
Algorithm Loop:	
Step 1	• For each individual of POP perform mutation and crossover and generate offspring OFS, $x_i^{;}$ • Produce mutant vector $v_i^t$by equation (39) • Produce trial vector element u_{ij}^t performing crossover based on equation (42) • Generate the trial vector u_i^t with every elements, which is OFS vector

	$x_i^{'}$
Step 2	• Using eq. (44) to eq. (46) for each individual $x_i^{'}\forall$u∈$\{1, . . . , Np\}$ of OFS, calculate objective function, constraint violation and constraint function. • Increase the nfes , function evaluation counter by Np.
Step 3	• POP members for the next generation are replaced with corresponding OFS members in the selection step if OFS is best corresponding to SF ruling. Wheather an OFS produces fewer constraint violations or zero constraint violations, as well as a lower fitness value (minimization problem), it is considered better than the
Step 4	old POP member. If OFS does not improve things, the old POP member is kept. • Whether OFS is superior, μF and μCR memory is updated in the manner described.
Step 5	• Calculate N_p^{t+1} according to Eq. (43); • if N_p^t<N_p^{t+1} then Sort individuals in N_p based on their fitness values and delete lowest N_p^t– N_p^{t+1} members; • Find if stopping criterion, max_nfesarrived? • If yes, STOP • If not, generation counter needs to be improved by 1, i.e. t= t +1. Go to algorithm loop STEP 1.

Fig. 5: Flowchart for implementation of L-SHADE-SF

The proposed algorithms were created with the help of MATLAB which simulates were programme on Intel Core i5 processor and 8GB of RAM Computer. The effects of the simulation are mentioned in section 5.

4. CASE STUDIES ANDN RESULT-

For the IEEE-30 bus system, two case studies are carried out. This section tabulates and describes the results of case studies using the L-SHADE algorithm. Both the algorithm's results are compared. During a single complete run of the procedure, each and every optimization record performs a total of 24000 function evaluations. To find the ideal objective function value and control variable values, each case is run five times.

Case 1: Minimization of generation cost

Case 1 optimises generation schedule for both steam and renewable energy generators in order to reduce overall generation costs as calculated by equation (11). Table 5 summarises the optimal settings for generator reactive power (Q),all control variables, total generation cost, and all further functional measured variables. The voltage at the i-th bus is denoted by V_i in the table; P_{loss} and *VD* are measured by equations (24) and (25) respectively. It's worth noting that $P_{ws,1}$denotes scheduled power from wind generator *WG1* and so on. With all the generation schedules mentioned on table, minimum cost of generation that can be obtained using SHADE-SF algorithm[21] is **782.503 $/h** and L-SHADE algorithm is**780.950 $/h**.

Case 2: Minimization of generation cost including carbon tax

This data seeks to reduce overall generation costs by stately a carbon tax on emissions from traditional steam power generators. The total expense, as calculated by equation (12), need to retain minimum. Ctax, or carbon tax, is assumed as $20 per tonne [1]. Since wind and solar power are renewable sources, the carbon tax aspect is expected to increase their penetration. Table 5 manifests the generator reactive capacity, optimum generation schedule, total cost of generation, and other measured parameters. When a carbon tax is imposed in Case 2, the penetration of both solar energy and wind is higher than when there is no carbon tax in Case 1. As a matter of facts, the amount of increase in the optimal generation schedule of renewable sources is dependent on the volume of emissions and the rate of carbon tax levied. In this case, the minimum generation cost achieved using SHADE-SF is **810.346 $/h**, while L-SHADE is **792.129 $/h**.

Table 5: Simulation results for optimization case studies: IEEE 30-bus system

Control variables	**Min**	**Max**	**Case 1**	**Case 2**	**Parameters**	**Min**	**Max**	**Case 1**	**Case 2**
P_{TG1}(MW)	50	140	134.90	123.28	Q_{TG1}(MVAr)	-20	150	10.996	10.553
P_{TG2}(MW)	20	80	27.382	32.295	Q_{TG2}(MVAr)	-20	60	17.751	16.629
P_{TG3}(MW)	10	35	10.000	10.000	Q_{TG3}(MVAr)	-15	40	40.000	40.000
P_{ws1}(MW)	0	75	42.970	45.465	Q_{ws1}(MVAr)	-30	35	24.901	24.589
P_{ws2}(MW)	0	60	36.370	38.379	Q_{ws2}(MVAr)	-25	30	19.096	18.864
P_{ss}(MW)	0	50	37.269	38.978	Q_{ss}(MVAr)	-20	25	21.865	21.708
V_1 (p.u)	0.95	1.10	1.100	1.100	Total cost($/h)			**780.95**	**792.12**
V_2 (p.u)	0.95	1.10	1.088	1.089	Emission (t/h)			1.7623	0.879
V_5 (p.u)	0.95	1.10	1.069	1.071	$Ploss$ (MW)			5.5008	5.007
V_8 (p.u)	0.95	1.10	1.099	1.100	VD (p.u.)			1.050	1.074
V_{11} (p.u)	0.95	1.10	1.100	1.100					
V_{13} (p.u)	0.9	1.1	1.095	1.095					

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5. CONCLUSION AND FUTURE SCOPE-

Here solution for the optimal power flow (OPF) problem in a network with stochastic solar and wind power is proposed. Different probability density functions are used to model the uncertainty of intermittent renewable energy sources. The method used to integrate all sources is discussed. The cost of generation from sources is optimised, with the variation of generation cost and changes on uncertain source cost coefficients is analysed.

The optimization is carried out using L-SHADE algorithm. The algorithm is used in conjunction with SF, a powerful constraint-handling technique. Violations of network component physical or security constraints may harm system security, result in excessive losses, malfunction, and, in the worst-case scenario, component failure. As a result, to achieve secure and reliable operation, operating the network within defined parameters is a essential. Limits on network parameters are frequently violated unknowingly if a suitable constraint handling method is not used. As a result, in constrained optimization problems, it is recommended to use a proper constraint handling method. L-SHADE-SF can also be successfully putted in other highly non-linear, multimodal and constrained optimization problems.

The authors propose integrating small hydro-generators, storage devices like battery storages, or pumping hydro in a network having a huge number of buses in future work on the OPF front. FACTS devices can be used to create an precise model of doubly fed induction generators for wind turbines.

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