Enhancement of genetic algorithm optimization on distribution operation control by fuzzy inclusion

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Abstract. The optimal control of distribution system operation is presented in this paper. The objective of the control is minimum real power loss simultaneously achieved with voltage profile improvement. The distribution system equipped with Load Tap Changer (LTC) and switchable Shunt Capacitors is optimally controlled by determining the tap position of LTC and switching status of Shunt Capacitor at every hour for the 24-hour period. Two Genetic Algorithms (GAs) are developed for load curve partition and hourly components status determination. The performance of GA for components optimal scheduling is further enhanced by integrating Fuzzy Strategies in fitness evaluation and constraints satisfaction. The scheme of Fuzzy Convex Decision Making (FCDM) that provides flexible objective achievement and soft constraints is employed. This enables considering more extensive solutions that may lead to better optimal control. The proposed control strategy is implemented on 30-bus distribution system and the system improvements are observed. The enhancement of fuzzy integration is highlighted.

Keyword: Distribution System, Optimal Control, Genetic Algorithms, Fuzzy Strategy

1. Introduction
With constantly increasing demand of electricity, distribution systems have become more complicated. The growing demand for electricity may be satisfied in both technically adequate and reasonably economical way by careful distribution system planning. The objective of distribution system planning is to ensure that this can be satisfied in an optimum way [1]. Constantly changing load makes the planning very complicated. If not carefully managed, this may cause several problems, such as voltage violation and additional power loss.

An adaptable enhancement is required to restore the voltage and to reduce the power loss. A modern distribution system is normally equipped with devices such as Load Tap Changer (LTC) and Shunt Capacitors that may be controlled to minimize power loss and to improve the voltage profile. The aim is maintaining the system voltage and minimizing system energy loss. This can be practically achieved by finding the set of adjustments of the controllable devices for 24-hour period [2,3].

The optimal dispatch of LTC and Shunt Capacitors for 24-hour period is a multi-phase decision-making problem with discrete variables and nonlinear objective function [4-6]. The interdependence
and interaction between these controllable devices lead to control complexity due to the switching effects of a device to the other devices [7]. This may cause oscillation of the controlled devices resulting in frequent switching that may reduce life expectancy and increase the maintenance cost. It is therefore preferable to achieve the control objectives in the least possible number of control steps. Simultaneous scheduling the controllable devices is the best approach to effectively solve the problem yet unfortunately, this will result in unavoidable complicated calculation [8].

The proposed method for the problem in hand is Genetic Algorithm (GA) [9,10]. In addition to its general features, GA is justified due mainly to its encoding ability that enables comprehensively considering the simultaneous dispatch of the switchable devices and confirming the switching limit before evaluating the possible dispatch schedules. The performance of GA will be further enhanced by including fuzzy approach. The scheme of Fuzzy Convex Decision Making [11] that provides flexible objective achievement and soft constraints enables the possibility of considering more extensive solutions leading to better optimal control. Implementation on a 30-bus distribution system confirms the enhancement the hybrid Fuzzy-GA method.

2. Genetic Algorithm
For solving optimization problem using Genetic Algorithm (GA), an initial population consisting of some chromosomes is initially constructed. Every chromosome represents a possible solution. This step is then followed by a cycle of three stages: fitness evaluation of each chromosome, selection of chromosomes for regeneration of new population and manipulation of chromosome by crossover and mutation [12]. Completing this cycle means that one generation has occurred. After some number of generations, the algorithm converges and the best chromosome represents an optimal solution. In this paper, 2 GAs are developed for determining load curve interval and optimal dispatch schedule.

In order to determine the intervals for entire load curve that result in an optimal LTC schedule, the number of interval in the load is initially assumed. GA is then employed to determine those intervals. The chromosome consists of several substrings where, every substring denotes the switching status for each Shunt Capacitor at substation, their number of hour at a switching, and feeder shunt capacitors installed. Every chromosome represents a possible solution. This chromosome is evaluated using the following fitness function [13]:

\[
F = F_{\text{max}} - \min \sum_{l=1}^{L} T(T_1 - P_{tl})^2 + (Q_{tl} - Q_{A})^2
\]

Subject to

\[
\sum_{l=1}^{L} T = 24
\]

Where \( F_{\text{max}} \) is a constant converting fitness function to standard form, \( P_{tl} \) and \( Q_{tl} \) are active and reactive power at load interval \( t \) and load interval \( l \), \( P_{A} \) and \( Q_{A} \) are average active and reactive power at load interval \( l \), \( T \) is number of hour at \( t \)th load interval, and \( L \) is number of assumed interval.

