UDC 519.6 DOI: 10.18698/1812-3368-2021-5-33-48

SOLVING OPTIMAL REACTIVE POWER DISPATCH PROBLEM BY POPULATION DISTINCTION AND PANDEMIC VIRUS ALGORITHMS

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Abstract

In this paper Noble, Depraved and Abhorrent (NDA) optimization algorithm and United Kingdom B117 Pandemic Virus algorithm (UPA) are applied for solving the power loss lessening problem. Power loss reduction has been done by with and without considering the voltage stability. In both cases power loss reduction has been achieved effectively. In NDA approach population passages in the direction of the noble member and evades the depraved member. Then abhorrent member plays a vital role in modernizing the population. In a perplexing change, the abhorrent member guides the population in circumstances opposite to people crusade. Position of the members in population is modernized in three subsequent segments. In the preliminary segment, population transfers in the direction of the noble member. Then UPA method is based on the idea of hoi polloi protection as a stratagem to battle the B117 COVID-19 coronavirus pandemic. Spreading of B117 COVID-19 variant is more influenced by the infested persons unswervingly come across other public associates. Communal separation is endorsed by health specialists to protect other populaces from the B117 COVID-19 variant infection. Hoi polloi protection progression is the Preliminary augmentation procedure. Rendering to the Fundamental Facsimile rate, the genetic factor unchanged or prejudiced by communal separation. Authenticity of the NDA optimization algorithm and UPA algorithm is substantiated in IEEE 30 bus system (with and without L-index). Factual power loss lessening is reached. Proportion of actual power loss lessening is augmented

Keywords

Noble, Depraved, Abhorrent, B117 COVID-19, optimal reactive power, transmission loss

Received 08.04.2021
Accepted 21.04.2021

Introduction. In power system droping of factual power loss is a noteworthy facet. Numerous scientific methods like gradient method, Newton method and linear programming [1–7] have been espoused to solve the optimal reactive power dispatch problem. Together the gradient and Newton methods has the convolution in dealing disparity constraints. When linear programming is rational then the input-output utility has to be articulated as fixed linear tasks which customarily clue to forfeiture of correctness. Problem of voltage constancy and breakdown performance lead a foremost part in power scheduling and action. Comprehensive optimization has acknowledged wide-ranging investigation responsiveness, and a prodigious number of approaches have been smeared to unravel this problem. Evolutionary algorithms are applied to solve the problem [8–10]. Evolutionary algorithm is a heuristic methodology used for minimization problems by employing nonlinear and non-differentiable unceasing space functions. In [11] adaptive configuration of particle swarm optimization has been utilized to solve optimal reactive power flow problem. In [12] Diversity-Enhanced Particle Swarm Optimization is projected to progress the voltage constancy index. In [13] Development of smart controller is developed to solve the problem. In [14] Sine Cosine algorithm is applied to solve the scheduling method. In [15] Whale optimization algorithm is applied to solve the optimal problem. In [16] Reactive power flow problem is resolved by a modified heuristic approach. In [17] a Hybrid search optimization algorithm is applied to solve AC-DC optimal reactive power flow model with the generator competence bounds. In [18] recommends an artificial immune system to appraise Reactive power reserves with reverence to working constraints and voltage constancy. In [19] a programming based projected methodology is applied to solve the problem by considering Load Uncertainty. In this paper Noble, Depraved and Abhorrent (NDA) optimization algorithm and United Kingdom B117 Pandemic Virus Algorithm (UPA) are applied to solve the actual power loss lessening problem. For the first time the NDA and UPA algorithms applied to solve the power loss reduction problem. Exploration and Exploitation has been balanced in both the algorithms. In both algorithms dispersal of population is done to achieve the global optimal solution. Noble, Depraved and Abhorrent optimization algorithm population is based on Noble, Depraved and Abhorrent members of the population. The noble is the distinguished quasi-optimal solution, and the depraved is deprived quasi-optimal solution rendering to the objective function value. Abhorrent Ugly is member of the population which guide the population in circumstances towards opposite direction. In this confounding segment, those circumstances of the exploration space which bid the appropriate quasi-optimal solutions are discovered. In the initial segment, population progress in the direction of the noble member. In the successive segment, population detach from the depraved member. In end stage, the abhorrent member guides the population to locations opposite to the movement of the population. Then in this paper UPA algorithm is applied to solve the problem. In United Kingdom B117 COVID-19 variant has been recognized at first and conception of hoi polloi shield as a system of fighting with the B117 COVID-19 pandemic and it is stimulus for the proposed procedure called as UPA algorithm. Hoi polloi protection is a circumstance that the people pass in, despite the fact that much of the communal is resilient, subsidizing to the preclusion of spread of infections. In positions of calculating the concepts, these characterizations are modelled. For hoi polloi protection, three variations of social cases, such as infested, vulnerable, and vaccinated, are utilized. It is to elect how thriving the freshly moulded solution with communal separation attitudes modernizes its genetic material. In UPA approach, the description of communal separation is acquired by setting the parting or split-up between the present entity and an identified individual from the communal, who might be vulnerable, infested, or vaccinated. Sagacity of the NDA algorithm and UPA algorithm is confirmed by corroborated in IEEE 30 bus system (with and without L-index). Factual power loss lessening is accomplished. Proportion of factual power loss reduction is amplified.

