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OPTIMAL PLACEMENT OF FACTS DEVICES BY EVOLUTIONARY MULTIOBJECTIVE OPTIMIZATION

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Abstract— The present paper is focused on Flexible AC Transmission Systems (FACTS) devices. The central technology of FACTS involves high power electronics, a variety of thyristor devices, microelectronics, communications and advanced control centres. FACTS, is a superior option, from technical and environmental points of view, to increase the utilization and stability of a transmission grid. Our preoccupation has to develop a strategy for the optimal placement of FACTS devices into power systems. Regarding the technical aspect of FACTS insertion in power systems and also their high investment cost, a multi-objective optimization technique is developed for solving this problem. We employed Multi-Objective Genetic Algorithms based approach (MOGA), which is used to characterize the Pareto Optimal Frontier (non-dominated solutions) and to provide to Decision Makers and engineers insightful information about the trade-offs to be made. In this paper two technical and economical objective functions are considered: maximization of system security and minimization of investment cost for FACTS devices. The optimization process is focused on three parameters: the location of FACTS in the network, their types and their sizes. For these proposals we employed a hybrid software developed in Matlab™ which uses the EUROSTAG™ software for load flow calculations. The developed MOGA are successfully tested on an IEEE 14-bus power system.

1. Nomenclature

DM: Decision Maker
FACTS: Flexible A.C. Transmission System
GA: Genetic Algorithm
MOGA: Multi-Objective Genetic Algorithm
MOP: Multi-Objective Problem
POF: Pareto Optimal Frontier
SVC: Static Var Compensator
TCSC: Thyristor Controlled Series Capacitor

2. Introduction

Nowadays the electric grid companies are facing many new challenges. These come from the fact that the electric sector is of combined business and public interest as never before. To be able to respond to these demands, technologies

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applied to the grid that can incorporate flexibility, environmental soundness, business orientations and competitiveness are very important. In this context, one possible solution to alleviate some but not all of these power systems difficulties was the use of FACTS technologies [1]. These are based on the *state of the art* concept that incorporates power electronics technologies, having a high efficiency, from technical and environmental impact point of view, in transmission grid utilization. The FACTS technology opens up new opportunities for controlling power and enhancing the usable capacity of present, as well as new and upgraded, lines. The possibility that current and therefore power through a line can be controlled enables a large potential of increasing the capacity of existing lines. These opportunities arise through the ability of FACTS controllers to control the interrelated parameters that govern the operation of transmission systems including series impedance, shunt impedance, current, voltage, phase angle and the damping of oscillations. All above presented FACTS applications depends by the FACTS location in the controlled power system. Hence, to obtain a biggest FACTS operational response an optimal location of these devices is necessary to be done.

The issue of optimal location of the FACTS devices in power systems has been researched and discussed widely and several strategies were proposed. But most of those studies have taken into account only the methods oriented towards technical criteria (the capability of FACTS to enhance the system loadability was shown in [2], the ability of this to control the power flows is studied in [3] and the benefits to eliminate the network congestions was presented in [4]) or to economical approach which has minimized the overall system cost function [5] and total generation fuel cost [6] or maximized the return of investment as in [7].

This paper mainly focuses on the development of a strategy for determination of optimal placement of multi – types FACTS devices into power systems, from both technical and economical point of view, in order to provide a better security level. To carry out these multi criteria optimization problems we employed a MOGA technique. The aim of this work is to test and to validate the proposed MOGA.

The outline of the paper is as follows: Section III presents the formulation of FACTS allocation problem, Section IV describes a multi-objective technique used to solve the MOP, in Section V is shown the description of MOGA adopted, and, in Section VI, an example system is used to test and validate the proposed MOGA technique. Finally, section VII presents the main conclusions of the paper.

3. Problem formulation

In the present study we have considered two classes of FACTS such as shunt controllers and series controllers. From the first category we studied the SVC, and from the second category the TCSC. The method developed is based on steady-state analyses, therefore, concerning the modeling of FACTS devices into a power system, it was used the steady-state model of FACTS which is implemented in EUROSTAG^{TM} software. All the models are presented in [8].

A. Problem formulation

The presence of FACTS devices into a power system brings many benefits, as quoted above. Nevertheless, in order to reach a defined goal, it is important to choose the suitable types of FACTS, an appropriate location and the rates of these.

