Microsystem Technologies
https://doi.org/10.1007/s00542-022-05399-1

TECHNICAL PAPER

A differential evolution modified quantum PSO algorithm for social welfare maximisation in smart grids considering demand response and renewable generation

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Received: 22 March 2022 / Accepted: 30 October 2022

Abstract

The power grids worldwide are changing both policy and infrastructure and are becoming Smart each day in order to support renewable energy sources (RES). These Smart Grids are offering interesting modern techniques like demand response (DR) for more profitable and sustainable operation of the grids in presence of RES. Traditionally demand response concentrates on electricity price which may invite many other technical challenges such as limit violation of vital system parameters like voltage, line flow, Power factor and security issues. To address this problem this work proposes an optimisation framework which tries to achieve security constrained social welfare optimisation by a novel application of DR technique, taking into account several operational issues such as intermittency of Renewable Generation, lowering of system inertia due to RES, degradation of bus PF, line stability,deviation of voltage etc. for all the Load Dispatch Centres (LDC)/consumers by the virtue of optimised curtailment, reduction of network losses, improvement of operating power factor and mitigation of line congestion. The proposed method uses Differential Evolution modified Quantum Particle Swarm Optimisation (DEQPSO) to achieve the proposed objective. When tested on modified IEEE 30 Bus system the proposed algorithm produced encouraging results.

Abbreviations

CR	Crossover probability
DISCO	Distribution Company
DR	Demand response
GUF	Generation uncertainty factor
GENCO	Generation Company
ISO	Independent system operator
LUF	Line utilization factor
RES	Renewable energy sources
SCOPF	Security constrained optimal power flow
TRANSCO	Transmission Company

List of symbols

a_n	Generation cost coefficient in Rs./Mw^2 of generation
α_i	Coefficient of consumer cost benefit function in Rs./Mw^2 of demand of electricity
b_n	Generation Cost coefficient in Rs./Mw of generation
b_{ij}	Susceptance of line ij
β_i	Coefficient of consumer cost benefit function in Rs./Mw of demand of electricity
C_n	Generation cost of *nth* generating unit
c_n	Generation cost coefficient in Rs
c_1	Coefficient of self confidence
d	The dimension of the state variables
δ_i	Coefficient of consumer cost benefit function in Rs

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Published online: 13 November 2022

δ_{ij}	Power (Phase) angle between ith and jth bus voltage
ε	A random number between 0 and 1
f_r	Rotor frequency
f_0	The frequency before the loss of active power
$g_{id}(t)$:	Gbest of the particle flock at tth iteration
g_{ij}	Conductance of line ij
J	The moment of inertia in kg-m^2
LQ_p	Transmission stability index
mbest	The average best position of all the particles
n_g	Number of generators
n	The number of particles
P_{lmaxj}	The maximum power flow in jth line
p_{1ij}	The penalty in Rs./ Mw of excess flow of power
p_{2ij}	The penalty in Rs./ Mw of transmission loss
p_3	The penalty in Rs./ unit of voltage
P_{gn}	The generation of the nth unit
P_D	The forecasted demand
p_4	The penalty in Rs./Mw of generation and demand imbalance
P_{ij}	Power flow in line ij in Mw
P_{gi}	Generation in Mw of bus i
P_{gj}	Generation in Mw of bus j
P_{di},P_{dj}	Requested or scheduled demand in Mw at bus i and j respectively
P_{ri}	Price of Electricity in ith node
$P_{gsurplus}$	Generation Surplus in Mw
P_{gimax}	Maximum limit of generation of the ith generator unit
P_{gimin}	Minimum limit of generation in Mw for ith generator unit
P_{ci}	Allowable load curtailment limit of ISO in Mw for ith Bus or node
P_{dimax}	Maximum limit of demand set by the consumer/ LDC in Mw at ith bus
P_{dimin}	Minimum limit of demand requested by the consumer/ LDC in Mw at ith bus
P	No. of poles
ΔP	Loss of generation in Mw
P_{gn0}	Base Case active power generation of the nth bus in Mw
P_{r1q},P_{r2q} , $P^T{}_{r3q}$, $P^T{}_{r4q}$	The four personal best positions randomly selected excluding global positions
P_i, Q_j	The bus injection active and reactive power in Mw and MVAr for ith and jth bus respectively
P_{di0}	Base case active power demand of the of the ith bus in Mw
P_{gn}, P_{di}	Generation of the nth generating unit and demand of the ith bus respectively in the present state in Mw
$p_{id}(t)$	P_{best} of the particle at ith iteration
P_{best} and G_{best}	Best positions of the solution particle in the solution plane personal and global respectively
P_K	The initial random position of the particle
P_{besti}	The best position of kth particle in its own well. $mbest(T)$
Q_{gi}	Reactive Power generation in MVAr at ith bus
Q_{di}	Reactive Power demand in MVAr at ith bus
q	1,2,3,………N
Rs.	Rupees (Indian currency)
Sb	Volt Ampere rating of the machine in MVA
T	The iteration number
T_m, T_e	The mechanical torque input and electrical torque output respectively in Nm
T_{Lmaxj}	The maximum limit of active power loss of jth transmission line
T_L	The total transmission line loss
T_{Lijmin}	Minimum possible active power loss of the line between Bus i and j in Mw
t_k^{T+1}	Replacement of state variable x_k^{T+1} after calculation of crossover probability
v_k^{T+1}	State variable of solution particle after mutation
V_i	Sending end voltage
V_i	Receiving end voltage
V_{min}	The minimum limit of voltage pu
ω :	Inertia constant
w	The angular velocity of the rotor in rad/s (mech)
W_0	The angular velocity of the rotor at synchronous in radian

x_k^{T+1}	State variable of kth solution particle
$x_{id}(t)$	Position of the particle in tth iteration
Y_{ij}	Admittance of line ij
Z_{ij}	Impedance of line ij
Φ_1, Φ_2	Uniformly distributed random number
θ_{ij}	Impedance angle for the line between bus i and j
$\varnothing_{jq}^T$	A state variable of general difference vector
λ	The contraction and expansion factor

1 Introduction

Integration of Renewable Energy Sources (RES) is important from both environmental perspective and prospective scarcity of fossil fuel to be witnessed in near future, for running the traditional thermal power plants (Weitemeyer et al. 2015; Owusu and Asumadu-Sarkodie 2016; Swain et al. 2017). The RES can strengthen the Power Grid through local generation and Micro grids which lessens the burden of power transmission, minimises subsequent losses and investment involved (Alsaif 2017). The incorporation of RES, however has certain drawbacks like intermittency of generation, degradation of power quality, reduction of storage energy of the grid and high investment associated with these projects (Dilshad et al. 2020; Hossain et al. 2018). The advancement of electronics and cyber physical sensor technology has already however opened a lot of scope of improving the existing power grid, fostering it to be compatible with RES (Butta et al. 2021). The new Smart Power Grid is now utilizing these techniques like advanced metering infrastructure, Real Time digital Monitoring and control, Demand Response, data analytics, high speed communication between the power market players, Phasor Measurement Units (PMUs)etc. (Nafi et al. 2016; Touzene et al. 2019). Demand side management through proper implementation of data analytics and demand response is one of these potential areas which can ensure optimisation of the hindrances of integration of RES in the power grid (Nigam et al. 2019; Huang et al. 2019). Use of demand response is of utmost importance since the RES is highly intermittent in nature and efficient and optimal demand management is necessary for maintaining the supply demand balance and the same also need to be implemented at optimal price of electricity (Tahir et al. 2019). In smart power market, thus the generation of generators and load demands of Load Dispatch Centres/ consumers are scheduled with the availability of generator cost characteristics and consumer cost benefit function data, a typical demand response (Yang et al. 2015; Arias et al. 2018), so that RES can be incorporated in the grid. The demand response programs are objected towards delivering maximum load as per willingness to pay of the LDCs/ Consumers and to provide incentives to the consumers who volunteers for load curtailment through demand response (Yu et al. 2018). Implementation of demand response is not free from challenges. Since it is a new concept, there is lack of knowledge and a lot of assumptions are to be made for its modelling and subsequent design of its objective and algorithm (Thoelen 2019). Absence of a perfect framework for all the conceptualized demand response is also an obstacle of its implementation. More over effects of demand response on vital parameters of the power grid also need to be studied and ways of mitigation of undue changes need to be devised. In a works presented in Chai et al. 2019a; Narimani et al. 2015; Bajool et al. 2017; Gao et al. 2020; Stawskaac et al. 2021), it has been proven that the implementation of demand response can influence the voltage stability, maximum line flow that is line congestion and distribution and transmission line active power loss. These difficulties arise from the fact that demand response characteristics of the LDCs/ Consumers are traditionally price based and its social or grid level impact is not estimated and compensated. The Independent system Operator (ISO) however has to ensure no limit violation as the same may be detrimental to Transmission Companies (TRNSCOs) and in long run the same may affect the operation of Distribution Companies (DISCOs) and Generation Companies (GENCOs). Hence ISO must have the regulatory monopoly to allow the techniques like innovative demand response algorithm in the optimisation program up tothe extent that it ensures benefit of all the power market players for Social Welfare (Balamurugana et al. 2015; Chanda and De 2014; Sen et al. 2015). This work presents such an algorithm and a supporting demand response framework to schedule both generators and LDCs/Consumers to optimise the price of electricity and operating condition of power system networks.