Problem formulation. Modal analysis for voltage stability evaluation is one among best methods for voltage stability enhancement in power systems. The steady state system power flow equations are given by

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} \mathbf{J}_{P\theta} & \mathbf{J}_{PV} \\ \mathbf{J}_{Q\theta} & \mathbf{J}_{QV} \end{bmatrix} \begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix}, \qquad (1)$$

where ΔP is incremental change in bus real power; ΔQ is incremental change in bus reactive power injection; Jacobian matrix $\mathbf{J}_{P\theta}$, $\mathbf{J}_{PV}$, $\mathbf{J}_{Q\theta}$, $\mathbf{J}_{QV}$ are the sub-matrixes of the system voltage stability is affected by both P and Q; $\Delta\theta$ is incremental change in bus voltage angle; ΔV is incremental change in bus voltage magnitude.

To reduce (1), let $\Delta P = 0$, then

$$\Delta Q = \left[\mathbf{J}_{QV} - \mathbf{J}_{Q\theta} \mathbf{J}_{P\theta}^{-1} \mathbf{J}_{PV} \right] \Delta V = \mathbf{J}_R \Delta V;$$

$$\Delta V = \mathbf{J}^{-1} - \Delta Q,$$

where $\mathbf{J}_R = \left(\mathbf{J}_{QV} - \mathbf{J}_{Q\theta} \mathbf{J}_{P\theta}^{-1} \mathbf{J}_{PV} \right)$ is called the reduced Jacobian matrix of the system.

Modes of voltage instability: voltage stability characteristics of the system have been identified by computing the eigen values and eigen vectors. Let

$$\mathbf{J}_R = \xi \wedge \eta, \tag{2}$$

where ξ is right eigenvector matrix of $\mathbf{J}_R$; η is left eigenvector matrix of $\mathbf{J}_R$; $\wedge$ is diagonal eigenvalue matrix of $\mathbf{J}_R$ and

$$\mathbf{J}_R^{-1} = \xi \wedge^{-1} \eta. \tag{3}$$

From (2) and (3), we have

$$\Delta V = \xi \wedge^{-1} \eta \Delta Q$$

or

$$\Delta V = \sum_I \frac{\xi_i \eta_i}{\lambda_i} \Delta.$$

Here ξ_i is the i-th column right eigenvector and η is the i-th row left eigenvector of $\mathbf{J}_R$; λ_i is the i-th eigen value of $\mathbf{J}_R$.

The i-th modal reactive power variation is

$$\Delta Q_{m\ i} = K_i \xi_i \Delta,$$

where

$$K_i = \sum_j \xi_{ij^2} - 1, \tag{4}$$

ξ_{ij} is the j-th element of ξ_i.

The corresponding i-th modal voltage variation is $\Delta V_{m\ i} = [1/\lambda_i] \Delta Q_{m\ i}$. If $|\lambda_i| = 0$, then the i-th modal voltage will collapse.

In (4), let $\Delta Q = ek$, where ek has all its elements zero except the k-th one being 1. Then

$$\Delta V = \sum_i \frac{\eta_{1k} \xi_1}{\lambda_1},$$

η_{1k} is k-th element of η_1; V–Q sensitivity at bus k,

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\mu_{1k} \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1}.$$

The objectives of the reactive power dispatch problem are to minimize the system real power loss and maximize the static voltage stability margins (SVSM).