With the load intervals in hand, the schedule of LTC tap position can be effectively decided, where the tape position is fixed in the same interval. This will take into account the overall daily load change and easily satisfy the switching constraint. For Shunt Capacitors at substation, their switching operation is limited by a maximum number. Therefore, the chromosome representing this schedule consists of several substrings where, every substring denotes the switching status for each Shunt Capacitor for 24-hour period. The shunt capacitors installed at distribution feeders are normally allowed to be switched on and off once a day. Therefore, it requires determining the time for switching the capacitor on and the duration for keeping it on. The final eligible chromosome representing the 24-hour scheduling of LTC and shunt capacitors is consecutively constructed by the eligible chromosomes of LTC, substation shunt capacitors, and feeder shunt capacitors. Every chromosome at each generation is evaluated using fitness function derived from objective function and voltage constraint.

\[
F = \max F_{\text{max}} \left( w_{\text{loss}} \sum_{p=1}^{24} \text{loch} + w_{p} \sum_{p=1}^{24} V_{p} \right)
\]
where $\text{loss}_i$ is per-unit real power loss of the system at hour $t$, $\Delta V_{it}$ is per-unit $rms$ voltage violation at bus $i$ at hour $t$, $w_{\text{loss}}$ is weighting coefficient of real power loss, and $w_V$: weighting coefficient of $rms$ voltage violation.

3. Fuzzy Inclusion

The previously developed GA is further enhanced by incorporating fuzzy into the existing GA forming hybrid GA-fuzzy method. The mode of fuzzy proposed is Fuzzy Convex Decision Making (FCDM) that facilitates a collaboration of objective function and constraints forming a fuzzy multi-objective optimization. The effectiveness of this approach is due to the ability of fuzzy providing soft restrictions for objective achievement and constraints satisfaction such that the modified GA enables maintaining the promising individuals while improving the solution.

For optimization using hybrid GA-fuzzy, membership functions that represent the objective and constraints are developed [14]. The membership functions are established to measure the accomplishment of objective function as well as fulfillment of constraints.

To minimize the energy loss, a membership function that rewards high membership value for minimum hourly power loss is used. A linear membership function with negative slope $(-(100/\text{loss}_0))$, declining from the maximum value of 100 is employed as represented by the following equation.

$$\tilde{\mu}_{\text{loss}} = \begin{cases} (\text{loss}_0 - \text{loss}) / \text{loss}_0 \times 100; & \text{loss} \leq \text{loss}_0 \\ \text{loss} / \text{loss}_0 & \text{loss} > \text{loss}_0 \end{cases}$$

(4)

Where $\tilde{\mu}_{\text{loss}}$ is membership value of real power loss reduction, $\text{loss}_0$ is real power loss for uncompensated system (MW), and $\text{loss}$ is real loss for compensated system (MW).

For voltage regulation purposes, a membership function that maintains voltage levels as close as possible to the preset value is employed. Exponential decreasing membership function is used in this paper as given in the following equation.

$$\tilde{\mu}_{\Delta V} = e^{-100 \Delta V}$$

(5)

Where $\tilde{\mu}_{\Delta V}$ is membership of voltage regulation and $\Delta V$ is absolute deviation of $rms$ voltage with respect to the preset voltage.

For the purpose of minimizing LTC tap movement, a membership function that keeps the switching number small is employed. The membership returns three values of membership as indicated in the following equation.

$$\tilde{\mu}_{\text{TAP}} = \begin{cases} 1; & 0 \leq \text{TAP} \leq 8 \\ \text{TAP} - TAP_{\text{max}} / (TAP_{\text{max}} - 8) & 8 < \text{TAP} \leq TAP_{\text{max}} \\ \text{TAP} > TAP_{\text{max}} & \end{cases}$$

(6)

Where $\tilde{\mu}_{\text{TAP}}$ is membership for LTC tap movement, $TAP$ is LTC switching number, and $TAP_{\text{max}}$ is maximum LTC switching allowed.

The abovementioned membership functions are clearly intended to reward the high membership values for the most preferred operating conditions. Therefore, the fuzzy fitness function of hybrid GA-fuzzy is constructed by simply maximizing the memberships rewarded by the membership functions. For optimal scheduling of the controllable devices, the fuzzy fitness function as given in the following equation is used.

$$F = \max \left[ w_{\text{loss}} \sum_{t=1}^{24} \tilde{\mu}_{\text{loss}_{it}} + w_V \sum_{t=1}^{24} \sum_{i=1}^{m} \tilde{\mu}_{\Delta V_{it}} + w_S \tilde{\mu}_{\text{TAP}} \right]$$

(7)

Where $\tilde{\mu}_{\text{loss}_{it}}$ is membership for real power loss of the system at hour $t$, $\tilde{\mu}_{\Delta V_{it}}$ is membership for voltage regulation at bus $i$ at hour $t$, $\tilde{\mu}_{\text{TAP}}$ is membership for LTC switching for the whole period, $w_{\text{loss}}$ is
weighting coefficient for real power loss, $w_r$ is weighting coefficient for \textit{rms} voltage regulation, and $w_s$ is weighting coefficient of LTC switching minimization.

The calculation flowchart for optimal dispatch scheduling of LTC and Shunt Capacitor using GA and Hybrid Fuzzy-GA is given in Figure 1.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{chart.png}
\caption{Optimization flowchart for optimal dispatch scheduling}
\end{figure}

Two GAs are developed, to determine optimal load curve partition and optimal components dispatch schedule, respectively. The second GA is further enhanced by Fuzzy inclusion. For comparison purpose, the calculation is initially run using GA and is then repeated using Fuzzy-GA. The improvement of the generated result is highlighted.

