# Optimized Voltage-Led Customer Load Active Service Using Genetic Algorithm in Distribution Networks

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**ABSTRACT** To mitigate the low frequency problem in a transmission system in an event of a power station failure or during low renewable generation production, UK National Grid (NG) Electricity System Operator has balancing mechanism in place with generators to provide temporary extra power, or with large energy users to reduce load demand or so call fast reserve services. This paper presents an alternative method to aggregately control the existing distribution network primary on load transformer tap changers as a voltage-led customer load active service. The main benefits of the proposed method are (i) to unlock the distribution network load demand flexibility without causing any negative impact on customers, and (ii) to provide the lowest cost of fast reserve service from a distribution network to transmission network. In this paper an optimal control strategy based on genetic algorithm is proposed and developed to achieve an optimized voltage-led customer load active service with the aim of finding the optimal dispatch of on load transformer tap changers by minimizing each transformer tap switching operation as well as network losses. Two practical 102 buses and 222 buses UK distribution networks have been modelled and used to demonstrate and compare the effectiveness of the proposed control methods under different operating conditions. The performances of the proposed method are also compared with both the rule-based and the branch-and-bound methods. The results show that the proposed optimal control strategy based on the genetic algorithm is more effective by achieving more accuracy and a faster solution for a large distribution network than other two methods. These are important findings as the fast reserve service by transmission network requires the accuracy of the load demand reduction delivery within 2 minutes.

**INDEX TERMS** Fast reserve, customer active load service, load demand reduction management, aggregately control of transformer tap changers, genetic algorithm, optimizations.

## I. INTRODUCTION

To support net zero carbon emission by 2050, it is imperative a need to have significantly increasing integration of renewable energy resources (RESs), such as wind and photovoltaic generation, into both transmission and distribution networks [1]. However, the increasing penetration of RESs into the existing power grids would cause more frequently short terms imbalance between generation and demand due to the intermittency of RESs [2]. To keep the short-timescales balance between the supply and demand of electricity, UK National Grid Electricity System Operator (NGESO) has several classes of reserve services: Balancing Mechanism

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Start-Up, Short-Term Operating Reserve, Demand Management and Fast Reserve [3]. These reserve services are needed especially when a power station fails or if forecast renewable generation differs from actual generation or if forecast demand differs from actual demand [4]. To support these services NGESO has contracts in place with generators to provide temporary extra power, or with large energy users to reduce load demand. While traditional generators are gradually replaced by renewable generation, fast reserve services supported by the declined traditional generation would become rarer and more expensive, hence load management (LM) would play an increasingly important role to make a short period load demand reductions [5], [6].

There are many different LM techniques and methods [7], but traditional LM schemes often require contracts with

customers. Particularly those focusing on load shifting, peak clipping techniques [8]–[11]. For example, load transfer scheme was reported in [10] and load shedding with smart direct load control was reported in [11]. Several load management modules have been designed to provide dynamic electricity pricing signals [12], [13]. The modules encourage the customers to participle load demand response by making savings in electricity bills without need of contracts. Researchers have also considered many different optimization techniques or methods [14]–[19]. In [14] a decentralized load management with considering both dual decomposition and sub-gradient methods was implemented in which the Lagrange multipliers were used to have a wider system coordination and optimization. For a single energy source system with multiple customers, the distributed Newton's method was employed in the design of an energy scheduling model [15]. An integer linear programming technique was used in the industrial LM [16]. A short-term load forecast based on machine leaning and the optimal contracted capacity was used to optimize LM for a shipyard drydock [17]. A decentralized framework was used to optimize residential load management in a microgrid with 50 residential customers [18]. Optimal residential load control with price prediction was reported in [19].

Since a large distribution network may involve hundreds or thousands residential load customers, LM would consider heuristic search optimization methods to find the global solution more quickly and accurately [20], [21]. There are many different heuristics search based methods [22]–[24]. In [22], a swarm optimization algorithm-based network load interaction model with fuzzy uncertain demand response was considered and presented. Similarly, in [23], load scheduling model based on an improved chicken swarm optimization algorithm was considered. The well-established generic algorithms have also been considered in load demand management optimization [24], [25].