1.1 Literature survey

Some recent contributions in the same field (Shigenobu et al. 2017; Chai et al. 2019b; Dong et al. 2018; Jabir et al. 2018) was found in incentive-based approaches, where the customer / LDC was given incentives for choosing its own demand response for sustenance of power grid system parameters within specified limit contributing to Social Welfare. The work presented in Hirotaka et al. (2018)

shows a synergism of social Welfare optimisation and incentive-based demand response. But in the work, the incentive was only calculated as per customer's comfort not on deviation of system parameters. Works reported in Long et al. (2019) concerning system parameter optimisation for social welfare but the same used FACTs devices support. The work in Nainar et al. (2021) addresses the issue and resolves the same by Battery Energy storage. The work presented in Mosaddegh et al. (2018); Viet et al. 2018) depicts the concern of limit violation and how smart loads can help in producing optimal solution to system operation. Through the review of these works, it has been found that an appropriate framework for data analytics of Social Welfare optimisation only has not been developed yet (Zhang et al. 2018) which can assess each of the GENCOs and DISCOs/LDC/consumers as per their ability to deliver or modulate consumption respectively for reaching a particular solution or schedule of the state variables of the grid, at minimal price and with no limit violation and which will provide incentives to the market players in terms of maximising the dispatch of power and appropriate nodal pricing of each of the LDCs/Consumers for keeping system vital parameters within limit. The Independent system Operator (ISO) is generally responsible for this Social Welfare analytics while the Market Players (GENCOs, TRANSCOs and DISCOs) are responsible for Individual Welfare Analytics (Munshiab and Mohameda October 2017; Lucas Melo et al. 2019; Palmintier et al. 2017). All the market players are thus, in this scenario, are presumes of data (Both producer and consumer). ISO however as per the bids and characteristics received from the participants executes an optimisation programme which ensures maximum possible dispatch of power at minimum price and cost of generation (Alotaibi et al. 2020). For the hour ahead market, in presence of RES it is important that the market players not only maximise their own benefit but also, they should contribute to the benefit of all the participants that is to cause Social Welfare and the same is possible only when the system parameters are also given the same importance in scheduling and load management (Mahanty and Singh 2018). Table 1 presents a summary of the related works in this field and the scope of developing the proposed Social Welfare optimisation algorithm.

In pursuit of developing such an algorithm, this work enunciates in Sect. 2 about the present framework of the power market and the proposed framework of security constrained social Welfare. In Sect. 3, the mathematical model of the proposed framework has been presented in contrast to the traditional Security Constrained Optimal Power Flow (SCOPF) (Mohammadi et al. 2018). The case studies in IEEE 30 bus system, considering worst possible contingencies and loading scenarios has been presented in Sect. 4, using the proposed DEQPSO (Liu et al. 2019) based Security Constrained Social Welfare Optimisation algorithm and its performance has been presented against traditional SCOPF. The major contributions of this research work can be summarised as follows:

i. A novel Framework for Security Constrained Social Welfare maximisation has been proposed in the paper, introducing various penalties and incentives from price responsive demand response for small deviation of operating point to encourage LDCs/Consumers to shift their demands from peak to lean periods.
ii. A novel method of determination of minimum load curtailment has been proposed for the LDCs based on generation uncertainty imposed by RES and the prevailing price of electricity decided by the DR of consumers.
iii. A novel method for maintaining required level of system inertia has been proposed through additional incentive to the consumers to maintain optimal dependence on grid power and RES.

2 Present and proposed social welfare optimization framework

This section presents the prevailing framework of social welfare optimisation and develops the proposed framework and its mathematical model.

2.1 Present frame work of social welfare optimisation in smart grid

The present framework for Social Welfare maximisation is presented in Hwang et al. (2018) as shown below in Fig. 1. Here the distribution Energy management (DEM) section optimises the benefit of both GENCOs and DISCOs or End Users (EU) for optimal pricing.

All the actions however in this framework is by virtue of price-based demand and generation response of the grid and the consideration of limit violation and security issue is only to the extent of willingness to pay of the LDCs. Thus, this framework is to be modified for the proposed Security Constrained Social Welfare Optimisation to ensure required level of security margin.

2.2 The proposed social welfare optimisation framework for smart grids

The Fig. 2 shows the proposed framework and its mathematical model. The proposed optimisation model of security constrained social welfare optimisation is crucial in presence of RES. The ISO in this model is the central data

Table 1 Summary of previous works justifying the need of the proposed Framework and Algorithm

References	Proposal	Findings	Limitation
Palmintier et al. (2017)	To develop An Integrated ISO-to-Appliance Scale Grid Modelling System which will take the characteristics of all the power market players in account to cause overall benefit	Integrated Grid Modeling System (IGMS) simulation platform to develop the system that simultaneously models hundreds or thousands of distribution systems in co-simulation with Independent System Operator (ISO) of various markets	The work identifies the physical constraints of optimization but does not quantify in terms of demand response (DR)
Hirotaka et al. (2018)	A Design Method for Incentive-based Demand Response Programs Based on a Framework of Social Welfare Maximization	Authors evaluate the negative consumer surplus, and convert it into the incentive payment in the DRs. Quantification of decrement of the consumers' comfort, which is caused by the DR cooperation, is calculated to provide appropriate incentive payment to consumers	The work quantifies consumer's discomfort but does not quantify operational standard (viz. voltage, congestion, stability) maintenance cost in terms of DR
Dong et al. (2018)	Demand-Response-Based Distributed Preventive Control to Improve Short-Term Voltage Stability	a novel approach aiming to counteract short term voltage fluctuations and transient instability by employing centralized emergency demand response	Does not incorporate congestion, transmission line active power loss and their influence on DR
Mahanty and Singh (2018)	Social welfare maximization for congestion management in multiutility market using improved PSO incorporating transmission loss cost allocation	The algorithm Quantified Transmission line active Loss and congestion Cost in terms of DR to maximise Social Welfare in a typical Smart power system	Did not estimate the penalties for stability, load curtailment etc. for obtaining appropriate results of optimisation
Long et al. (2019)	An Effective Method for Maximizing Social Welfare in Electricity Market via Optimal TCSC Installation	Implementation an OPF algorithm which is formulated as a nonlinear optimization problem with equality and inequality constraints in a power system for social welfare maximization via the optimal installation of TCSC devices	Involvement of additional devices like like FACTs (TCSC) will associate additional expenses
Alotaibi et al. (2020)	Proposed a new framework of DR modelling by surveying all the available Smart Grid Models	A perfect framework associating all the power market players is still absent in the present Smart Grid markets round the globe	Presents a suitable framework but does not highlight how the same framework can be implemented in Smart Grid scenario
Nainar et al. (2021)	Incentive Price-Based Demand Response in Active Distribution Grids	Utilization of battery energy storage system (BESS) by DSOs for maintaining the grid voltages within limits	Battery Energy Storage System (BESS) will increase costing to address the said problem

**The framework and Demand Response based algorithm proposed in this paper addresses all the above limitations of the previous works in the same field and quantifies all the constraints of optimization in terms of DR so that optimal schedule of both generators, renewable energy sources and LDCs/controllable loads obtained can cause benefit of all the market players simultaneously. The proposed work in this paper does not use devices like FACTs or BESS so that it can be a low cost optimal solution

analytics authority and the market players like GENCOs, DISCOs submit their cost, consumption hour ahead characterises to ISO. In this dynamic market, ISO in this optimisation, as shown in fig., can consider the security constraints of social welfare.