As indicated above, the goal of optimization was the determination of optimal allocation of FACTS devices into a power system in order to enhance the systems security level keeping in the same time a low investment cost in the new equipments. Therefore, the problem presented becomes a multi-objective optimization problem, with two different criteria to be optimized and this can be expressed, in equation form, as:

$$\begin{aligned} &Min \quad F(x) = [F_t(x), F_e(x)] \qquad (1)\\ &Subject \quad to \quad x \in \Omega \\ &\qquad c_j(x) = 0 \quad j = 1 \ldots n \\ &\qquad h_k(x) \le 0 \quad k = 1 \ldots p \end{aligned}$$

where F is known as the objectives vector, x represents a decision vector, Ω is the solution domain and $c_j(x)$ and $h_k(x)$ are the equality and inequality problem constraints respectively.

In this MOP, $F_t(x)$ and $F_e(x)$ represents technical and economical criterion to be optimized respectively. Therefore, from the technical point of view, the FACTS devices are located in order to remove the overloads, to distribute uniformly the loads flows and also to prevent the under or over bus voltages. Consequently, we consider following technical objective function [9]:

$$F_t = \sum_{l=1}^{a} w_l \left(\frac{S_l}{S_{l\max}} \right)^{2q} + \sum_{m=1}^{b} w_m \left(\frac{V_{m\mathrm{ref}} - V_m}{V_{m\mathrm{ref}}} \right)^{2r} \qquad (2)$$

where S_l and $S_{l\max}$ are the apparent power in line l and the apparent power rate of line l respectively. V_m is the voltage magnitude at bus m and $V_{m\,\mathrm{ref}}$ is the bus m nominal voltage. The weights w_l and w_m are determined in order to have the same index value for 10% voltage difference and for 100% branch loading. The coefficients q and r are used to penalize more or less the overloads and voltage variations respectively. For the presented study they are considered to be equal to 2.

As mentioned previously, it is important to take into account the economical aspects of the FACTS devices presence in the power systems due to high investment and operating costs. Hence, the economical objective function presented in (1) is represented by the total investments cost of SVC, $c_{inv\ SVC}$, and TCSC devices, $c_{inv\ TCSC}$:

$$F_e = c_{inv\,SVC}(r_{re\,SVC}) + c_{inv\,TCSC}(r_{re\,TCSC}) \qquad (3)$$

where $r_{re\ SVC}$ and $r_{re\ TCSC}$ are the operating rate of the FACTS devices in MVar.

According to [5], the investment cost shown above, given in US$/kVar, are determined by the following relations:

$$c_{inv\,SVC}(s) = 0.0003 r_{re\,SVC}^2 - 0.3051 r_{re\,SVC} + 127.38 \qquad (4)$$

$$c_{inv\,TCSC}(s) = 0.0015 r_{re\,TCSC}^2 - 0.713 r_{re\,TCSC} + 153.75 \qquad (5)$$

The determination of suitable location and parameters of FACTS devices must be made by respecting the power flow balance and the bounds of FACTS devices parameters. Therefore, taking into account these aspects and considering the equations (2)-(5), the formulation of the FACTS devices optimal allocation problem can be expressed as follows:

$$\begin{aligned} &Min \quad F(x) = [F_t(x), F_e(x)] \qquad (6) \\ &Subject \quad to \quad x \in \Omega \\ &\qquad E(f,g) = 0 \\ &\qquad B(f) \geq b_1 \ ; \ B(f) \leq b_2 \end{aligned}$$

where f is a vector that represents the variables of FACTS devices, g represents the power systems operating state, $E(f,g)$ represents the active and reactive power balance equations correspondent to equality constraints and $B(f)$ is the inequality constraint concerning the FACTS devices bounds limits (lower and upper limits represented by b_1 and b_2 respectively).

B. Solving methods

Seeing that the optimization process was oriented towards three parameters: FACTS location, their types and their rates, which can take discrete and continues values, the case discussed above becomes a *combinatorial optimization problem*. There are several possible solutions which can be used to solve these types of problems [10], among these we are used Genetic Algorithms [11], [12], which are stochastic search techniques based on the mechanics of natural selection and natural genetics.