Although the traditional LM methods work well when generation productions are predictable and load demand are measurable, they would face serious challenges when the intermittency productions of RESs are difficulty to be accurately estimated. In addition, there will be a challenge task if a power utility would need to sign load demand reduction contract with each individual residential customer. Dynamic price driven LM method would also face a problem if not many residential customers are willingly to participate. Since different individual loads can be categorized into three types (i) impedance expressed as Z, (ii) current expressed as I and power expressed as P, the sum of all individual loads can be modelled as ZIP load model where both the impedance load Z and the current dependent load I have a direct proportional relationship with voltage change [26]. As a result, control of voltage change at a substation can result in control of load demand changes in the substation. This led to the voltage-led customer active load demand reduction method which was proposed and implemented by Customer Load Active Service System (CLASS) project [27].

The proposed load demand reduction method in CLASS project aggregately controls a large numbers of transformer on-load tap changers (OLTCs) at substations to manage customer load demand reduction under the statutory voltage limit constraints, so that the method has no impact on customer load usages [27]. In facts the method saves money for all resistance and current types of loads, for example slightly lower voltage for the conventional lighting type of loads would not affect their usages. Also, for example, an electric water kettle having a lower voltage would take more time to boil water, but the energy for boiling the same amount of water remains the same. The comprehensive assessments for the CLASS load demand reduction in distribution networks have been reported in [28], [29]. Results show the distribution network has load demand reduction capacity which can be released at each of the time periods required by load demand reduction active services. The CLASS load demand reduction method has also successfully entered in the UK Firm Frequency Response (FFR) and Fast Reserve (FR) market since March 2019 [30]. However, the current CLASS uses the branch-and-bound optimization method in a large distribution network has sometimes experienced larger errors and slower search convergence. This led to a need to consider an alternative optimization method to overcome the problem.

This paper presents an improved optimal load demand reduction control strategy for the operation of primary transformer tap-changers in distribution networks, provided that the upstream transmission system requires active load demand reduction services during periods of low generation production or generation loss. Since frequent operation of OLTCs would impact the asset health of OLTC [31], the objective is thus to find an optimal dispatch solution of transformer OLTCs to achieve the required load demand reduction service by minimizing OLTC tap switching operations and the network power losses. Similar to the optimization method used in [32], but this paper optimizes transformer tap changers switching operations and network active power loss to provide load demand reduction supports to the upstream transmission network. In this paper two UK high voltage (HV) distribution network, i.e. 102-bus and 222-bus, the GA based optimized load demand reduction method is demonstrated and compared with other optimization control methods, i.e. rule-based and branch-and-bound [33].

Main contributions of this paper are as follows:

i) Considering time series studies of ''flexible control of distribution network transformer taps changers'' with the permitted voltage limits to achieve voltage-led load demand reduction which would be required by the upstream transmission system to maintain frequency in case of generation loss.

ii) Formulating an improved optimal load demand reduction control strategy based on GA with the aim to solve a Mixed-Integer Nonlinear Programming (MINLP) problem faster.

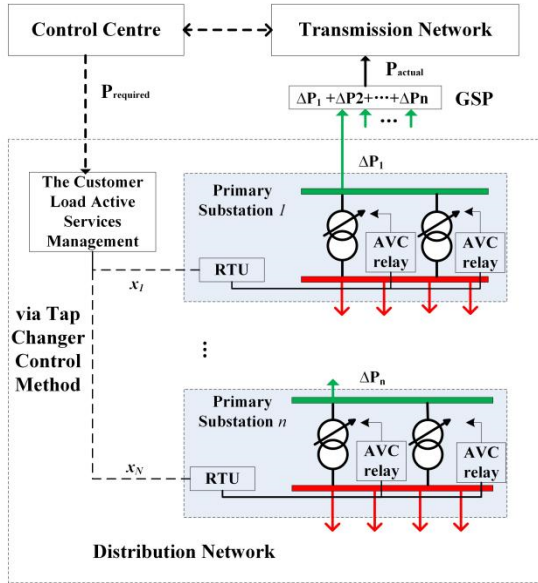iii) Determining suitable GA parameters to ensure the balance between the optimization results on the total

**FIGURE 1.** Schematic of the tap changer control method for a medium voltage (MV) distribution system.

network power loss and the number of OLTC switching operations.

iv) Demonstrating two important key findings by achieving:
- more accuracy between the required power reduction and actual load reduction,
- a faster optimal solution for a larger distribution network to ensure the method can meet the fast reserve service within 2 minutes requirement.