3 Mathematical modelling of the proposed framework

In this section the mathematical model of the proposed Security Constrained Social Welfare optimisation has been developed compared to SCOPF model. This section also

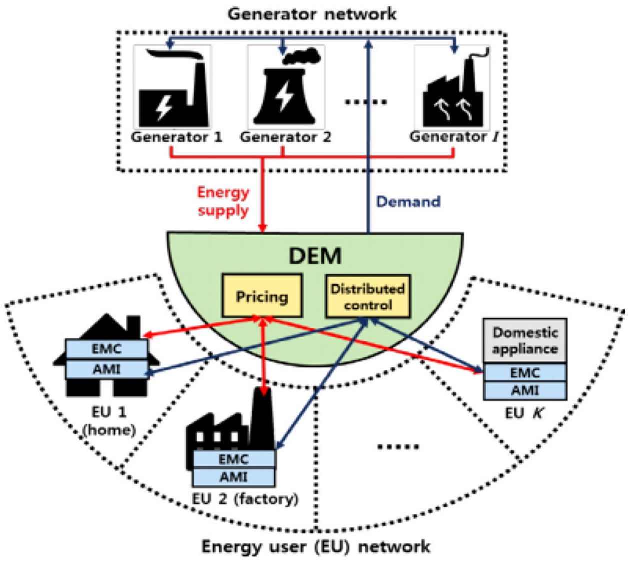


Fig. 1 Present framework of Social Welfare Optimisation with demand response

depicts some novel methods for estimation of penalties and incentives for transmission line Congestion, uncertainty of Generation due to RES, increase in power loss of the network and poor power factor. The incentives and penalties formulated in this section directly relates the consumers with the Social Welfare optimisation problem.

3.1 The traditional security constrained optimal power flow (SCOPF) in smart grid

The fundamental objective of any optimal power flow program is to minimize the total generation cost as shown in Eq. 1.

$$\text{Minimize } f(C_i) = \sum_{n=1}^{n_g} C_n \quad \text{Rs./hour,} \tag{1}$$

where $C_n = a_n P_n^2 + b_n P_n + c_n$

In Smart Grid along with minimizing the generation cost, the operational standard in terms of reliability, efficiency and quality of power has to be maintained. Combing all the constraints, the objective function for security constrained optimal power flow (SCOPF) is given by

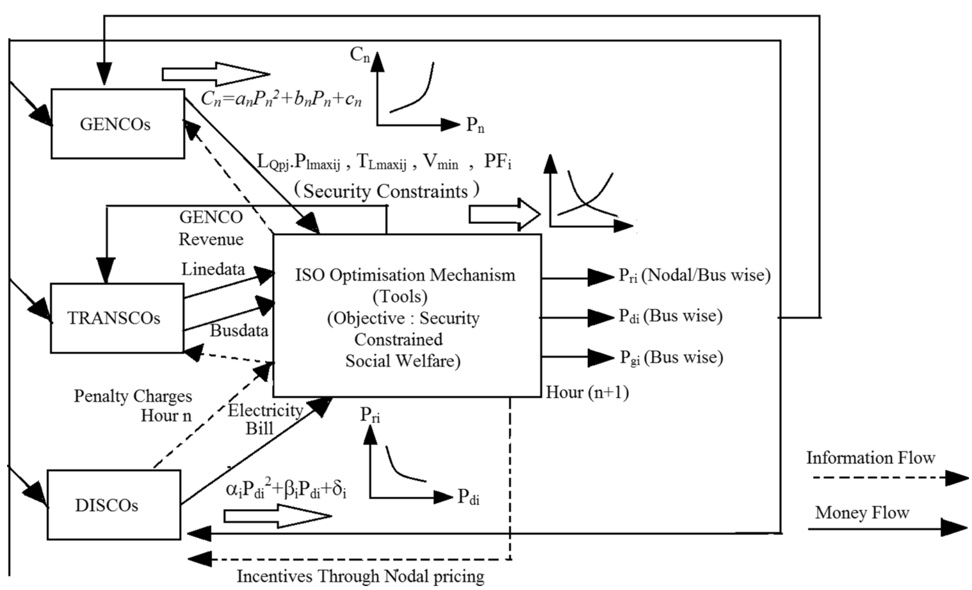
$$\begin{aligned} &\text{Minimize } f(C_n, P_{\text{lmaxj}} T_{Lmaxj}, V_{min}) \\ &= \sum_{n=1}^{n_g} C_n + \sum_{ij=1}^{nlns} P_{lmaxij} \cdot p_{1ij} + \sum_{ij=1}^{nlns} T_{Lmaxij} \cdot p_{2ij} + V_{min} \cdot p_3 \\ &+ \left(\sum_{n=1}^{ng} P_{gn} - P_D - T_L \right) \cdot p_4 \end{aligned} \tag{2}$$

3.2 Limitations of SCOPF in representing constraints of optimization

In SCOPF only the maximum line flow is considered for the penalty to be applied to the objective function. This makes all the line flows below the maximum limit but makes the other lines underutilized. Similar in case of Transmission line loss, in SCOPF, a single limit of transmission line loss is traditionally assumed. Thus, the scope of SCOPF becomes confined and fails to motivate the solution with optimal demand side management. Hence, general expression for the limits also to be estimated.

Considering lumped circuit model Fig. 3, the power loss in transmission line is given by (Eq. 3)

Fig. 2 Optimisation model of proposed security constrained social welfare optimisation



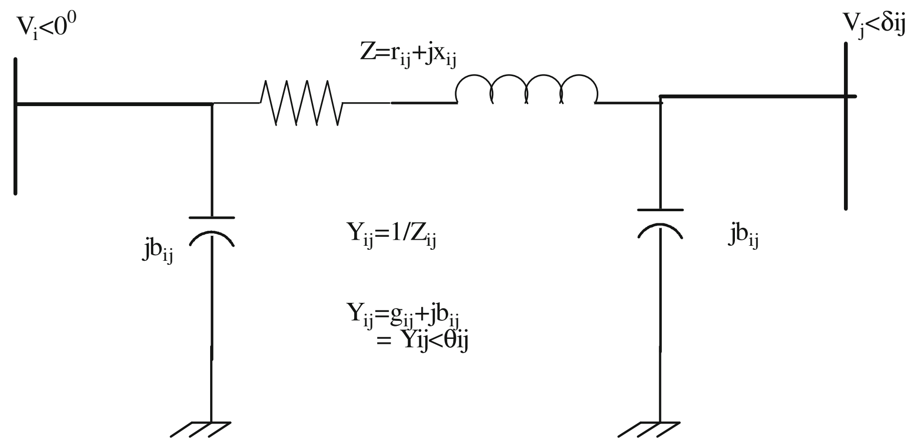


Fig. 3 Lumped circuit model

$$T_{Lij} = g_{ij}\left(V_i^2 + V_j^2\right) - 2V_iV_jCos\delta_{ij} \tag{3}$$

If Eq. 3 is differentiated with a change in V_i (Eq. 4)

$$\frac{dT_{Lij}}{dV_i} = 2V_ig_{ij} - 2V_jCos\delta_{ij} \tag{4}$$

For minimum transmission line active power loss in line i–j (Eq. 5)

$$V_i = \frac{V_jCos\delta_{ij}}{g_{ij}} \tag{5}$$

Substituting the value of V_i, the minimum possible active power loss in transmission line i–j (Eq. 6)

$$T_{Lijmin} = V_j^2\left(g_{ij} - \frac{Cos^2\delta_{ij}}{g_{ij}}\right) = g_{ij}\left(V_j^2 - V_i^2\right) \tag{6}$$

Considering Fig. 3 the expression for line flow is given by (Eq. 7)

$$P_{ij} = V_iV_jY_{ij}Cos\left(\theta_{ij} + \delta_{ij}\right) - V_i^2Y_{ij}Cos\theta_{ij} \tag{7}$$

Differentiating the equation with respect to V_i (Eq. 8)

$$\frac{dP_{ij}}{dV_i} = V_jY_{ij}Cos\left(\theta_{ij} + \delta_{ij}\right) - 2V_iY_{ij}Cos\theta_{ij} \tag{8}$$

For maximum line flow as shown below (Eq. 9)

$$V_i = \frac{V_jCos\left(\theta_{ij} + \delta_{ij}\right)}{2Cos\theta_{ij}} \tag{9}$$

Substituting the value of V_i (Eqs. 10, 11 and 12)

$$P_{ij} = \frac{V_j^2Cos^2\left(\theta_{ij} + \delta_{ij}\right)Y_{ij}}{4Cos\theta_{ij}} \tag{10}$$

$$= \frac{V_iV_jCos\left(\theta_{ij} + \delta_{ij}\right)Y_{ij}}{2} \tag{11}$$

$$= P_{lmaxij}Cos\left(\theta_{ij} + \delta_{ij}\right) \tag{12}$$

where

$$P_{lmaxij} = \frac{V_iV_jY_{ij}}{2} \tag{13}$$

This expression can be treated as maximum line flow limit for general conditions (irrespective of no. of buses and lines). This formula can be however approximated as Surge Impedance loading (SIL) of the line as V_i, V_j are the maximum values and if the *rms* values of the bus voltages V_i, V_j should be assumed as 1 pu. Hence the line flow limit for testing congestion may be assumed as (Eq. 14)

$$P_{lmaxij} = Y_{ij}\,\mathrm{Mw} \tag{14}$$

3.3 Augmenting demand side management in the proposed optimization framework

In the model expressed in Eq. 1, in traditional SCOPF, the distribution companies were participating with a fixed forecasted demand. This mode of participation can however be changed if LDCs can participate with a flexible demand which are depicted (Huang et al. 2019). In the present work such a demand response model is proposed and implemented where as per the price of electricity in every hour, the LDCs alter their consumption for staying in the market with their willingness to pay characteristics or price responsive characteristics.