Minimization of the real power loss (P_{loss}) in transmission lines is mathematically stated as follows:

$$P_{loss} = \sum_{\substack{k=1 \\ k=(i,j)}}^{n} g_k \left(V_i^2 + V_j^2 - 2 V_i V_j \cos \theta_{ij} \right),$$

where n is the number of transmission lines; g_k is the conductance of branch k; V_i, V_j are voltage magnitude at bus i and bus j; θ_{ij} is the voltage angle difference between bus i and bus j.

Minimization of the voltage deviation magnitudes (VD) at load buses is mathematically stated as follows:

$$\text{minimize } VD = \sum_{k=1}^{nl} \left| V_k - 1.0 \right|,$$

where nl is the number of load busses and V_k is the voltage magnitude at bus k.

System constraints. Objective functions are subjected to these constraints shown below. Load flow equality constraints:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nb} V_j \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, \ \ i = 1, 2, \ldots, nb;$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nb} V_j \begin{bmatrix} G_{ij} & \sin\theta_{ij} \\ B_{ij} & \cos\theta_{ij} \end{bmatrix} = 0, \ \ i = 1, 2, \ldots, nb,$$

where nb is the number of buses; P_G and Q_G are the real and reactive power of the generator; P_D and Q_D are the real and reactive load of the generator; G_{ij} and B_{ij} are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage (V_{Gi}) inequality constraint:

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \ \ i \in ng.$$

Load bus voltage (V_{Li}) inequality constraint:

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, \ \ i \in nl.$$

Switchable reactive power compensations (Q_{Ci}) inequality constraint:

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, \ \ i \in nc.$$

Reactive power generation (Q_{Gi}) inequality constraint:

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \ \ i \in ng.$$

Transformers tap setting (T_i) inequality constraint:

$$T_i^{\min} \le T_i \le T_i^{\max}, \ \ i \in nt.$$

Transmission line flow (S_{Li}) inequality constraint:

$$S_{Li}^{\min} \le S_{Li}^{\max}, \ \ i \in nl.$$

Here nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

Noble, Depraved and Abhorrent optimization algorithm. Design of NDA algorithm population is based on Noble, Depraved and Abhorrent members of the population. In NDA, exploration agents examine the problem exploration space under the stimulus of three explicit members of the entire population. Every population member is a projected solution which delivers particular value for the defined parameters in the procedure.

Population initialized as follows:

$$\mathbf{Y} = \begin{bmatrix} Y_1 \\ . \\ . \\ . \\ Y_i \\ . \\ . \\ . \\ Y_P \end{bmatrix}_{P\times Q} = \begin{bmatrix} y_1^1 & \cdots & y_1^Q \\ \vdots & \ddots & \vdots \\ y_P^1 & \cdots & y_P^Q \end{bmatrix}_{P\times Q},$$

where $\mathbf{Y}$ is symbolize the matrix of population; Y_i is the i-th member of population; P, Q are number of population and variables.

For objective function a precise value is computed for every member of the population it signifies the projected values for the variables

$$Objective\ function\ matrix\,(OFM) = \begin{bmatrix} OFM_1(Y_1) \\ . \\ . \\ . \\ OFM_i\,(Y_i) \\ . \\ . \\ . \\ OFM_P\,(Y_P) \end{bmatrix},$$

where $OFM_i\,(Y_i)$ indicate the i-th member of population.

Value of the objective function specifies about the quality of solution is noble or depraved. Then the pre-eminent quasi-optimal and poorest quasi-optimal solution is generated by which member of the population is found out based on the value. In NDA algorithm population is modernized rendering to Noble, Depraved and Abhorrent members of the population. The noble is the pre-eminent quasi-optimal solution, and the depraved is poorest quasi-optimal solution rendering to the objective function value. Abhorrent Ugly is member of the population which guide the population in circumstances towards opposite direction. In this perplexing segment, those circumstances of the exploration space which bid the appropriate quasi-optimal solutions are revealed. Noble, Depraved and Abhorrent members of the population are defined as follows:

$$Noble = Y_N \left| OFM_N \right. = \text{matrix minimum condition}; \tag{5}$$

$$Depraved = Y_D \left| OFM_D \right. = \text{matrix maximum condition}; \tag{6}$$

$$Abhorrent = Y_A \ \text{ and } \ A \in \left[1, 2, 3, \ldots, P - \{N, D\}\right]. \tag{7}$$

Position of the members in population (iteration's) is modernized in three subsequent segments. In the initial segment, population transfers in the direction of the noble member. In the subsequent segment, population detach from the depraved member. In conclusion, in third segment, the abhorrent member guides the population to locations opposite to the movement of the population.