## II. TAP CHANGER CONTROL METHOD

The methodology of the distribution network tap changer control strategy is shown in Figure 1. The medium voltage (MV) distribution network is connected to a transmission network via a Grid Supply Point (GSP). There are '$N$' number pairs of parallel transformers (e.g. 33/11kV and 33/6.6kV in the UK) with OLTCs in the distribution network, Remote Terminal Units (RTUs) and Automatic Voltage Controller (AVCs) relays being installed, which allow on-load tap control.

The implementation of the tap changer control method is on the primary side of a distribution substation transformer. To change the transformer primary side winding ratio would result in the transformer secondary side voltage change. To reduce the voltage at the transformer secondary side where all individual loads are connected would reduce load demand at the substation [26].

When the transmission network requires a load demand reduction service at GSP from the distribution, the customer load active service system (CLASS) would issue the tap changer operation commands to the optimal dispatch of OLTCs via RTUs to the AVC relays to control OLTCs taps to reduce load demand. For the $i^{th}$ primary substation transformer as shown in Figure 1, reducing voltage via

OLTC will result in $\Delta P_i$ load demand reduction at the $i^{th}$ primary substation. The total load reduction $P_{actual}$ aggregated at the GSP is the sum of all primary substation load reduction $\Delta P_1 + \Delta P_2 + \ldots + \Delta P_n$. To achieve fast solutions for optimal dispatch of OLTCs, minimum tap changers operation and network active power loss, a GA-based optimization method is used and described in the following section.

## III. GENETIC ALGORITHM BASED OPTIMAL CONTROL

The implementation of the tap changer control strategy uses the genetic algorithm which is a global optimal search method for finding the optimal solution through natural selection [34]. The corresponding fitness function, penalty function, inequality constraints, control variables and genetic operators for the proposed voltage-led customer load active service method are defined as follows.

### A. FITNESS FUNCTION

The OLTC tap positions of the transformers are the control variables for the GA-based tap changer optimization. There are two objectives: the first objective ($J_1$) is to minimize the number of tap changer switching operations and the second objective ($J_2$) is to minimize the total network power loss. The control method should also satisfy the load demand reduction target at GSP which is required by the upstream connected transmission network. Therefore, considering two objectives and the fulfilment of the load power reduction requirement at the same time, the fitness function of GA can be expressed as below:

$$minF = w_1 \cdot J_1 + w_2 \cdot J_2 + w_3 \cdot f(e)$$

$$= w_1 \cdot \sum_{i=1}^{N} x_i + w_2 \cdot \Delta P_{loss}(\mathbf{x}) + w_3 \cdot f(e) \quad (1)$$

$$f(e) = \begin{cases} 0, & \text{if } e \leq e_{limit} \\ e - e_{limit}, & \text{otherwise} \end{cases} \quad (2)$$

$$e = \frac{|P_{actual}(\mathbf{x}) - P_{required}|}{P_{required}} \times 100\% \quad (3)$$

where,

| | |
|---|---|
| $x_i$ | Number of tap steps different from the initial tap positions on the $i^{th}$ transformers (e.g. $x_i = 2$ indicates that the transformer will step down its tap position by two steps; $x_i = 0$ denotes that this transformer will keep its initial position). |
| $N$ | Total number of transformers involved in the tap changer optimization. |
| $\Delta P_{loss}(\mathbf{x})$ | Network active power loss in the distribution network due to the tap changers control of load demand reduction. |
| $P_{required}$ | The load power reduction measured at the GSP required by the transmission network d. |

| $P_{actual}(\boldsymbol{x})$ | The actual load power reduction measured at GSP by using aggregated tap changer control method for load demand reduction in the distribution network. |
| $e_{limit}$ | Maximum permissive error (%) between the required active power reduction, $P_{required}$, by the transmission network and the actual load power reduction, $P_{actual}$, in the distribution network. |
| $w_1$ | The weighting coefficient of minimising the operation of tap changers. |
| $w_2$ | The weighting coefficient of minimising the total power loss in the distribution network. |
| $w_3$ | The weighting coefficient for delivering the active power reduction service. |