In this market, electricity price is discovered by the intercepting point of aggregated generation cost curve and individual cost benefit function curve of each LDC or consumer. As willingness to pay of different customers are different, the load curtailment and the price at different node or LDC will be different. (Fig. 4).

3.3.1 Incentive on line utilization through DR

In demand response scenario, it is expected that all the transmission lines will be used to their fullest capacity without exceeding the maximum allowable line flow limit.

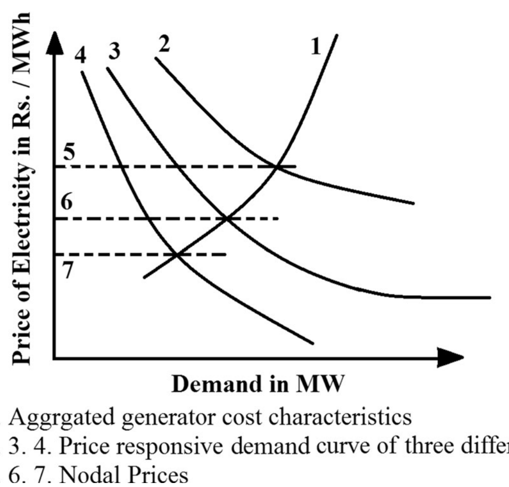


Fig. 4 Nodal pricing with price elasticity of demand

For the measurement of this ability for each and every load bus the transmission line utilization factor may be proposed as (Eq. 15)

$$\text{Line utilizationfactor (LUF)} = \frac{P_{ij}}{P_{lmaxij}} \tag{15}$$

The maximum value of this utilization factor is obviously unity. For offering this incentive, nodal pricing should be influenced in the power system by LUF. The buses which are responsible for the improvement of the factor should be eligible for this incentive.

Considering Fig. 5 The active power flow in transmission line i–j is (Eq. 16), Eqs. 17 and 18 can be obtained

$$P_{lij} = P_{gi} - P_{di} - P_{gj} + P_{dj} \tag{16}$$

$$\frac{P_{lij}}{P_{lmaxij}} = \frac{P_{gi} - P_{di} - P_{gj} + P_{dj}}{P_{lmaxij}} \tag{17}$$

$$\frac{d\frac{P_{lij}}{P_{lmaxij}}}{dP_{di}} = -\frac{1}{P_{lmaxij}} \tag{18}$$

Considering P_{dj} constant. As the effect of demand response has been considered, P_{gi} and P_{gj} have been assumed to be constants.

Now, Considering P_{di} and its characteristics (Fig. 6) with the price of electricity. The base case refers to an operating point where there was balance between generations and demand and P_{di} was constant. Considering small

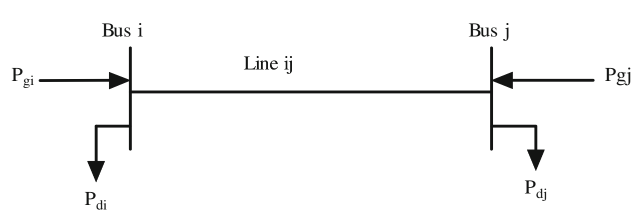


Fig. 5 Elementary power system

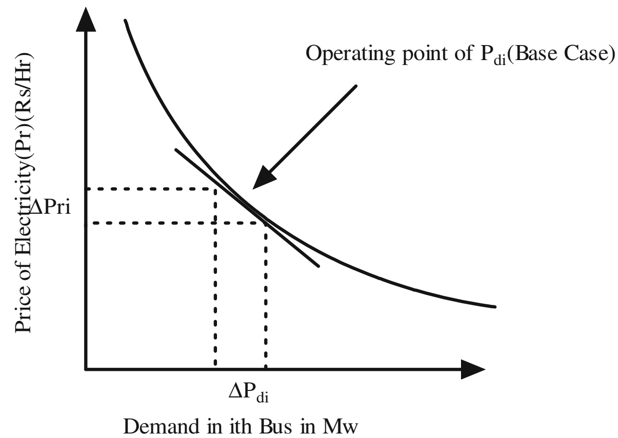


Fig. 6 Small variation in demand characteristics

change in demand a tangent can be drawn about the operating point and from the slope of the tangent $\frac{\Delta P_{ri}}{\Delta P_{di}}$ can be calculated.

Considering quadratic price responsive demand, as per willingness to pay, the price responsive demand characteristics of LDCs / Consumers, can be assumed as (Eq. 19)

$$P_{ri} = \alpha_i P_{di}^2 + \beta_i P_{di} + \delta_i \tag{19}$$

where $\alpha_i, \beta_i, \delta_i$ are the coefficients of consumer cost benefit function as shown in the Fig. 8 for the LDC or consumers of ith Bus. For a small variation of the demand the slope of the quadratic curve can be found as (Eq. 20)

$$\frac{\mathrm{dP_r}}{\mathrm{dP_{di}}} = 2\alpha_i \mathrm{P_{di}} + \beta_i \tag{20}$$

Penalty for change in price due to change in line utilization factor

$$(P_{LUF}) = \frac{dp_{ri}}{dLUF} \tag{21}$$

$$= \frac{dP_r}{dP_{di}} \cdot \frac{dP_{di}}{dLUF}$$

$$= (2\alpha_i P_{di} + \beta_i)(-\frac{1}{P_{lmaxij}}) \tag{22}$$

Thus, the DR program proposed, in every iteration will be calculating the P_{LUF} using equation no.21 to 22 and will appropriately move the solution towards the best solution where the consumers / LDCs that are more responsible for line utilization through DR will be provided incentives by reduced nodal pricing.

3.3.2 Penalty imposed to minimise load curtailment

The weather dependant unpredictable generation capacity of RES may create immense difficulty in balancing power generation with demand. The uncertainty of generation can be measured by generation surplus of the upcoming hour. The generation surplus for the upcoming hour may be given as (Eq. 23).

$$P_{gsurplus} = \sum_{i=1}^{ng} P_{gimax} - \sum_{i=1}^{ng} P_{gi} \tag{23}$$

The factor of generation uncertainty can be represented as Generation Uncertainty factor (Eq. 24)

$$(\mathrm{GUF}) = \frac{\sum_{i=1}^{ng} P_{gimax} - \sum_{i=1}^{ng} P_{gi}}{\sum_{i=1}^{ng} P_{gimax} - \sum_{i=1}^{ng} P_{gimin}} \tag{24}$$

The proposal for load curtailment in each LDC/customer in this work is that when the generation uncertainty factor is zero, the load curtailment should be minimum that is the dispatch should be P_{dimax} and when the GUF is 1 then the curtailment can be maximum (P_{dimax}–P_{dimin}) that is where P_{dimax} is the maximum value of dispatch requested by the consumer in ith bus when the price of electricity is appropriately low and P_{dimin} is the sum of minimum dispatch. Thus, the expression for allowable curtailment in the ith bus can be written as (Eq. 25)

$$P_{ci} = (P_{\mathrm{dimax}} - P_{\mathrm{dimin}}) \cdot \mathrm{GUF} \tag{25}$$

Thus, the higher of the GUF, the higher is the curtailment. During intermittency of generation, the maximum value of generation of RES reduces and subsequently the GUF increases. Thus, this load curtailment strategy ensures minimum despatch for ith bus if the value of GUF remains between 0 and 1. If however, the value increases above unity due to uncertain generation the curtailment may increase accordingly.

The change of allowable curtailment P_{ci} in the ith bus with respect to P_{di} is given by (Eq. 26–28)

$$\frac{dP_{ci}}{dP_{di}} = \frac{d}{dP_{di}}\left((P_{dimax} - P_{dimin}) \cdot \frac{\sum_{i=1}^{ng} P_{gimax} - \sum_{i=1}^{ng} P_{gi}}{\sum_{i=1}^{ng} P_{gimax} - \sum_{i=1}^{ng} P_{gimin}}\right) \tag{26}$$

$$= \frac{d}{dP_{di}}\left((P_{dimax} - P_{dimin}) \cdot \frac{\sum_{i=1}^{ng} P_{gimax} - \sum_{i=1}^{ng} P_{di} - T_L}{\sum_{i=1}^{ng} P_{gimax} - \sum_{i=1}^{ng} P_{gimin}}\right) \tag{27}$$

$$= (P_{dimax} - P_{dimin})\left(-\frac{1}{\sum_{i=1}^{ng} P_{gimax} - \sum_{i=1}^{ng} P_{gimin}}\right) \tag{28}$$

It has been assumed under small variation change of active power transmission line loss is TL with respect to small change in T_L is negligible.