The NDA algorithm population modernization is based on the Noble member is written as:

$$y_{i,ghN}^{d} = y_i^d + \text{random}\left(Noble^d - 2y_i^d\right); \tag{8}$$

$$Y_i = \begin{cases} Y_i^{ghN}, \ OFM_i^{ghN} \le OFM_i; \\ Y_i, \ \text{otherwise}. \end{cases} \tag{9}$$

Here $y_{i,ghN}^{d}$ is i-th member 'sd' variable value based on Noble member; Y_i^{ghN} symbolize the new-fangled position of the i-th member based on Noble member; OFM_i^{ghN} is objective function.

NDA algorithm population modernization is based on the Depraved member is defined as

$$y_{i,ghD}^{d} = y_i^d + \text{random}\left(Depraved^d - 2y_i^d\right); \tag{10}$$

$$Y_i = \begin{cases} Y_i^{ghD}, \ OFM_i^{ghD} \le OFM_i; \\ Y_i, \ \text{otherwise}. \end{cases} \tag{11}$$

Here $y_{i,ghD}^{d}$ is i-th member 'sd' variable value based on Depraved member; Y_i^{ghD} symbolize the new-fangled position of the i-th member based on Depraved member; OFM_i^{ghD} is objective function.

NDA algorithm population modernization is based on the Abhorrent member is described as

$$y_{i,ghA}^{d} = y_i^d + \text{random}\left(Abhorrent^{\,d} - 2y_i^d\right); \tag{12}$$

$$Y_i = \begin{cases} Y_i^{ghA}, & OFM_i^{ghA} \le OFM_i; \\ Y_i, & \text{otherwise.} \end{cases} \tag{13}$$

Here $y_{i,ghA}^{d}$ is i-th member 'sd' variable value based on Abhorrent member; Y_i^{ghA} symbolize the new-fangled position of the i-th member based on Abhorrent member; OFM_i^{ghA} is objective function.

NDA optimization algorithm

a. Start
b. Input the problem data
c. Parameters are set
d. Engender the preliminary population
e. Objective function computed
f. For $i = 1:T$
g. Modernize the values of Noble, Depraved and Abhorrent
h. Formula (5)
i. Formula (6)
j. Formula (7)
k. For $i = 1:P$
l. Modernize the value of Y_i based on Noble
m. Formula (8)
n. Formula (9)
o. Modernize the value of Y_i based on Depraved
p. Formula (10)
q. Formula (11)
r. Modernize the value of Y_i based on Abhorrent
s. Formula (12)
t. Formula (13)
u. End for i
v. Most excellent quasi-optimal solution saved
w. End iteration
x. Objective function's most excellent quasi-optimal solution is output
y. End

United Kingdom B117 Pandemic Virus algorithm. In United Kingdom B117 COVID-19 variant has been identified at first and concept of hoi polloi protection as a method of fighting with the B117 COVID-19 pandemic and it is stimulus for the proposed procedure called as UPA algorithm to solve the problem. UPA is based on the idea of hoi polloi protection as a stratagem to battle the B117 COVID-19 coronavirus pandemic. Spreading of B117 COVID-19 variant is more influent by the infested persons unswervingly come across other public associates. Communal separation is endorsed by health specialists to protect other populaces from the B117 COVID-19 variant infection. Hoi polloi protection is a circumstance that the people pass in, despite the fact that much of the communal is resilient, subsidizing to the preclusion of spread of infections. In positions of calculation concepts, these characterizations are modelled. For hoi polloi protection, three varieties of social cases, such as infested, vulnerable, and vaccinated, are utilized. It is to choose how thriving the recently moulded solution with communal separation attitudes modernizes its genetic material. The approach constructs on the hypothesis of shielding people from the infection by transmuting the greater part of the non-infected vulnerable people to protection. Subsequently, even the left over vulnerable cases would not be infected because the resistant population will not be stretched in the infection spreading. The populace of entities with hoi polloi protection is alienated into vulnerable, infested, and resilient.

In UPA approach, the description of communal separation is acquired by setting the parting or split-up between the present entity and an identified individual from the communal who might be vulnerable, infested, or vaccinated.