The penalty function $f(e)$ here is to measure the dissatisfaction on the load power reduction target. Considering the satisfaction of the active power reduction target as the key factor, $w_3$ associated with violation of constraints should have a larger value over $w_1$ and $w_2$. If we set that $w_3 = 1$, $w_1$ and $w_2$ can be determined as:

$$w_1 = \frac{\mu_1}{N_{taps\_max}}, \quad 0 \le \mu_1 \le 1 \tag{4}$$

$$w_2 = \frac{\mu_2}{\Delta P_{loss\_max}}, \quad 0 \le \mu_2 \le 1 \tag{5}$$

$$\mu_1 + \mu_2 = 1 \tag{6}$$

where $\mu_1$ and $\mu_2$ are the parameters to balance the total system loss reduction saving and the minimization of tap changer operations, which can be adjusted through a sensitivity study mentioned in Section IV. $\Delta P_{loss\_max}$ and $N_{taps\_max}$ are the maximum total system power loss and maximum permissive number of tap changer switching operations, respectively. And by setting all transformers with the maximum taps down to have maximum voltage setting at transformer secondary terminals, $\Delta P_{loss\_max}$ and $N_{taps\_max}$ can be pre-calculated through a power flow study. And then to normalize the objectives $J_1$ and $J_2$ to the same order of magnitude, (4) and (5) are used here.

### B. CONSTRAINTS
The fitness function is subject to the constraints (7) and (8):

$$ATAP_{i,min} \le TAP_i + x_i \le TAP_{i,max} \tag{7}$$

$$0 \le x_i \le TC_{limit} \text{ for } i = 1, \dots, N \tag{8}$$

where,

| $TAP_i$ | Initial tap positions on the $i^{th}$ transformer. |
| $TAP_{i,max};$ | Maximum and minimum tap positions on the |
| $TAP_{i,min}$ | $i^{th}$ transformer, respectively. |
| $TC_{limit}$ | Limited tap changer operation numbers at one time. |

### C. CONTROL VARIABLES
The variable $x_i$ in (1) is a control signal that instructs the parallel transformer OLTCs as a master and a slaver to tap

down or up together. A set of such variables will constitute a candidate solution to (1). For this GA-based optimization problem, a candidate solution is termed as an individual and the chromosome of each individual can be represented as a row vector:

$$\boldsymbol{x} = x_1 x_2 x_3 \dots x_i \dots x_N \tag{9}$$

where based on (8), $x_i$ is an arbitrary integer in the range from 0 to $TC_{limit}$. If the maximum permissive tap position operation $TC_{limit}$ is 4, the corresponding search space size will be $(1 + TC_{limit})^N = 5^N$. The GA method generates random individuals as the first generation, and then it creates the next generation according to the current population. The population would finally lead to an optimal solution.
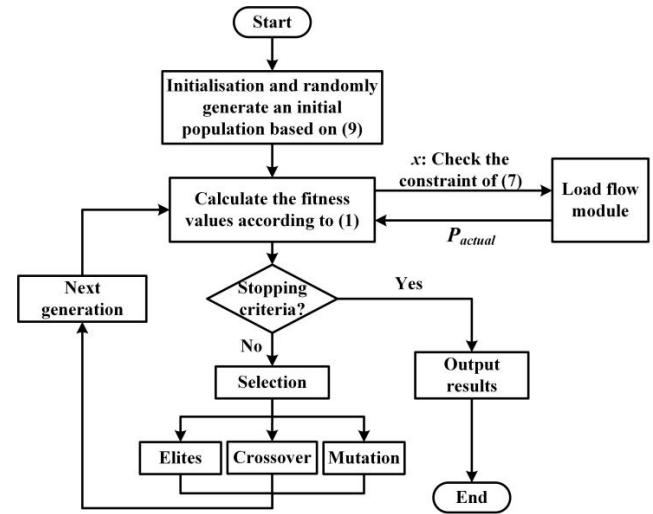


**FIGURE 2.** Flowchart of the GA-based solution procedure.

### D. GENETIC OPERATORS
The fitness of each individual in each GA generation is measured according to objective function (1). The GA uses the current population to produce the children for the next generation. The individuals who have the best fitness values (i.e. elites) are automatically kept in the next generation. The remained non-elite individuals in the parent generation are selected for crossover and mutation using a stochastic uniform sampling method to avoiding trapped in a local optimal solution [32]. The crossover function produces the children through the scattered crossover of their parents. The rest children are created by the mutation. The procedure of the mutation generates random individuals that will lead to the total number of tap changer switching operations (i.e. $\sum_{i=1}^{N} 2x_i$) one fewer than or equal to the best solution at current time. The mutation allows the GA to find more promising solutions rather than being trapped in local minima.