Considering small variation of demand from the operating point, the change in charge for demand with respect to the change in load curtailment can be expressed as (p_5) (Eq. 29)

$$\frac{dP_r}{dP_{ci}} = (2\alpha_i P_{di} + \beta_i) \cdot (P_{dimax} - P_{dimin})\left(-\frac{1}{\sum_{i=1}^{ng} P_{gimax} - \sum_{i=1}^{ng} P_{gimin}}\right) \tag{29}$$

This penalty in every iteration may be applied to the curtailment of ith bus in order to guide the solutions towards optimality.

3.3.3 Incentive for maintaining bus power factor

The bus power factor may get affected by the changes in demand as suggested in optimal solution. This may affect the bus voltage, and in turn may increase the losses and regulation of bus voltage may be lost. The power factor for a particular ith (Fig. 7) bus can be represented as (Eq. 30)

$$PF_i = \frac{P_{gi} - P_{di}}{\sqrt{(P_{gi} - P_{di})^2 + (Q_{gi} - Q_{di})^2}} \tag{30}$$

Change in the value of PF_i with respect to change in P_{di} can be expressed as (Eq. 31)

$$\frac{dPF_i}{dP_{di}} = \frac{P_{gi} - P_{di}}{\sqrt[3/2]{(P_{gi} - P_{di})^2 + (Q_{gi} - Q_{di})^2}} \tag{31}$$

The penalty for change in power factor can be expressed as Eq. 32 (p_6)

$$\frac{dP_r}{dPF_i} = (2\alpha_i P_{di} + \beta_i) . \frac{\sqrt[3/2]{(P_{gi} - P_{di})^2 + (Q_{gi} - Q_{di})^2}}{P_{gi} - P_{di}} \tag{32}$$

This penalty will be reflecting for the consumers / LDCs with reduced nodal pricing and will motivate them to keep a good power factor in order to get lower nodal priceas they manage demand.

3.3.4 Incentive for improving line stability

To secure a stable operation of power system, the line stability index should be maintained below unity. The Eq. 33 shows the relation between line stability index and power system parameters.

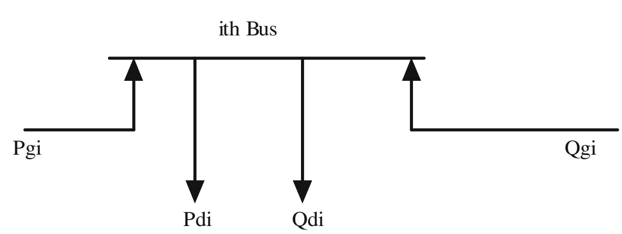


Fig. 7 Elementary bus power flow

$$LQ_p = 4\left(\frac{x}{V_i^2}\right)\left(\frac{x}{V_i^2}.P_i^2 + Q_j\right) \tag{33}$$

where the line reactance of the line is x, connected between bus i and bus j. V_i is the bus voltage of the ith bus.

Now bus injection power,

$$P_i = P_{gi} - P_{di} \tag{34}$$

$$LQ_p = 4(\frac{x}{V_i^2})(\frac{x}{V_i^2}.(P_{gi} - P_{di})^2 + Q_j) \tag{35}$$

$$\frac{dLQ_p}{dP_{di}} = 4\left(\frac{x}{V_i^2}\right)\left(\frac{x}{V_i^2}\right).2.(-1) = \frac{-8x^2}{V_i^4} \tag{36}$$

Now considering Eq. 37,

$$\frac{dP_r}{dP_{di}} = 2\alpha_i P_{di} + \beta_i \tag{37}$$

Thus $\frac{dP_r}{dLQ_p}$ =Penalty for change in price, due to change in LQ_p due to change in demand (considering Eqs. 34–37, Eq. 38 can be obtained)

$$p_7 = \frac{dP_{di}}{dLQ_p}.\frac{dP_r}{dP_{di}} = -\frac{V_i^4}{8x^2}.(2\alpha_i P_{di} + \beta_i) \tag{38}$$

Hence determination of this penalty is necessary in order to penalise the calculated value of LQ_p in every iterations to reach its optimal value in the given set of constraints. As stated earlier this technique will influence the nodal pricing in a way that the LDCs / consumers responsible for poor values of LQ_p

3.3.5 Incentive for power utilities to maintain high inertia constant

The operation of the grid and the corresponding optimal generation and demand schedule should be able to maintain substantial or optimal value of the inertia constant in order to combat unexpected disturbances or contingencies. From Newton's law, the force balance equation in a rotational system is given by (Eq. 39),

$$J\frac{dw}{dt} = T_m - T_e \tag{39}$$

The inertia constant is expressed as the ratio of kinetic energy stored at synchronous speed to the volt Ampere rating of the machine (S_b), with W_0 is the angular velocity of the rotor at synchronous speed (Eq. 40)

$$H = \frac{1.Jw_0^2}{2.S_b} \tag{40}$$

Now, the synchronous frequency is given by (Eq. 41)

$$f = \frac{P}{2}f_r \tag{41}$$

where $P =$ No. of poles and f_r = Rotor frequency and $w = 2.\pi.f_r$

From these equations, an expression for the change in frequency is given by (Eq. 42)

$$\frac{df}{dt} = \frac{-\Delta P}{2.H.S_b}f_0 \tag{42}$$

ΔP is the change of active power due to loss of intermittent renewable energy source and $f_0 =$ the frequency before the loss of active power. For the nth generator unit this change or loss of active power generation will be reflected in change in the generation surplus and thus the minimum limit of load curtailment as expressed in (25). The loss of active power can be expressed as

$$\Delta P = \sum_{n=1}^{n_g}(P_{gn0} - P_{gn}) - \sum_{i=1}^{n_d}(P_{di0} - P_{di}) \tag{43}$$

The lowest or optimal value of inertia constant may be assumed from the base case operation of the grid. The optimal power flow objective function should be motivated towards minimum value of ΔP, corresponding to maximum value of inertia constant. This will maximise the generation of other generators which are not subjected to intermittency and will try to minimise the demand of each bus to retain the inertia constant of the base case. Thus, penalty should be added in the objective function to motivate the solutions towards a higher inertia constant, even in case of intermittency of generation.

3.4 Formulation of the proposed security constrained social welfare optimisation objective function

For the benefit of all the power market participants, Social Welfare Optimisation could be taken as the objective function of the grid with the suitable modifications as explained in previous section. A more potential objective function is explained in (Eq. 44).

$$\text{Maximise} f(C_n, P_{lmaxj}, T_{Lmaxj}, V_{min}) = \sum_{i=1}^{i=n_d} \alpha_i P_{di}^2 + \beta_i P_{di} + \delta_i - \left(\begin{array}{r} \sum_{n=1}^{n_g} C_n + \sum_{j=1}^{nlns} P_{lmaxij}.p_{1ij} + \sum_{ij=1}^{nlns} T_{Lmaxij}.p_{2ij} + V_{min}.p_3 \\ + \left(\sum_{n=1}^{ng} P_{gn} - P_D - T_L \right).p_4 + \sum_{i=1}^{i=n_d} (P_{dimax} - P_{di}).p_5 + \sum_{i=1}^{i=n_d} PF_i.p_6 \\ + \sum_{j=1}^{nlns} L_{Qpj}.p_7 + \sum_{n=1}^{n_g} (P_{gn0} - P_{gn}) - \sum_{i=1}^{n_d} (P_{di0} - P_{di}).p_8 + LUF_{ij}.P_{LUF} \end{array} \right) \tag{44}$$

The left part of this objective function contains the consumer /LDC cost benefit function. This characteristics or function can be derived from the willingness to pay of the LDCs and their bid data. The right-hand side is the operational standard constrained generation cost function. The first term of it is the total generation cost of all the generators or GENCOs participating. The second term is the transmission line congestion management cost, the third term is the transmission line power loss cost, the fourth term is the cost for maintenance of bus voltage at a minimum value (0.95 PU), the fifth term is the generation and demand balance management cost, the sixth term is the optimal load curtailment cost, the seventh term is the power factor management cost, the eighth term is the line stability index management cost, the ninth term is the higher inertia maintenance cost and the 10th term is for transmission line utilization.

