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Real Power Loss Reduction by Mutually Dependent Creature Investigation Algorithm

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Abstract

In this paper, Mutually Dependent Creature Investigation (MI) algorithm for solving optimal reactive power problem has been presented. Mutually Dependent Creature Investigation (MI) algorithm replicates the mutually dependent communication approach implemented by creatures to undergo and propagate in the ecosystem.The proposed Mutually Dependent Creature Investigation (MI) algorithm has been tested in standard IEEE 118 & practical 191 bus test systems and simulation results show the commendable performance of the proposed Mutually Dependent Creature Investigation (MI) algorithm in plummeting the real power loss.

Keywords: Optimal Reactive Power, Transmission loss, Mutually Dependent Creature Investigation.

1. Introduction

Optimal reactive power problem is to minimize the real power loss and bus voltage deviation. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the complexity in managing inequality constraints. If linear programming is applied then the input- output function has to be uttered as a set of linear functions which mostly lead to loss of accuracy. The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is proposed to improve the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to solve the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes Mutually Dependent Creature Investigation (MI) algorithm for solving optimal reactive power problem. Proposed MI algorithm replicates mutually dependent method that creatures use to undergo in the ecosystem. Key

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benefit of the Mutually Dependent Creature Investigation (MI) algorithm is no need of precise algorithm parameters. The proposed has Mutually Dependent Creature Investigation (MI) algorithm been evaluated in standard IEEE 118 & practical 191 bus test systems & the simulation results show that the proposed Mutually Dependent Creature Investigation (MI) algorithm outperforms all reported algorithms in minimization of real power loss.

2. Problem Formulation

2.1 Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (1)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (2)$$

Where g_k: is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

2.2 Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (3)$$

Where ω_v: is a weighting factor of voltage deviation.
VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (4)$$

2.3 Equality Constraint

The equality constraint of the optimal reactive power dispatch power (ORPD) problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \quad (5)$$

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

2.4 Inequality Constraints

The inequality constraints reflect the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \qquad (6)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \qquad (7)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \qquad (8)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \qquad (9)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \qquad (10)$$

Where N is the total number of buses, N_T is the total number of Transformers; $N_c$is the total number of shunt reactive compensators.

3. Mutually Dependent Creature Investigation (MI) algorithm

The proposed Mutually Dependent Creature Investigation (MI) algorithm imitates the converse behavior seen among creatures in nature. Creatures hardly ever live in isolation due to reliance on other species for sustenance and even existence. This reliance-based relationship is known as Mutually Dependent.

Mutually Dependent relationships may be either obliges, or two organisms depend on each other for survival [21, 22].The most common Mutually Dependent relationships found in nature are mutualism, commensalism, and parasitism. Mutualism denotes Mutually Dependent relationship between two dissimilar species in which both profit. Commensalism is Mutually Dependent relationship between two different species in which one benefits and the other is unaffected or unbiased.

Parasitism is Mutually Dependent relationship between two different species in which one benefits and the other is vigorously affected. Generally speaking, creatures develop Mutually Dependent relations as a dodge to amend to adjustment in their environment. Mutually Dependent relationships may also help creatures upsurge fitness and endurance advantage over the long-term. Consequently, it is sensible to accomplish that interdependence has built and endures to shape and endure all recent ecosystems.

Mutually Dependent Creature Investigation (MI) algorithm imitates interdependent communications within a paired organism rapport that are used to exploration for the fittest creature. The projected Mutually Dependent Creature Investigation (MI) algorithm was developed primarily to solve numerical optimization over a continuousexploration space.Alike to other population-based algorithms; the projected algorithm iteratively uses a population of candidate solutions to encouraging areas in the exploration space in the procedure of seeking the optimal global solution. Mutually Dependent Creature Investigation (MI) algorithm starts with an initial population called the ecosystem. In the primary ecosystem, a group of creatures is producedarbitrarily to the exploration space. Each creature epitomizes one candidate solution to the analogous problem.

Each creature in the ecosystem is related with a definite fitness value, which imitates degree of alteration to the desired objective. Almost all metaheuristic algorithms apply a sequence of operations to solutions in each iteration in order to producenovel solutions for the subsequent iteration. In Mutually Dependent Creature Investigation (MI) algorithm new-fangled solution generation is governed by emulating the biological interaction between two organisms in the ecosystem. Three phases that be similar to the real-world biological interaction model are presented. A.Mutualism stage, B.Commensalism stage, and C.Parasitism stage.

The character of the communication describes the chief principle of each phase. Interactions profit on both sides in the mutualism phase; profit one side and do not impact the other in the commensalism phase; profit one side andvigorouslydamage the other in the parasitism phase. Each creature inter-mingles with the other creature arbitrarily through all phases. The procedure is recurrent until termination criteria are met.