### E. COMPUTATIONAL PROCEDURE
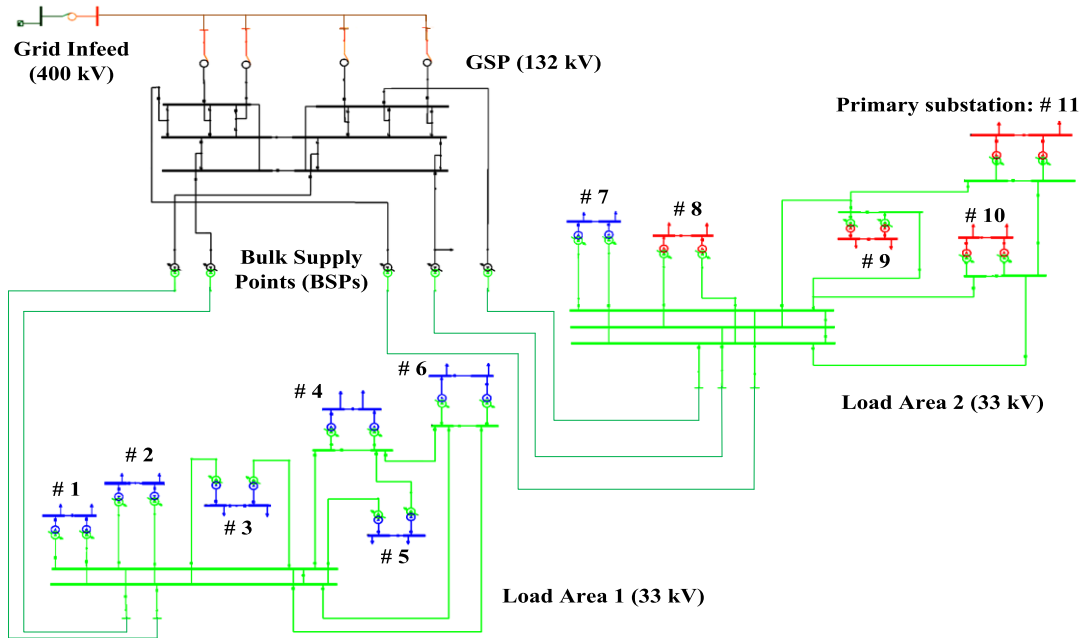The flowchart of the GA-based solution optimal algorithm is shown in Figure 2.

**FIGURE 3.** Single line diagram of 102 bus distribution network.

A power flow module is involved to calculate actual load reduction power ($P_{actual}$) in the network. Any distribution network power flow simulation tool with suitable data conversion interfaces to the GA-based solution algorithm can be used to implement this power flow module. The settings of $P_{required}$, $e_{limit}$ and $TC_{limit}$ is required for the initialization. When measuring the fitness value, the tap positions will be set firstly according to the chromosome $x$. And then the corresponding value $P_{actual}$ will be calculated through the load flow module. If the constraint of (7) is reached, the position of the OLTCs will remain at the minimum positions. If the GA generations' max number is achieved or the best fitness value in the population shows negligible changes after consecutively several generations, the GA process will stop.

## IV. STIMULATION RESULTS AND COMPARISONS

The GA-based optimization for load demand reduction method was implemented on two practical UK HV distribution networks with 102-bus and 222-bus, correspondingly. The MATLAB Global Optimization Toolbox was used to develop the GA-based optimization algorithm based on the flowchart in Figure 2. The load flow model associated the network in Figure 2 were implemented using the Open Distribution System Simulator (OpenDSS) software [35]. OpenDSS is an open-source simulation tool for power flow calculations, harmonics analyses and fault studies in electric distribution systems. It can interface with MATLAB via the Common Information Model. All network parameters can be set and changed in MATLAB. After running the network load flow, GA optimization is carried out in the MATLAB program to obtain the results. Repeating the different network parameters settings in MATLAB, load flow in OpenDSS

**TABLE 1.** Parameters of the GA optimization method.

| Parameter | Value |
|---|---|
| Population size ($N_p$) | 100 |
| Number of elites ($N_e$) | 2 |
| Crossover fraction | 0.5 |
| Maximum number of generations | 100 |
| Stall generations | 20 |
| Convergence tolerance | $1 \times 10^{-6}$ |

and optimization in MATALB, time series results were obtained.