Objective function defined by

$$\min_{y} f(y) y \in \left[Lower\,Bound\left(LB\right),\ Upper\,Bound\left(UB\right)\right].$$

Hoi polloi protection populace (*HPP*) engendered as follows:

$$HPP = \begin{bmatrix} y_1^1 & \cdots & y_n^1 \\ \vdots & \ddots & \vdots \\ y_1^{HPP} & \cdots & y_n^{HPP} \end{bmatrix}.$$

Hoi polloi protection progression is the Preliminary augmentation procedure. Rendering to the Fundamental Facsimile rate (*FF*), the genetic factor unchanged or prejudiced by communal separation:

$$y_i^j\left(t+1\right) = \begin{cases} y_i^j(t), \ \text{Random}\left(R\right) \geq FF; \\ A\left(y_i^j(t)\right), \ \text{Random}\left(R\right) < \dfrac{1}{3} FF\left(\text{infested}\right); \\ B\left(y_i^j(t)\right), \ \text{Random}\left(R\right) < \dfrac{2}{3} FF\left(\text{vulnerable}\right); \\ C\left(y_i^j(t)\right), \ \text{Random}\left(R\right) < FF\left(\text{vaccinated}\right). \end{cases} \tag{14}$$

The infested case is 0 to $(1/3)FF$. The new-fangled genetic factor value is abridged by communal separation, and it is a derivative obtained through the transformation between the genetic factor from the infested and the present genetic factor:

$$y_i^j(t+1) = A\left(y_i^j(t)\right);$$
$$A\left(y_i^j(t)\right) = y_i^j(t) + \text{Random}(R)\left(y_i^j(t) - y_i^a(t)\right),$$

where $y_i^a(t)$ arbitrarily chosen from infested case.

The vulnerable case is in the variety of $(1/3)FF$ *to* $(2/3)FF$, the assessment of the new-fangled genetic factor is abridged by communal separation, and it obtained through the transformation between the genetic factor from the infested and the present genetic factor:

$$y_i^j(t+1) = B\left(y_i^j(t)\right);$$
$$B\left(y_i^j(t)\right) = y_i^j(t) + \text{Random}(R)\left(y_i^j(t) - y_i^b(t)\right),$$

where $y_i^b(t)$ arbitrarily chosen from vulnerable case.

The resistant case is in the variety of $(2/3)FF$ *to* FF, the assessment of the new-fangled genetic factor is abridged by communal separation, and it obtained through the transformation between the genetic factor from the infested and the present genetic factor:

$$y_i^j(t+1) = C\left(y_i^j(t)\right);$$
$$C\left(y_i^j(t)\right) = y_i^j(t) + \text{Random}(R)\left(y_i^j(t) - y_i^c(t)\right),$$

where $y_i^c(t)$ arbitrarily chosen from pre-eminent resistant case,

$$f\left(y^c\right) = \arg \min_{j \sim \{Z | W_Z = 2\}} f\left(y^j\right).$$

In each engendered case, the protection rate is computed, and the present solution is swapped by the engendered case, when $f\left(y_i^j(t+1)\right) < f\left(y_i^j(t)\right)$. In each iteration, the value of W_j is rationalized based on the threshold of hoi polloi resistant as follows:

$$W_j = \begin{cases} 1, \; f\left(y_i^j(t+1)\right) < \dfrac{f(y)^j(t+1)}{\Delta f(x)} \wedge W_j = \\ \quad = 0 \wedge \text{ is UK B117}\left(\text{COVID-19}\right)\left(f\left(y_i^j(t+1)\right)\right); \\ 2, \; f\left(y_i^j(t+1)\right) < \dfrac{f(y)^j(t+1)}{\Delta f(x)} \wedge W_j = 1. \end{cases} \quad (15)$$

If for a specified iteration, as defined by the Maximum Oldness parameter, the resistant rate of the current pretentious case could not upsurge, and then this procedure is measured as defunct. And it renewed as follows:

$$y_i^j(t+1) = LB_i + (UB_i - LB_i) \times \cup (0,1).$$

UPA algorithm

a. Start
b. Input the parameters
c. Estimate the locations of the hoi polloi resistant entity
d. Categorization is applied to identify the most excellent entity
Formula (14)
e. Modernize the population position
Formula (15)
f. Modernize the iteration $(t = t+1)$
g. If $t <$ maximum iteration, then go to step c
h. Otherwise, present position is computed
i. Return the optimal solution
j. End