Mutualism stage

An illustration of mutualism, which profits both creature participants, is the rapport between bees and flowers. Bees fly amongst flowers, collecting nectar to turn into honey – an action that profits bees. This movement also profits flowers because bees dispense pollen in the progression, which expedites pollination. This MI phase imitates such mutualistic relationships. In MI, X_i is a creature matched to the ith member of the ecosystem.

Another creature X_j is then selected arbitrarily from the ecosystem to interrelate with X_i. Both creatures involve in a mutualistic association with the objective of growing joint endurance benefit in the ecosystem. New-fangled candidate solutions for X_i and X_j are calculated based on the mutualistic interdependence between creature X_i and X_j, which is modelled in Equations. (11) and (12).

$$X_{inew} = X_i + rand(0,1) * (X_{best} - mutual\_vector * PF_1) \quad (11)$$

$$X_{jnew} = X_j + rand(0,1) * (X_{best} - mutual\_vector * PF_2) \quad (12)$$

$$mutual\_vector = \frac{X_i+X_j}{2} \quad (13)$$

Rand (0,1) in Eqs (11) and (12) is a vector of arbitrary numbers.

The role of PF1 and PF2 is described as follows. In nature, somemutualism relationships might give a superior favourable advantagefor just one creature than another creature. In other words, creature A might receive a huge benefit when interacting withcreature B. Meanwhile, creature B might only get satisfactory ornot so important profit when interrelating with creature A. Here, profit factors (PF1 and PF2) are determined arbitrarily as either 1or 2.

These factors represent level of profit to each creatures, i.e., whether a creature incompletely or completely profits from the relations.Equation (13) shows a vector called ''Mutual_Vector'' that epitomizes the relationship characteristic between creature X_i and X_j. Thepart of equation$(X_{best} - mutual_vector * BF_1)$, is imitating the mutualisticstruggle to attain their goal in increasing their enduranceadvantage. The X_{best} is needed here because X_{best} is representing the highest degree of adaptation. Therefore, we use X_{best}/global solution to model the uppermost degree of alteration as the target pointfor the fitness increment of both creatures.Finally, creatures are modernized only if their new fitness is better than their pre-interaction fitness.

Commensalism stage

An illustration of commensalism is the association between remorafish and sharks. The remora attaches itself to the shark and eatsfood remnants, thus receiving a profit. The shark is unaffected byremora fish activities and obtains negligible. Analogous to the mutualism phase, a creature, X_j, is selected arbitrarily from the ecosystem to interact with X_i.

In this condition, creature X_i makes efforts to profit from the relations. Conversely, creature X_j itself neither profits nor hurts from the relationship.The new candidate solution of X_i is calculated according to thecommensal interdependence between creature X_i and X_j, which is modelled in Eq. (14). Subsequent to the rules, creature X_i is modernized only ifits new fitness is better than its pre-interaction fitness.

$$X_{inew} = X_i + rand(-1,1) * (X_{best} - X_j) \quad (14)$$

The part of equation$(X_{best} - X_j)$, is imitating as the favourable advantage provided by X_j to help X_i increasing its endurance advantagein ecosystem to the highest degree in current creature (denoted by X_{best}).

Parasitism stage

An illustration of parasitism is the plasmodium parasite, whichuses its relationship with the anopheles mosquito to pass betweenhuman hosts. While the parasite flourishes and breeds inside thehuman body, its human host suffers malaria and can die as anoutcome. In MI, creature X_i is given a role analogous to the anophelesmosquito through the formation of an artificial parasite called''Parasite_Vector''. Parasite_Vector is produced in the exploration spaceby replicating creature X_i, then modifying the arbitrarily selecteddimensions using an arbitrary number.

Creature X_j is selected arbitrarily from the ecosystem and serves as a host to the parasitevector. Parasite_Vector tries to swap X_j in the ecosystem. Bothcreatures are then appraised to measure their fitness. IfParasite_Vector has a improved fitness value, it will kill creature X_j and assume its position in the ecosystem. If the fitness value of X_j is superior, X_j will have immunity from the parasite and the Parasite_Vector will no longer be able to live in that ecosystem.

Mutually Dependent Creature Investigation (MI) algorithm for solving reactive power problem

Step 1. Ecosystem Initialization
Number of creatures (eco_size), initial ecosystem, termination criteria, num_iter=0, num_fit_eval=0, max_iter, max_fit_eval

Step 2.Categorize best creature (Xbest)
Select one creature arbitrarily, X_j, where $X_j \neq X_i$

Step 3. Mutualism stage

Determine mutual relationship vector (Mutual_Vector) and profit factor (PF)

$$\mathrm{mutual\_vector} = \frac{X_i + X_j}{2}$$

PF1= arbitrary number either 1 or 2; PF2= arbitrary number either 1 or 2

Alter creature X_i and X_j based on their mutual relationship

$$X_{inew} = X_i + \mathrm{rand}(0,1) * (X_{best} - \mathrm{mutual\_vector} * PF_1)$$

$$X_{jnew} = X_j + \mathrm{rand}(0,1) * (X_{best} - \mathrm{mutual\_vector} * PF_2)$$