4. Multi – Objective Technique

A. Multi-Objective Optimization

The problem described in *Section III* is, like mentioned above, a *multi-objective combinatorial optimization problem*, and thus it was necessary to use a multi-objective technique for solving it. The use of multi-objective techniques gives information on the consequences of the decision with respect to all the objective functions defined [13]. While traditional optimization procedures result in one solution point only, the MOP usually has no unique, perfect (or Utopian) solution, but a set of *non-dominated*, alternative solutions, known as the Pareto-optimal set which define the POF (Fig. 1). The POF was named after the work of the engineer and economist Vilfredo Pareto, who postulated the following theorem: starting from a Pareto solution, one objective can only be improved at the expense of at least one other objective [14]. Therefore, the POF offers complete information about the optimal solutions of the problem and becomes an important knowledge for the DM.

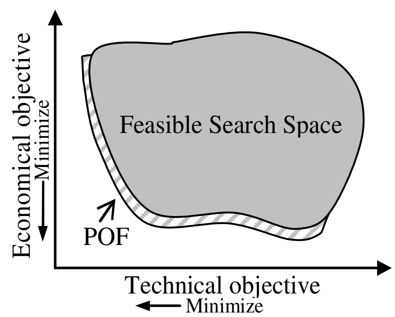

Fig. 1: POF representation.

In this paper, the aim of the optimization is to determine the POF of the problem described in the section above. The choice of the optimal solution among the POF points remained to DM. For these types of problems the Evolutionary Algorithms (EAs) represent a standard tool. There are many EAs described in the literature, reviews of this can be found in [15]. For the present work, among the EAs, we chose to employ MOGA technique.

B. Multi-Objective Genetic Algorithms

The MOGA technique was firstly proposed by Fonseca and Fleming in 1993 [13]. It is an extension a classical GAs. The main difference between a conventional GAs and a MOGA resides in the assignment of fitness. Once fitness has been assigned to individuals, selection can be performed and genetic operators applied as usual. The MOGA proposed a Pareto-based ranking procedure of the individuals, where each individual is assigned a rank which counts how many individuals in the current population dominate them. In this way, non-dominated individuals are always assigned the same rank, independently of the shape of the trade-off surface.

The assignment of fitness according to rank, for the MOGA, which was used in this paper by modifying the traditional GAs, may be extended as follows:

- For the each t generation, sort population in descendent order according to rank $rank(x_i,t)$ of the individual x_i. The individuals rank is given by:

$$rank(x_i, t) = 1 + p_i^{(t)} \tag{7}$$

where $p_i^{(t)}$ are the number of individuals, in current population, which dominate the individual x_i. All

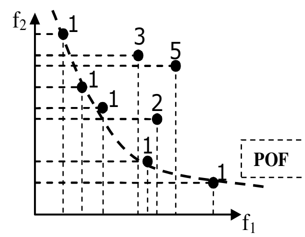

Fig. 2: Multi-objective Pareto ranking.

non-dominated individuals are assigned rank 1, see Fig. 2.

- Assign fitness to each individual by interpolating from the best (rank 1) to the worst, applying the *linear ranking fitness scaling* technique [13], [16].
- Average the fitnesses of individuals with the same rank, so that all of them will be sampled at the same rate.
- Apply the *fitness sharing* [17] in the objective space to maintain a population diversity.
- Select of the individuals for reproduction, by applying a Stochastic Universal Sampling or Roulette Wheel Selection techniques [11]-[13].

5. Description of the used MOGA

To reach the aim of the optimization problem described in the *Section III* we developed a hybrid MOGA, which we describe below.

A. Individual representation

MOGA require the parameter set of the optimization problem to be coded as a finite-length string over some finite alphabet. Since the goal of optimization was to allocate the FACTS devices taking account three parameters (location, type and rate), an individual is represented by three strings of length n_{FACTS}, where n_{FACTS} is the number of FACTS devices which want to locate optimally in the power system [2], [5], [9].

In the first individual string, one can find information about the location of the FACTS devices in the power system. It contains the integer numbers from 1 to n_B, where n_B is the total number of branch system. In this string a number can occur only once, which means that only a FACTS device is allowed into a branch. The SVC device is allocated to the middle of branch, by the introduction of a new bus.