Simulation results. With considering *L*-index (voltage constancy), NDA optimization algorithm and UPA algorithm is substantiated in IEEE 30 bus system [20]. The IEEE 30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches — (6–9), (6–10), (4–12) and (28–27) — are with the tap setting transformers. The lower voltage magnitude limits at all buses are 0.95 PU and the upper limits are 1.1 for all the *PV* buses and 1.05 PU for all the *PQ* buses and the reference bus. Appraisal of loss has been done with Standard PSO-TS [10], Basic TS [10], Standard PSO [10], ALO [11], QO-TLBO [12], TLBO [12], Standard GA [13], Standard PSO [13], HAS [13], Standard FS [14], IS-FS [14] and Standard FS [16] algorithms. Power loss abridged competently and proportion of the power loss lessening has been enriched. Predominantly voltage constancy enrichment achieved with minimized voltage deviancy. In Table 1 and Fig. 1 show the loss appraisal. Voltage deviancy values of NDA, UPA is 0.0844 PU and 0.0847 PU. Voltage constancy values of NDA, UPA is 0.1006 PU and 0.1008 PU.

Table 1

Assessment of factual power loss lessening

Algorithms	Factual power loss, MW	Algorithms	Factual power loss, MW
Standard PSO-TS [10]	4.5213	Standard PSO [13]	4.9239
Basic TS [10]	4.6862	HAS [13]	4.9059

End of the Table 1

Algorithms	Factual power loss, MW	Algorithms	Factual power loss, MW
Standard PSO [10]	4.6862	Standard FS [14]	4.5777
ALO [11]	4.5900	IS-FS [14]	4.5142
QO-TLBO [12]	4.5594	Standard FS [16]	4.5275
TLBO [12]	4.5629	NDA	4.5005
Standard GA [13]	4.9408	UPA	4.5007

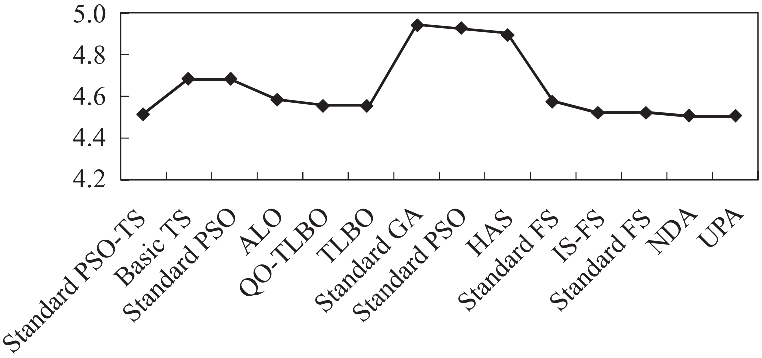

Fig. 1. Appraisal of factual power loss

Then projected NDA optimization Algorithm and UPA algorithm are corroborated in IEEE 30 bus test system deprived of L-index. Loss appraisal is shown in Table 2. Figure 2 gives graphical appraisal between the approaches with orientation to factual power loss. Comparison done with Amended PSO [21], Standard PSO [22], Standard EP [23], Standard GA [24], Basic PSO [12], DEPSO [12] and JAYA [12] algorithms.

Table 2

Assessment of true power loss

Algorithms	Factual power loss, MW	Proportion of lessening in power loss, %
Base case value [21]	17.5500	0
Amended PSO [21]	16.0700	8.40000
Standard PSO [22]	16.2500	7.40000
Standard EP [23]	16.3800	6.60000
Standard GA [24]	16.0900	8.30000
Basic PSO [12]	17.5246	0.14472
DEPSO [12]	17.5200	0.17094
JAYA [12]	17.5360	0.07977
NDA	14.3900	18.0000
UPA	14.5000	17.3700

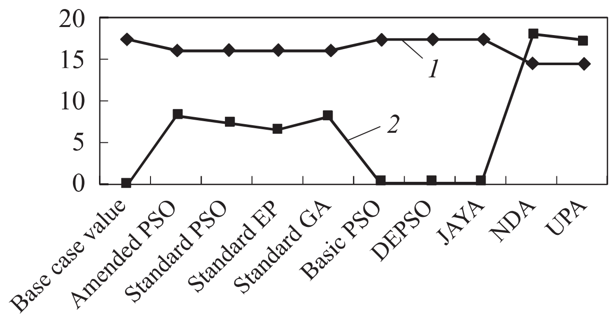

Fig. 2. Appraisal of factual power loss, MW, and proportion of lessening in power loss, %

Table 3 shows the convergence characteristics of NDA optimization algorithm and UPA algorithm. Figure 3 shows the graphical representation of the characteristics.