4. Results and Discussion
The proposed strategy is implemented on a 30-bus distribution system as shown in Figure 2. The system data is available in [13].
The following is the evolutionary strategies of GA used in this study. The initial chromosomes representing possible solutions are randomly generated and those that satisfy the switching constraints are selected to construct the initial population. The selection of parent for crossover uses the tournament method and the children are generated by one-point crossover from their parents. The probability of crossover and mutation, population size, and weighting coefficients are fixed throughout the iteration. The best chromosome at every iteration is saved and transferred directly to the next population. The optimization parameters are given in Table 1.

| Parameter               | Value  |
|-------------------------|--------|
| Population Number       | 30     |
| Generation Number       | 50     |
| Probability of Crossover| 60%    |
| Probability of Mutation | 1%     |

| Weighting factor for GA |   |
|-------------------------|---|
| Voltage Improvement     | 75% |
| Real Power Loss Minimization | 25% |

| Weighting factor for Fuzzy - GA |   |
|---------------------------------|---|
| Voltage Improvement             | 60% |
| Real Power Loss Minimization    | 20% |
| LTC Switching Minimization      | 20% |

The result of optimal dispatch scheduling of LTC and Shunt Capacitors may be represented in terms of voltage control and real power loss minimization. The complete operation schedule of the controllable devices cannot be displayed in this paper due to the space limitation. However the generated schedules have been checked to confirm that all switching constraints are satisfied.

For the purpose of controlling the voltage, the hourly voltage at every bus is observed before and after implementing the optimization strategy. It should be noted that the voltage at every bus is allowed to deviate at no higher than 5% from the nominal voltage. Since it is impossible to indicate the hourly voltage profile of all buses, the bus with worst voltage profile is detected. The improvement of voltage profile of the bus is then figured. It is to assure that the voltage profile of the entire buses is within the maximum deviation of 5%. For the simulated distribution system, the optimization result of voltage improvement is shown in Figure 3.
Figure 3. Voltage Profile Improvement of the Worst Bus

It may be observed from Figure 3 that for the worst bus, Fuzzy-GA may perform better by completely controlling the voltage to be within the deviation limit of 5%. Although GA may generally improve the voltage, in this case, the method may not entirely maintain the voltage to be within the limit. Detail inspection of the optimization results presented by GA, the voltage magnitude at hour 11 a.m. and 01 p.m. are slightly lower than 95%, which are 94.38% and 94.79%, respectively.

To further observe the performance of the proposed methods, the reduction of real power loss is presented. The hourly power loss for the system is presented in Figure 4. It may be observed from the figure that in general, the assigned optimization methods enable reducing the real power loss of the system. However, Hybrid Fuzzy-GA presents the better losses reduction. The energy saving provided by GA and Fuzzy-GA is 177.834 MWh and 205.023 MWh, respectively.

Figure 4. Hourly Real Power Loss
The advantage of fuzzy inclusion into the existing GA is due mainly to the possibility of the hybrid method providing soft restriction of objective achievement and constraints satisfaction. This feature enables exploring more extensive possible solution leading to better solution. Every possible solution represented as chromosome is evaluated based on its level of objective achievement and constraints satisfaction. The objective and constraints are all represented as Fuzzy Membership Function that accommodates the potential solutions to still be considered in the optimization process. These will be further refined in the following iterations (generations) to arrive the best solution.

Genetic Algorithm strictly checks the constraints fulfillment prior to include the chromosome in fitness evaluation and some following steps. This may lead to disregarding the potential solutions resulting in less optimal solution. The refinement process is limited since the number of eligible solution is not many. However GA ensures the solution that is totally eligible for the problem in hand.

In term of calculation process, GA is simpler and, sometimes, gets convergence rapidly. It is because of the variation of solution is small. In contrast, Hybrid Fuzzy-GA that considers more solutions normally requires more iteration to find best solution or even oscillates before converges. Figure 5 illustrates the iteration progress of GA and Hybrid Fuzzy-GA.

It may be seen from the figure that Fuzzy-GA starts from wider solution area may even cause lower best-fitness value. But it leads to a better solution. It also encounters some oscillations before getting the convergence. Therefore, the computation time required by Hybrid Fuzzy-GA is longer than that required by GA. For the optimization problem in hand, the computation time needed by GA and Hybrid Fuzzy-GA is 46.8 sec and 53.6 sec, respectively.

![Figure 5. Iteration Progress of Optimization Calculation](image)

5. **Conclusions**
Optimization methods, GA and Hybrid Fuzzy-GA are developed and implemented for the optimal dispatch scheduling problem of controllable devices. The followings are the main conclusions from the study:
1. The optimal dispatch scheduling of LTC and Shunt Capacitor may improve the voltage profile and reduce the real power loss,
2. Genetic Algorithm is considered to be suitable for the optimal dispatch problem due to the ability of the method simultaneously taking into account the objective and constraints in the calculation,
3. Inclusion of Fuzzy into the existing GA may extend the solution space leading to better solution,
4. While Hybrid GA-Fuzzy enables finding better solution, it causes higher computation charge and longer computation time.
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