The second string represents the coding for the types of FACTS and can be assigned discrete values 1 or 2, the first corresponding to a SVC and the second to a TCSC device, respectively.

The last individual string corresponds to the rate of FACTS devices. Here, the special encoding was made to take into account the FACTS devices bounds constraints presented in (6) [1]. The encoded rates in this string, r_{enc}, take continue values between 0 and 1, corresponding to the minimal rate which FACTS devices can take and to maximal rate respectively.

In the Fig. 3 is shown an example of individual representation composed of four FACTS devices on a 14-branch network.

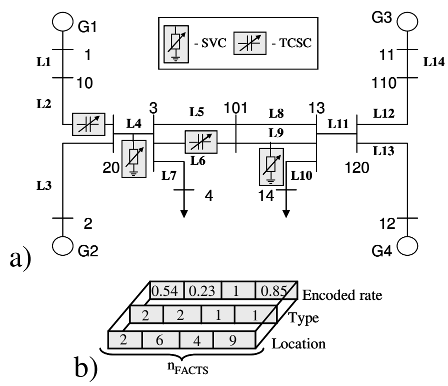

Fig. 3: Individual representation. (a) Power system. (b) Individual.

The real rated value of each FACTS device can be obtained according to the different FACTS model under the following criteria:

- SVC

As mentioned above, the EUROSTAG software was used to load flow calculations and the FACTS models implemented in this. Thus, the SVC is implemented in EUROSTAG load flow module like a power injection in a bus, declaring it as the PV node. Therefore, the SVC occurs in the load flow by the control of the voltage in the bus where it operating. Consequently, the rate value of the SVC, r_{SVC}, in the GAs encoding, is represented by the bus voltage reference, the real rate, $r_{re\ SVC}$, being obtained form the load flow results. Furthermore, we considered a PV node with reactive power limits.

For this study it was considered that the SVC has an operating range between -200 MVar and 200 MVar and a reference voltage between 0.95 p.u. and 1.05 p.u. Hence, r_{SVC} is given by the following expression:

$$r_{SVC} = 0.95 + 0.10 \cdot r_{enc} \qquad (8)$$

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TCSC

Similarly, it was used a TCSC device model from EUROSTAG software. There, the TCSC is modelled, for the load flow computation, like a controllable reactance inserted in the system branch, which can increase or decrease the line reactance, X_{line}. Therefore, the rate value of the TCSC, r_{TCSC}, in the GAs encoding, is represented by a reactance which depends on the line reactance where TCSC operates. The real rate, $r_{re\ TCSC}$, is obtaining after the application of TCSC device sizing and rating algorithm described in [18] and [19].

In this paper, it was considered that the TCSC had a working range between $-0.8X_{line}$ and $+0.2X_{line}$ [2]. Thus, the r_{TCSC} value can be obtained by using the following formula:

$$r_{TCSC} = -0.8 X_{line} + X_{line} \cdot r_{enc} \qquad (9)$$

B. Fitness evaluation

After the first step of the MOGA, which is initial population generation, the fitness function is evaluated. In general, the fitness coincides with the objective function, if it is an unconstrained problem or an adaptation of this for a constraints problem. For the MOP presented in the *Section III* the constraints are eliminated in the following manner: the first constraints presented in (6) are implicit respected through the load flow computation and the seconds set of constraints are eliminated by encoding in the first string individual representation. Hence the objective function form (6) becomes a fitness for the MOGA.

Seeing that it is studied a bi-objective MOP, the fitness evaluation was done in two steps. In the first step was evaluated the technical objective through EUROSTAG program. To this end, one decoded an individual and from it a new data file **.ech* was generated, which serve to compute the load flow of power system with the EUROSTAG. From the load flow results one can obtain all the information needed to compute the technical objective function, F_t. In the second step was read the load flow results, extracting from them the rate values for the FACTS devices, $r_{re\ SVC}$ or $r_{re\ TCSC}$. With these values was evaluated the economical objective function, F_e. These procedures are performed for all the individuals in population.