### A. LOAD POWER REDUCTION ON 102-BUS NETWORK

The implemented GA-based optimization method has been applied to one practical distribution system as shown in Figure 3 below. The network has total 102 buses, 11 primary substations and total 33 transformers either 33/11 kV or 33/6.6 kV. All these transformers are equipped with OLTCs and each OLTC has a total of 16 tap positions. According to load modeling method in [26], the ZIP models based on real measurement data across 102 buses are used and the total loads in the networks are 170 MW and 54 MVAr.

The tap changer control has been applied to the 11 pairs primary substation transformers, i.e. $N = 11$. Since only the substation systems are involved, the 102 buses network can be simplified as a radial system. Considering a potential impact of too many tap switching operations on OLTCs [31], the limited tap changer switching operation numbers $TC_{limit}$ has been set to 4 (i.e. $M = 4$). The error (%)
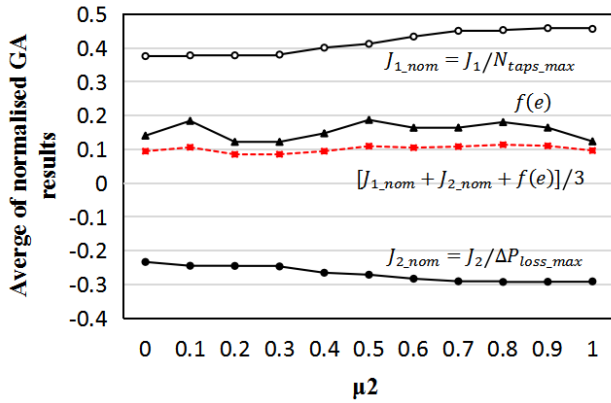
**FIGURE 4.** GA optimization results of the normalized objectives J1 and J2 and the penalty value f(e), with different weighting parameter $\mu 2$.

$e_{limit}$ between fast reserve $P_{required}$ and actual load power reduction $P_{actual}$ is set within 1% according to the accuracy required by the fast reserve service [36]. The parameters of GA-based method are set and listed in Table 1. The length of each chromosome is 11, which means there are $(1 + M)^N = 5^{11}$ possible solutions. To evaluate the effectiveness of the GA method, two previously implemented optimization methods: the rule-based control scheme and the branch-and-bound method were compared. The details of the rule-based control scheme and the branch-and-bound methods can be found in [33].

### 1) DETERMINAITON OF GA PARAMETERS

As the GA based method has number of variables, the determination of these variable initial values as start points of search is necessary. In (1), parameters of $w_1$, $w_2$ and $w_3$ were determined through a sensitivity analysis. Firstly, $w_3$ was set to 1, which ensure the GA to take the fulfilment of the active power reduction as the dominant part. $w_1$ and $w_2$ were then calculated based on (4) - (6). And then a sensitivity study was carried out to determine the weighting parameters $\mu_1$ and $\mu_2$. The study started from $\mu_2 = 0$ to 1 with a step of 0.1. According to (6), $\mu_1 + \mu_2 = 1$, for each given value of $\mu_2$, we have $\mu_1$ value. The GA ran a total of 100 times with different load power reduction requirements of $P_{required}$ increased from 0.1 MW to 5 MW with a step of 0.05 MW.

Figure 4 shows the results of the normalized objectives $J_{1\_nom}$, $J_{2\_nom}$, and penalty function $f(e)$ based on the average of the 100 optimization results for each $\mu_2$. As can be seen $J_{2\_nom}$ decreases slightly with $\mu_2$, while $J_{1\_nom}$ increases. The penalty function $f(e)$ slightly varies with $\mu_1$. The red dashed line shows the average of three variables of $J_{1\_nom}$, $J_{2\_nom}$ and $f(e)$ which does not change much with $\mu_1$ due to the interactions among the variables. This leads the determination of GA parameters of $\mu_1$ to be fixed to 0.5 to keep the balance between the optimization results on the total system power loss and the number of OLTC switching operations in the following studies.
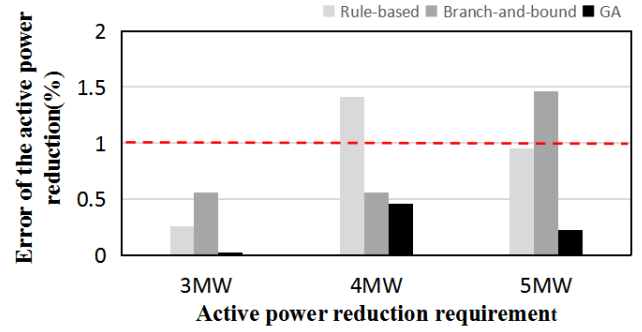