Compute Fitness Value of the modified creatures; num_fit_eval = num_fit_eval + 2

Are the altered creatures fitter than the previous?
If yes accept the modified creatures to swap the previous
If no reject the modified creatures and retain the previous

Step 4. Commensalism stage
Select one creature arbitrarily, X_j, where $X_j \neq X_i$

Transform creature X_i with the contribution of creature X_j

$$X_{inew} = X_i + \mathrm{rand}(-1,1) * \left(X_{best} - X_j\right)$$

Compute Fitness Value of the new creature; num_fit_eval = num_fit_eval + 1

Is the modified creature fitter than the previous?
If yes Accept $X_{i\,new}$ to swap X_i
If no Reject X_{inew} and retain X_i

Step 5. Parasitism stage

Select one creature arbitrarily, X_j, where $X_j \neq X_i$
Generate a Parasite (Parasite_Vector) from Creature X_i
Compute Fitness Value of the new creature; num_fit_eval = num_fit_eval + 1
Is Parasite_Vector fitter than creature X_j?
If yes Swap organism X_j with Parasite_Vector
If no Retain creature Xj and scratch Parasite_Vector

Step 6. i = eco_size?
If yes move to next step7 or go to step step 2

Step7.
Is end criteria attained? (num_iter>max_iter and/or num_fit_eval>max_fit_eval) if yes we get optimal solution or else go to step 1

4. Simulation Results

At first Mutually Dependent Creature Investigation (MI) algorithm has been tested in standard IEEE 118-bus test system [23].The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95 -1.1 per-unit., and on load buses are 0.95 -1.05 per-unit. The limit of transformer rate is 0.9 -1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 1, with the change in step of 0.01.

Table 1. Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results of 50 trial runs have been list in Table 2 and the results clearly show the better performance of proposed MI approach.

Table 2. Comparison results

Active power loss (p.u)	**BBO [24]**	**ILSBBO/ strategy1 [24]**	**ILSBBO/ strategy1 [24]**	**Proposed MI**
Min	128.77	126.98	124.78	116.26
Max	132.64	137.34	132.39	120.18
Average	130.21	130.37	129.22	117.32

Then the Mutually Dependent Creature Investigation (MI) algorithm has been tested in practical 191 test system and the following results have been obtained. In Practical 191 test bus system – Number of Generators = 20, Number of lines = 200, Number of buses = 191 Number of transmission lines = 55. Table 3 shows the optimal control values of practical 191 test system obtained by MI method. And table 4 shows the results about the value of the real power loss by obtained by Mutually Dependent Creature Investigation (MI) algorithm.

Table 3. Optimal Control values of Practical 191 utility (Indian) system by MI method

VG1	1.10		VG 11	0.90
VG 2	0.76		VG 12	1.00
VG 3	1.01		VG 13	1.00
VG 4	1.01		VG 14	0.90
VG 5	1.10		VG 15	1.00
VG 6	1.10		VG 16	1.00
VG 7	1.10		VG 17	0.90
VG 8	1.01		VG 18	1.00
VG 9	1.10		VG 19	1.10
VG 10	1.01		VG 20	1.10

T1	1.00		T21	0.90		T41	0.90
T2	1.00		T22	0.90		T42	0.90
T3	1.00		T23	0.90		T43	0.91
T4	1.10		T24	0.90		T44	0.91
T5	1.00		T25	0.90		T45	0.91
T6	1.00		T26	1.00		T46	0.90
T7	1.00		T27	0.90		T47	0.91
T8	1.01		T28	0.90		T48	1.00
T9	1.00		T29	1.01		T49	0.90
T10	1.00		T30	0.90		T50	0.90
T11	0.90		T31	0.90		T51	0.90
T12	1.00		T32	0.90		T52	0.90
T13	1.01		T33	1.01		T53	1.00
T14	1.01		T34	0.90		T54	0.90
T15	1.01		T35	0.90		T55	0.90
T19	1.02		T39	0.90			
T20	1.01		T40	0.90			

Table 4. Optimum real power loss values obtained for practical 191 utility (Indian) system by MI method.

Real power Loss (MW)	**MI**
Min	144.032
Max	148.126
Average	145.012

Conclusion

In this paper, the Mutually Dependent Creature Investigation (MI) algorithm has been successfully implemented to solve Optimal Reactive Power problem. The main advantages of the Mutually Dependent Creature Investigation (MI) algorithm are easily handling of non-linear constraints. The proposed algorithm has been tested in standard IEEE 118 & practical 191 bus test systems. The optimal setting of control variables are well within the limits. The results were compared with the other heuristic methods and proposed Mutually Dependent Creature Investigation (MI) algorithm demonstrated its efficiency and heftiness in minimizing the real power loss.

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