C. Specifics MOGA operators

After the evaluation of both problem objectives one can apply the specific MOGA operators [13], which have been defined in the *Section IV-C*. Hence, a rank of each individual is determined according with (7), then a Pareto ranking procedure is applied for all the individuals and a first trade-off surface is drawn. After this, the population is sorted in descendent order according to the rank and one assigns the scaled fitness to each individual according with its position in ordered population but not with its original fitness. This is done in order to obtain a population which was assigned a single fitness raw, suitable to the application of classical GAs operators. As shown above, it was used a linear ranking fitness scaling technique. The linear ranking takes the following form:

$$fitness(x_{ind}) = 2 - MAX + 2(MAX - 1)\frac{x_{ind} - 1}{n_{ind} - 1} \qquad (10)$$

where *fitness*(x_{ind}) is the scaled fitness of the individual *ind*, x_{ind} is the position in the ordered population of individual *ind* and the parameter *MAX* is the *selective pressure*, towards the most fit individuals. In this paper it was used a selective pressure equal a 2, which means that the best individual will have a scaled fitness equal to 2, the worst individual equal to 0 and other ones between these values.

After that, a single value of fitness is derived for each group of individuals in a population with the same rank, through averaging, so that all of them will be sampled at the same rate, during the selection. Although all preferred individuals (non-dominated) are assigned the same fitness, their actual number of offspring may differ. The imbalance can easily accumulate with the generations and result in the population drifting towards an arbitrary region of the trade-off surface, a phenomenon known as *genetic drift* [20]. To counteract the genetic drift, the fitness sharing was applied. This technique, aims at promoting the formulation and maintenance of stable subpopulations (*niches*). It is based on the idea that individuals in a particular niche have to share the available resources. The more individuals are located in the neighbourhood of a certain individual, the more its fitness value is degraded. The neighbourhood is defined in terms of a *Euclidean distance* measure between the individuals and specified by the so-called *niche radius.*

The procedure for the application of fitness sharing is described in [17]. The use of fitness sharing is restricted by the difficulty to determine the appropriate value for niche radius. In the present paper we used a solution given in [21] for a bi-objective problem.

Therefore, the application of all procedures mentioned above leads to a population, special prepared, which is ready to be reproduced.

D. Reproduction

Reproduction is a process in which individuals are copied according to their fitness, which means that individuals with good characteristics have a higher probability of contributing one or more offspring in the next generation. The reproduction operator may be implemented in algorithmic form in a number of ways [11]. In this work we considered Stochastic Universal Sampling (SUS) and Roulette Wheel Selection (RWS) methods [11]-[13].

After applying the reproduction operator, the matting pool of the next generation is obtained and in the follow we use the crossover and mutation operators.

E. Iterative process

Following reproduction, crossover and mutation, the new population is ready to be tested. For this, we decode the new individuals created by the MOGA and calculate the fitness function like mentioned above. Hence, the operation of fitness evaluation, non-dominated solutions determination, reproduction, crossover and mutation are repeated until the maximal number of generation, n_{gen}, is reached, this representing the stop criterion of MOGA.

F. POF

Following the initial generation, repeated selection of non-dominated individuals and production of offspring soon produces a reasonable description of the trade-off surface of the problem, at each generation the MOGA bringing the solutions of the problem closer to the POF.

The proposed MOGA is summarized in Fig. 4.

G. Developed software

The MOGA proposed above was implemented into a software package developed in the Matlab™ language. For the load flow computation one has employed the EUROSTAG™ software version 4.3.

For the validation of the proposed MOGA we used the IEEE 14-bus power system. The simulations are done in order to testing the MOGA and to characterize the Pareto Optimal front, in fact to proof the robustness of the MOGA.