4 Implementation of the proposed optimization framework—case study on IEEE 30—bus system

In this section of the work, the proposed Differential Evolution modified Security Constrained Social Welfare Optimisation Algorithm has been described step by step. This section also depicts the case studies conducted to demonstrate the efficacy of the proposed algorithm with respect to the traditional SCOPF. The mathematical model of DEQPSO algorithm and description of modified IEEE 30 bus System have been presented in the Appendix section.

4.1 The proposed DEQPSO based social welfare optimisation framework

The step-by-step descriptions of the proposed optimisation algorithm are as follows:

Step 1. Appropriate parameters of DEQPSO, error gradient (0.01X 10^{-25}), Dimension of the swarm (27 (6 generator bus, 19 load bus)), number of iterations (T = 300), Population size(35), random numbers ($\varepsilon = 0.35$), Contraction and Expansion factor (λ = 0.25) are chosen. For the first iteration arbitrary values of penalties are assumed.

Step 2. Position of the solution particles which are random combinations of 6 generation in Mw and 19 Load in Mw within the maximum and minimum limit is calculated by equation no. 3A and 4A.

Step 3. For each of the solution particle, the fitness function or the Social Welfare objective function is calculated as per Eq. 44. For the 1st iteration positive arbitrary values of penalty is assumed. The base case data is either available or assumed to be same as 1st iteration random data.

Step 4. The average of all the best positions is calculated using Eq. 5A as available in appendix section. As the objective is maximisation of social welfare, solution particles with maximum values of objective function are the best values.

Step 5. All the positions of the particles are updated as per Eqs. 6A and 7A with the knowledge of mbest in the next iteration. Before moving to the next iteration, the penalties for present iteration is calculated which are applied in the next iteration.

Step 6. In each iteration the fitness or the objective function as in Eq. 44 is calculated. The maximum value of the objective function corresponds to the best solution and the pbest, gbest and mbest are calculated corresponding to this best solution. In the next iteration, the optimiser looks for better solution particle with respect to the previous best solution. The error gradient between two consecutive iterations is also calculated which is the stopping criteria.

Step 7. In each iteration the incentives and penalties are estimated to be imposed in the objective function.

Table 2 Case studies with security constrained optimal power flow (SCOPF)

Sl no.	Case study particulars	Minimum bus voltage ($V_{min} in P.U$)	Transmission line power loss (Mw)	Maximum line flow (Mw)	Generation cost In Rs
1	Base case	0.9818	9.0089	81	11,772.00
2	Active power loading 50% increment on 30th Bus	0.9877	8.7	81.44	12,542.00
3	Active power loading 100% increment on 30th Bus	0.9827	8.8112	81.13	13,002.00
4	Active power loading 150%increment on 30th bus	0.9871	8.71	81.49	13,789.00
5	Reactive power loading 50% increment on 30th Bus	0.9771	8.873	81.46	12,300.00
6	Reactive power loading 100% increment on 30th Bus	0.9681	9.01	81.4	12,553.00
7	Reactive Power loading 150% increment on 30th Bus	0.9648	8.92	81.59	12,874.00
8	(N-1) contingency in line 1–2	0.9903	15.38	140.38	18,311.00
9	(N-2) contingency in line 1–2 and 2–5	0.9796	23.39	148.52	19,951.00
10	(N-3) contingency in lines 1–2,2–5 and 6–7)	0.97	23.65	148.6	19,965.00

Table 3 Case studies with security constrained social welfare optimization with demand response

Sl No.	Case study particulars	Minimum bus voltage ($V_{min} in P.U$)	Transmission line power loss(Mw)	Maximum line flow (Mw)	Generation cost In Rs
1	Base case	0.9745	6.7	60	3280.8
2	Active power loading 50% increment on 30th bus	0.9757	6.705	60	3875
3	Active power loading 100% increment on 30th bus	0.9807	6	55	4255.7
4	Active power loading 150%increment on 30th bus	0.9771	6.72	64	4768.7
5	Reactive power loading 50% increment on 30th bus	0.9690	6.7332	61	3577.1
6	Reactive power loading 100% increment on 30th bus	0.9635	6.75	62.5	3625
7	Reactive power loading 150% increment on 30th bus	0.9566	6.79	61.75	3745.5
8	(N-1) contingency in line 1–2	0.9767	7.0990	83.3032	11,597
9	(N-2) contingency in line 1–2 and 2–5	0.9729	10.87	84.9	12,136
10	(N-3) contingency in lines 1–2,2–5 and 6–7)	0.9753	10.78	84.85	13,124

Step 8. In each iteration load curtailment limit is also calculated to penalise the objective function accordingly so that minimum dispatch requested by the LDC/ Consumer through Demand Response can be ensured.

Step 9. In each iteration the donor vectors are calculated in as per Eqs. 8A and 9A. The difference vectors add versatility to the solution particles so that solutions with better fitness can be obtained.

Step 10. The knowledge of crossover probability (CR) in this step decides the ultimate position of the solution particle which may be better than or equal to QPSO results as per Eq. 10A.

Step 11. The solution particle meeting step 6 criteria are tested for its feasibility of implementation in the power network.

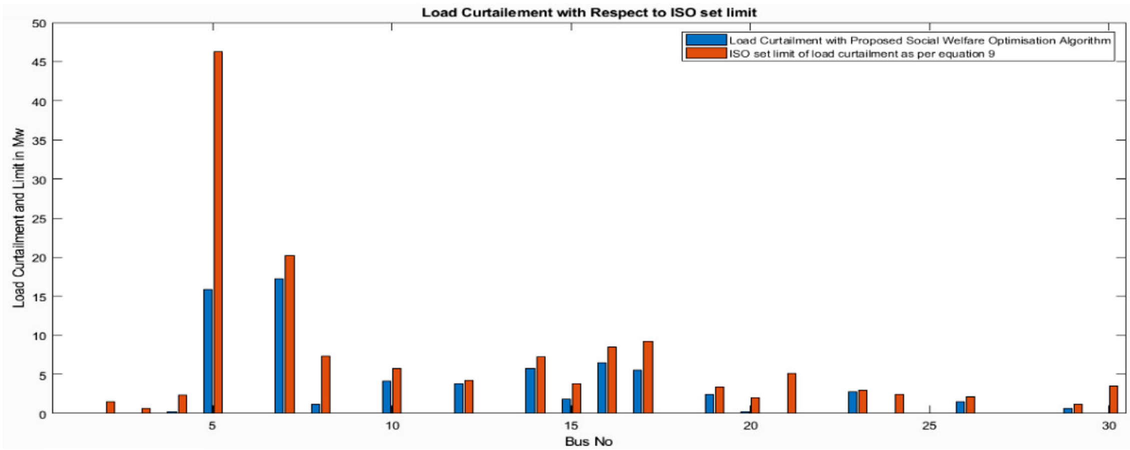


Fig. 8 Load curtailment with the proposed algorithm with respect to ISO set limit of each bus

5 Implementation of the proposed framework in IEEE 30-bus system

In the base case (Sl no. 1, Table 2), the DEQPSO based optimizer, with the SCOPF objective (Eq. 2) produces minimum generation cost at standard operating condition in respect of bus voltage, transmission line Power Loss and maximum power flow. But as Active power loading (Sl. No. 2, 3, 4 of Table 3), reactive power loading (Sl. No. 5, 6, 7) and (N-1), (N-2) and (N-3) contingencies worsen, the generation cost increases for sustainable operation of the grid.

The Table 3 shows the results for the proposed security constrained Social Welfare optimization technique with demand response. Imposing the same loading conditions with social welfare as objective and with the incentives on maintaining better Transmission line stability and demand response, better operating condition with remarkably less generation cost was found. However, there is a considerable load curtailment which is a threat to reliability of supply. In Eq. 25, a formula related to maximum allowable load curtailment has been derived in this paper. Hence although the LDCs/consumers are subjected to load curtailment, the system can operate within safe limit of reliability if the allowable load curtailment is not violated. The same fact is substantiated in Fig. 8 which shows that although the nodal price of Social Welfare optimization is less than that of SCOPF, the load curtailment in case of former is more but the same is within safe limit as formulated in Eq. 25.