Table 3

Convergence characteristics

IEEE 30 bus system	Factual power loss, MW, with *L*-index / without *L*-index	Proportion of lessening in power loss, %	Time, s, with *L*-index / without *L*-index	Number of iterations with *L*-index / without *L*-index
NDA	4.5005 / 14.3900	18.00	22.19 / 16.98	27 / 25
UPA	4.5007 / 14.5000	17.37	25.37 / 19.75	31 / 29

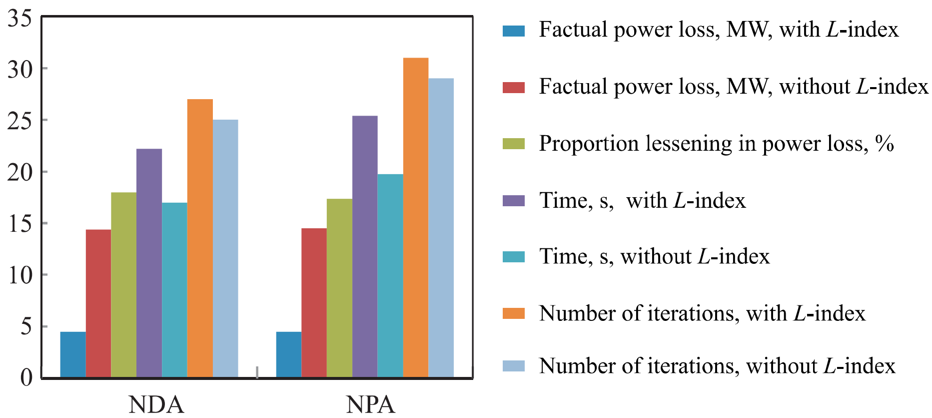

Fig. 3. Convergence characteristics of NDA optimization algorithm and UPA algorithm

Conclusion. Noble, Depraved and Abhorrent (NDA) optimization algorithm and UPA algorithm condensed the factual power loss inventively. In NDA value of the objective function specifies about the quality of solution is noble or depraved. Then the pre-eminent quasi-optimal and poorest quasi-optimal solution is generated by which member of the population is found out based on the value. Population is modernized rendering to Noble, Depraved and Abhorrent members of the population. The noble is the pre-eminent quasi-optimal solution, and the depraved is poorest quasi-optimal solution rendering to the objective function value. Abhorrent Ugly is member of the population which guide the population in circumstances towards opposite direction. In this perplexing segment, those circumstances of the exploration space which bid the appropriate quasi-optimal solutions are revealed. In UPA hoi polloi protection applied and three varieties of social cases, such as infested, vulnerable, and vaccinated, are utilized. It is to choose, how thriving the recently moulded solution with communal separation attitudes modernizes its genetic material. This approach constructs on the hypothesis of shielding people from the infection by transmuting the greater part of the non-infected vulnerable people to protection. Subsequently, even the left over vulnerable cases would not be infected because the resistant population will not be stretched in the infection spreading. The populace of entities with hoi polloi protection is alienated into vulnerable, infested, and resilient. Then in UPA approach, the description of communal separation is acquired by setting the parting or split-up between the present entity and an identified individual from the communal who might be vulnerable, infested, or vaccinated. Noble, Depraved and Abhorrent (NDA) optimization algorithm and UPA algorithm substantiated in IEEE 30 bus system (with and without L-index). Proposed algorithms creditably condensed the power loss and proportion of factual power loss lessening has been elevated. Convergence characteristics show the better performance of the proposed NDA and UPA algorithms. Valuation of power loss has been done with other customary reported algorithms.

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Please cite this article as:

Lenin K. Solving optimal reactive power dispatch problem by population distinction and pandemic virus algorithms. *Herald of the Bauman Moscow State Technical University, Series Natural Sciences*, 2021, no. 5 (98), pp. 33–48.
DOI: https://doi.org/10.18698/1812-3368-2021-5-33-48