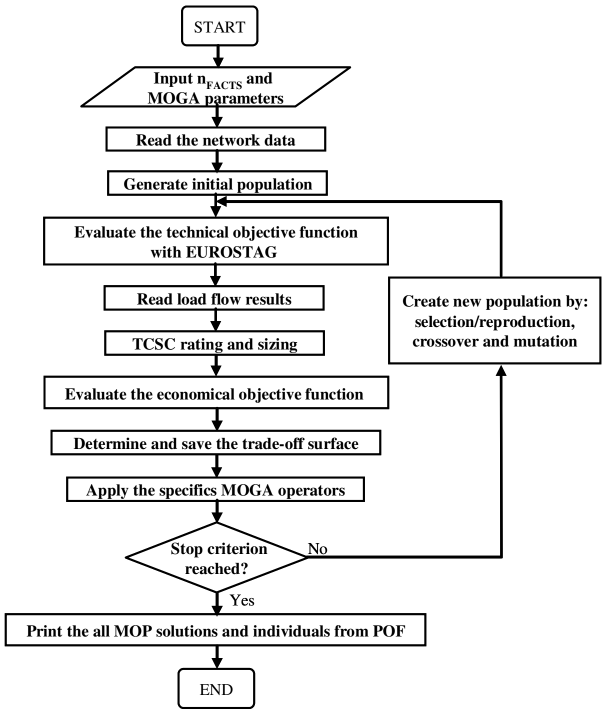

Fig. 4: Flow chart of the proposed MOGA.

6. Method validation

a) b)

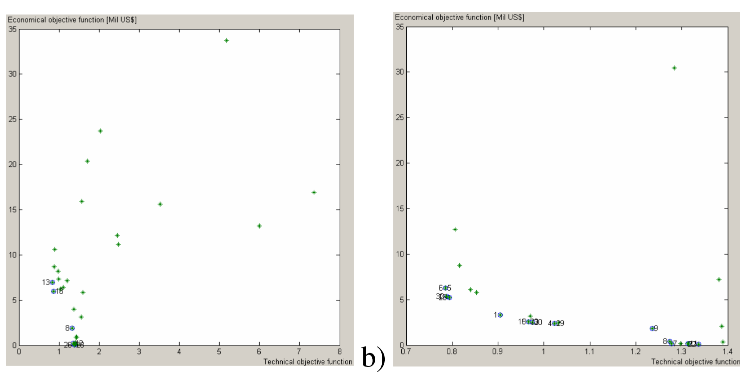

Fig. 5: Trade - off representation for 2 FACTS (n_{ind}=30 and n_{gen}=200).
(a) First generation. (b) Last generation (POF representation).

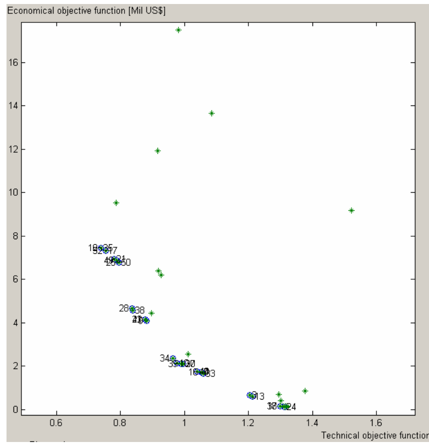

Fig. 6: POF representation for 2 FACTS (n_{ind}=50 and n_{gen}=300).

For the considered power system, the MOGA was applied considering several sets of parameters in order to prove its capability to provide acceptable trade-offs close to the POF. Thus, a first simulation was done, with an initial population having 30 individuals and with maximal number of generations equal to 200. For the second simulation we used a 50 individuals population, MOGA runs 300 generations. For these simulations were optimal allocated two FACTS devices, the types chosen being SVC and TCSC, whit different rate values.

In Fig. 5 and Fig. 6 are shown the trade-off surfaces obtained for the first simulation and second simulation, respectively. In Fig. 5,a are presented the solutions to the first generation and in Fig. 5,b and Fig. 6 the solutions to the last generation. It can be see that problem solutions converge to POF from the first to last generation, the two objectives of the problems being minimized. Furthermore, the number of the non-dominated solutions increases from a generation to other, which shows the convergence of trade-off surface to POF. For the simulations presented, in the last generation, one has 17 non-dominated solutions for first case and 30 for the second case, these constituting the Pareto optimal solutions of our problem. Hence, the DM has useful information about the optimal allocation of FACTS devices in studied network.

It can be seen that for both simulations one has obtained almost the same trade-off surface, which can well characterize the POF of our problem. Hence, we shown the capability of MOGA to converge to the same POF, at the different parameters sets.

7. Conclusions

The present paper makes use of recent advances in multi-objective evolutionary algorithms to develop a method for the combinatorial optimal allocation of SVC and TCSC into power systems. Implementation of the proposed MOGA has performed well when it was used to determine to characterize POF of the FACTS optimal location problem.

The results show that the proposed MOGA can produce good solutions and illustrate the effectiveness and vigorousness of the proposed approach.

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