In addition, the proposed social welfare optimization algorithm in stressed condition of the power network produces improvement in Bus PF (Fig. 9), reduction in nodal price (Fig. 10), improvement in LSI (Fig. 11) creating a more secure operational zone of the network. The reduction in nodal price is due to the incentives provided by the

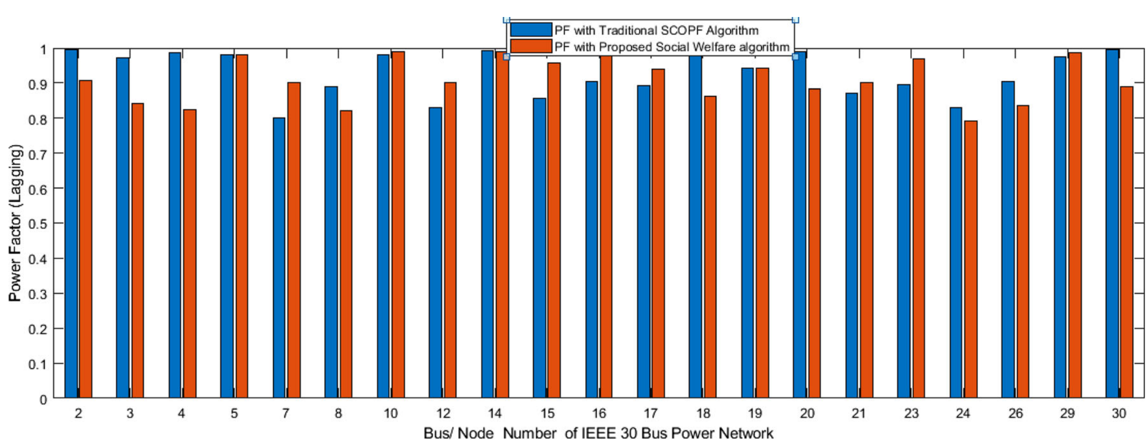


Fig. 9 Improvement of PF in proposed social welfare optimization

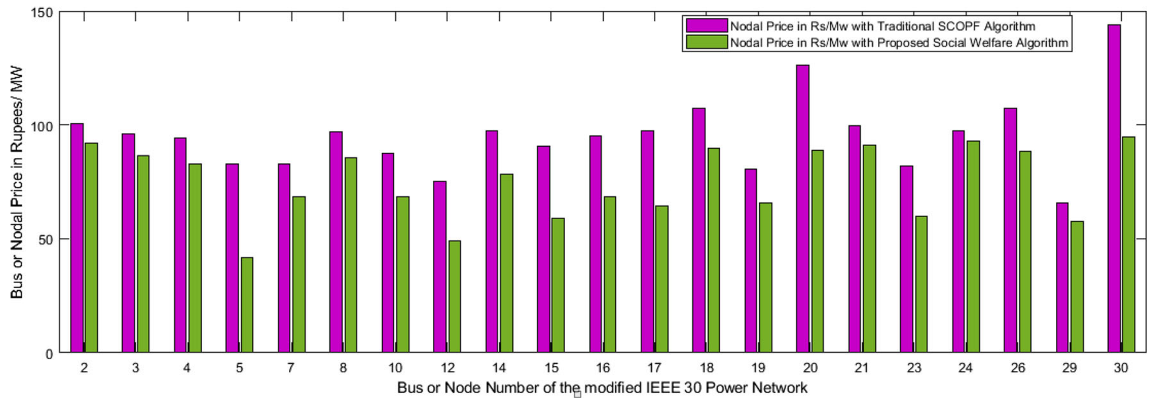


Fig. 10 Nodal or bus-wise price of electricity per MW

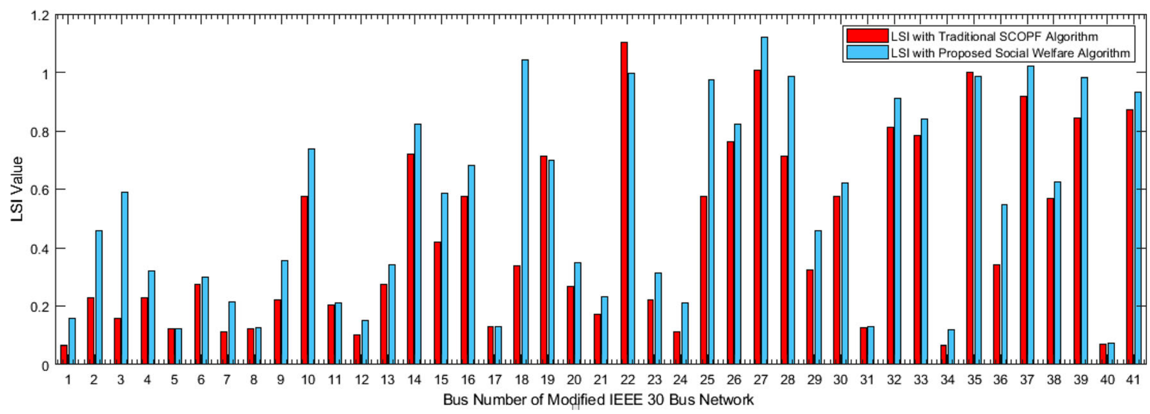


Fig. 11 Improvement of LSI with proposed algorithm

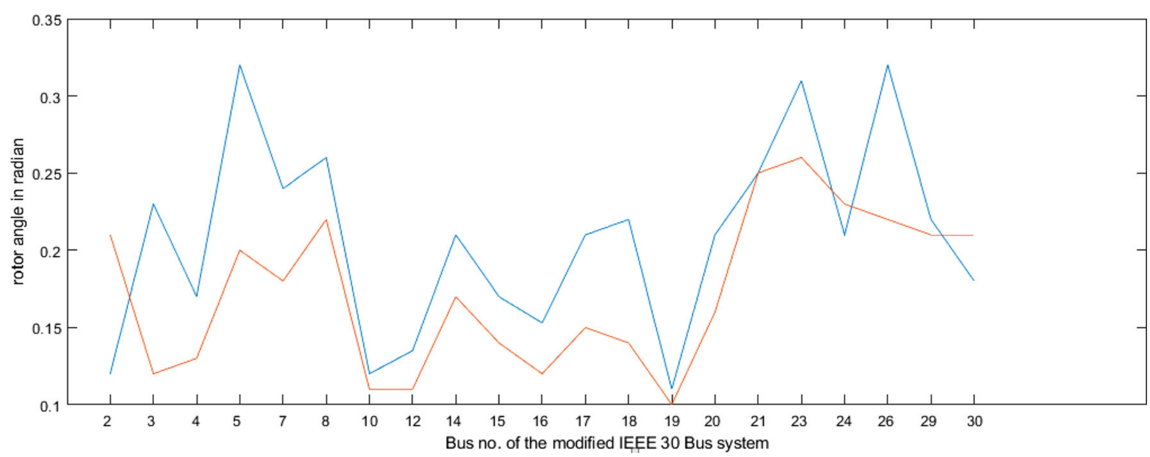


Fig. 12 Improvement of rotor angle stability

solution being driven by penalties against each social contribution of the LDCs/Consumers.

The proposed algorithm also is capable of producing generation and demand schedule with higher degree of dynamic rotor angle stability. In the extreme stressed condition of active power loading, it was examined that due to the incorporation of generation demand balance in the objective function, the result produced also optimises the rotor angle and thus contributes to the improvement of stability margin of the grid (Fig. 12). All the simulations are performed in MATLAB 2018a.

6 Conclusion

For balancing the generation with load demand, smart grids use techniques like demand response to ensure Optimal Power Flow leading to maximisation of Social Welfare in terms of reduced electricity prices. However, existing OPFs are generally more biased towards reduction of electricity prices for consumers, often at the cost of violating operational constraints and challenging system security. It is imperative that a well-thought of Social Welfare Optimisation Framework must fulfil objectives likeoptimal load curtailment, maintaining adequate stability margins, maintaining high system inertia and line stability as well as maintaining acceptable bus voltages and power factor, apart from minimizing the nodal prices of electricity. This work proposed an optimisation framework which strived to achieve security constrained social welfare optimisation through DR technique, taking into account several operational issues such as intermittency of Renewable Generation, lowering of system inertia due to RES, degradation of bus PF, line stability, deviation of voltage etc. The algorithm developed in this paper ensured optimized load curtailment, reduction of network losses, improvement of operating power factor and mitigation of line congestion, among several other benefits, while ensuring nodal prices of electricity to be optimal. Differential Evolution modified Quantum Particle Swarm Optimisation (DEQPSO) was used in this research work to achieve the proposed objective. The case study on modified IEEE 30 Bus system presented in the paper established that the proposed algorithm outperformed the existing Social Welfare optimization algorithms delivering encouraging results.