(a)    Errors in % between P$_{required}$ and P$_{actual}$
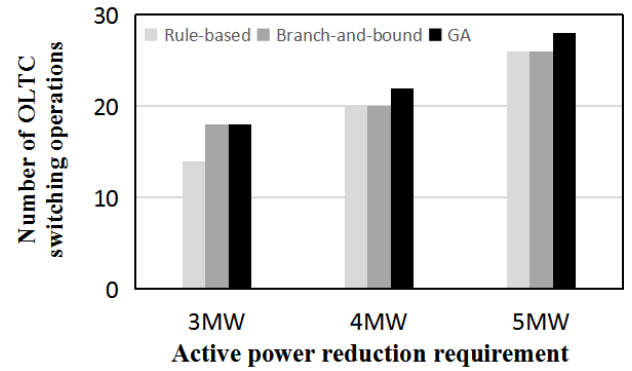


(b)    Number of tap changers switching operations
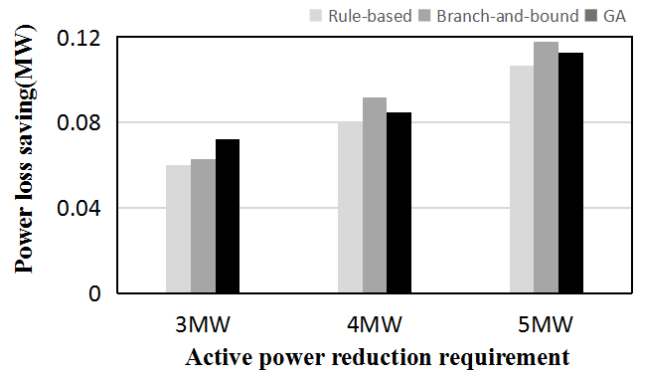


(c)    Network power loss saving introduced by tap changer

**FIGURE 5.** Optimization results with different optimization methods for the 102-bus distribution system hen e$_{limit}$ is set at 1%).

### 2) PERFORMACNES UNDER DIFFERENT P$_{REQUIRED}$

Considering the maximum loading only in the network is 120MW + 37.8MVar (70% of rated load), the performance of GA was simulated and obtained. The GA optimization method has been compared with other two methods and results are shown in Figure 5.

Figure 5(a) shows the errors $e_{limit}$ of load power reduction between $P_{required}$ required at GSP in the transmission and $P_{actual}$ provided in distribution network for three $P_{required}$ cases of 3MW, 4MW and 5MW, respectively. As can be seen that GA produce the best accuracy results for all cases which are well below 1%. However, both rule-based and

**TABLE 2.** Computation time for 102-bus distribution system studies.

| $P_{required}$ (MW) | Violation for methods at maximum load point ($e > e_{limit}$) | | | Computation time (s)[#] | | |
|---|---|---|---|---|---|---|
| | Rule Based | Branch and Bound | GA | Rule Based | Branch and Bound | GA |
| 3 | 0 | 0 | 0 | 10.65 | 14.47 | 19.26 |
| 4 | 1 | 0 | 0 | 11.29 | 14.88 | 23.15 |
| 5 | 0 | 1 | 0 | 12.54 | 27.54 | 35.47 |

[#] ON MATLAB VERSION 7.11 AND WITH I7-3.4 GHz / 8 GB RAM

branch-and-bound methods may sometime be higher than the required accuracy of 1%. This is because both methods estimate the value of $P_{actual}$ using linear approximation rather than calculating it through load flow studies.

As expected, the results in Figure 5(b) show that the total number of OTLC switching operations are increasing as $P_{required}$ increasing from 3 MW, 4MW and 5 MW, respectively. Results also show GA optimization method has a lightly increasing number of OLTC switching operations in comparing with other two methods under $P_{required}$ of 4 MW and 5 MW, respectively. Rule-based optimization has smallest number of OLTC switching operations. This may be explained that GA method took a few more steps to ensure that the errors are below the required 1%, hence more accurate results than other two methods were obtained.