Appendix

Generation and demand scheduling using stochastic DEQPSO optimisation tool

In this work the Differential Evolution modified Quantum Particle Swarm Optimisation (DEQPSO) algorithm has been used to optimise social welfare and to produce optimised generation and load schedule for the next hour. In the previous works the authors used particle swarm optimisation (PSO) for the same type of convex nonlinear objective function. particle swarm optimisation (PSO) is a stochastic optimization strategy introduced by Kennedy and Ebarharth in 1995. The method was inspired by fish schooling and bird flocking where each solution, that is a particular generation and demand schedule, is a particle that hovers around the solution space, that is the feasible range of generation of generators and demand. Each particle has a position and velocity which is updated in each iteration with respect to their individual best referred as Pbest and global best referred as Gbest position and velocity in terms of objective or fitness function. The Eqs. 45 and 46 are responsible to change the position and velocity as per individual and social influence of the particle flock and guide the particles towards best possible solution.

$$v_{id}(t+1) = \omega . v_{id}(t) + c_1 . \Phi_1(p_{id}(t) - x_{id}(t)) + c_2 . \Phi_2(g_{id}(t) - x_{id}(t)) \tag{45}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{46}$$

$v_{id}(t+1)$= Updated velocity of the particle, $x_{id}(t+1)$= Updated position of the particle.

This particle Swarm Optimisation Suffers from local convergence. Since P_{best} and G_{best} positions can be a very small part of the solution plane, the algorithm suffers from social metaphor as it can converge locally. The quantum particle swarm optimisation (QPSO), an application of Quantum Mechanics Theory to PSO, has proven to be better alternative of PSO. In QPSO, the position of a particle is determined by probability distribution function, hence the production of alternative solution can be ensured and also the possibility of global solution increases. In QPSO each particle is resident of quantum well δ, which is multi-dimensional in Quantum Space. In the same space the position of the particle is defined as Monte- Carlo method

$$x_K^T = P_K + \frac{A}{2} \ln\left(\frac{1}{\varepsilon}\right) \tag{47}$$

where P_K is the initial random position of the particle, ε is a random number between 0 and 1. A is calculated from the following expression

$$A = 2.\lambda.|P_K - x_K^T| \tag{48}$$

where T is the iteration number and λ is the contraction and expansion factor which helps maintaining position of the particle during collapse of the well δ. The local convergence is avoided in QPSO by introducing mbest which is the average best position of all the particles.

$$mbest(T) = \frac{1}{n} \sum_{k=1}^{n} P_{besti} \tag{49}$$

n is the number of particles and P_{besti} is the best position of kth particle in its own well $mbest(T)$, however, is the best positions with respect to all the wells or in other words when all the wells collapse.

Now with the knowledge of $mbest(T)$, A is updated as

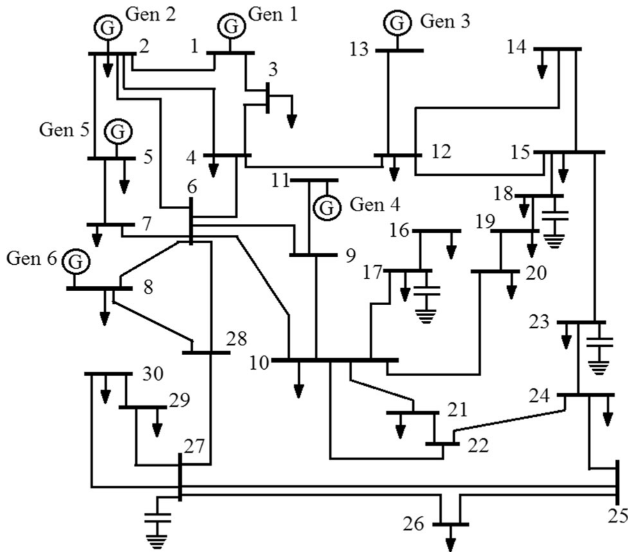


Fig. 13 The IEEE 30 bus system

Table 4 IEEE 30 bus system

System parameters	Description
Branches	41
Generator	6
Total Demand (MW)	554.6

Table 6 Consumer's price responsive characteristics

Bus no.	Load dispatch		Co-efficient of benefit function		
	Min	Max	α_i (Rs/MW2)	β_i (Rs/MW)	δ_i (Rs)
2	11.7	21.2	− 0.2	67.1	0
3	3.2	5.5	− 0.10	70.5	0
4	8	10.6	− 0.3	65.5	0
5	114.2	215	− 0.2	87	0
7	12.7	40.2	− 0.035	60	0
8	20	55	− 0.21	70	0
10	7.8	10.6	− 0.35	78	0
12	10.5	15.8	− 0.16	60	0
14	5	17.5	− 0.125	60.6	0
15	7.2	10.5	− 0.25	50	0
16	2.5	15	− 0.25	60	0
17	5.5	14.5	− 0.005	55.5	0
18	2.5	6.2	− 0.17	90.2	0
19	8.25	10.1	− 0.255	56.2	0
20	3.15	5	− 0.15	80	0
21	27.5	60	− 0.152	63.8	0
23	2.5	5.2	− 0.52	75	0
24	3.8	8.5	− 0.12	70	0
26	2.5	5.7	− 0.13	70.2	0
29	1.2	5.5	− 0.15	82	0
30	11.2	17	− 0.12	72	0

$$A = 2.\lambda.\left|mbest(T) - x_K^T\right| \tag{50}$$

In the next iteration the position of the particle is updated as

$$x_k^{T+1} = P_K \pm \lambda.\left|mbest_K^T - x_K^T\right|.\ln(\frac{1}{\varepsilon}) \tag{51}$$

This algorithm reaches global optimum but even the presence of mbest can take a lot of iteration. Thus, avoiding local convergence in PSO introduces higher number of iterations in QPSO. In order to accelerate the global search, since same may help the power market participants in taking quicker decisions, differential evolution (DE) algorithm can be introduced alongside QPSO algorithm. The result algorithm, known as DEQPSO algorithm, can demonstrate better result with lesser number of iterations depending on the nonlinearity and complexity of the objective function. In the DEQPSO algorithm, a donor vector is developed by adding the weighted subtracted values of two or more personal best position. Thus the donar vector is given by

$$v_k^{T+1} = P_K + \sum_{q=1}^{N} \varnothing_{kq}^T / N \tag{52}$$

Table 5 Generator characteristics of thermal and RES

Bus No.	Output of the generator in MW		Generator cost coefficients		
	Min	Max	a_i (Rs/MW2)	b_i (Rs/MW)	c_i (Rs)
1 (Thermal)	100	200	0.0071	7.3335	1881
2 (Thermal)	10	35	0.0083	8.22	2020
5 (Thermal)	15	50	0.092	10.11	2350
8 (Wind)	50	115	0	1.1682	2886.1
11 (Solar)	50	80	0	1.308	2320
13 (thermal)	10	30	0.01	11.2	2500

where $\varnothing_{jq}^{T}$ is a state variable of general difference vector defined as $\Delta_q = [\varnothing_{1q}, \varnothing_{2q}, \varnothing_{3q}, \varnothing_{4q}, \varnothing_{5q}.\varnothing_{dq}]$

Here d is the dimension of the state variables. Also q = 1,2,3,…,N

$$\varnothing_{jq}^{T} = [(P^{T}{}_{r1q} - P^{T}{}_{r2q}) + (P^{T}{}_{r3q} - P^{T}{}_{r4q})]/2 \tag{53}$$

where P_{r1q}, $P_{r2q,}$, $P^{T}{}_{r3q}$, $P^{T}{}_{r4q}$ are the four personal best positions randomly selected excluding global positions and r1, r2,r3 and r4 and the four random integers. The value of N can be 2 or more but for simplification in the present problem it is assumed as 2. In canonical DE, after mutation by the donar vector a crossover operation is used to create new solutions to the problem. For this operation a trial individual is developed in DEQPSO algorithm by the mutated individual$V_k = [v_{k1}, v_{k2}, v_{k3}, \ldots . v_{kd}]$.

And personal best position P_K as is expressed as

$$t_k^{T+1} = \begin{cases} v_k^{T+1}, rand(j) \le CR \\ P_k^{T}, rand(j) > CR \end{cases} \tag{54}$$

Here CR $\in (0, 1)$ is the crossover probability. With this technique the confluence DE with QPSO either retains QPSO results or improves the result with respect to QPSO by the mutation and crossover operation. This trial individual t_k^{T+1} replaces the x_k^{T+1} if it can show better fitness with respect to the objective function. Thus DEQPSO results are not lesser in quality of solution than QPSO and thus PSO or DE itself.

The feasibility and effectiveness of the proposed algorithm has been tested in presence of renewable energy sources on a modified IEEE 30 bus system Fig. 8 and Table 1.

System description and characteristics of generators and LDCs / consumers

See Fig. 13 and Table 4.

In Table 5 the incremental cost characteristics of Thermal Power Plants and RES has been presented. One wind and one solar power plant have been assumed in bus no. 8 and 11. Table 6 presents the consumer cost benefit functions in the form of demand response of the LDCs. These cost benefit functions will depend on the willingness to pay of the LDCs and their subsequent bids.

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