As shown in Figure 5(c), if comparing with rule-based method, GA approach has slightly more power loss saving than rule-based method for all cases. This may also be explained that that rule-based method uses load flow study knowledge for prioritizing selection of those OLTCs that would produce more load power reduction contribution to $P_{actual}$ with minimum tap switching operations. As a result, the lowest number of taps switching operations leading to lowest network losses. When comparing GA with branch-and-bound method, it has slightly higher loss than the branch-and-bound method when $P_{required}$ at 3MW, but it has less losses than the branch-and-bound method when $P_{required}$ at 4MW and 5 MW, respectively. This may be explained that GA method may get more quicker and more efficient to search the solution when tap operation numbers associated with $P_{required}$ are increased when comparing them with small tap operation numbers.

The computation time for the GA method, the rule-based and the branch-and-bound methods are monitored during the simulation. Results are listed in Table 2.

For 102 buses network, the GA approach takes a longer time to find the solution than both rule-based and the branch-and-bound methods. This may be explained that the 102 buses network is radial with small number of transfer tap changers. It would be easier for both rule-based and the branch-and-bound methods to use linear approximation calculation, but GA method has still to calculate the load power reduction through load flow studies. However, GA method has achieved the required accuracy of less than 1% for all cases.
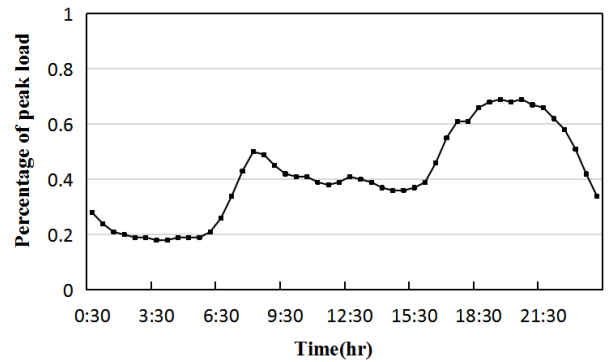


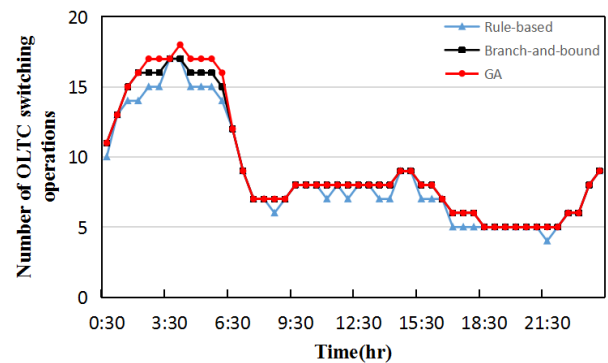**FIGURE 6.** Load profile used in 102-bus distribution system.



**FIGURE 7.** Number of OLTC switching operations for 3 methods using summer load profile.

### 3) TIME-SERIES STUDIES

From the data provided by the UK Energy Research Centre, a typical daily domestic load profile has been selected to perform the time-series studies [37]. As illustrated in Figure 6 there are 48 load points with a half-hour interval over 24- hours.

In this 102 network study assuming a required power reduction of $P_{required}$ is 2MW. The numbers of all tap changers operations to produce the required 2MW load demand reduction in corresponding to each one load profile point under 24 hours for of all three optimization methods, respectively, are simulated and illustrated in Figure 7. Both GA and the branch-and-bound approaches show very close results except for those in the early morning between 2:30am – 5:30am when loads are very light. To achieve the required load power reduction of 2MW, a lower demand requires more OLTC tap switching operations than a higher demand. Also GA method shows slightly a few more OLTC tap operation numbers than the Branch-and-bound during the early morning between 2:30am – 5:30am. The rule-based method has less OLTC tap switching operations than both GA and branch-and-bound methods as the rule-based method does not have the load flow correlation of tapping transformers at different locations.

### B. LOAD POWER REDUCTION STUDIES ON 222-BUS NETWORK

GA method along with other two optimization methods are also simulated and tested using HV 222 bus network with 28

**TABLE 3.** 24-h optimization results for the 222-bus distribution system.

| $P_{required}$ (MW) | Number of violations over 24 hours (48 load points) (e > $e_{limit}$) | | | Computation time (s)# | | |
|---|---|---|---|---|---|---|
| | Rule Based | Branch and Bound | GA | Rule Based | Branch and Bound | GA |
| 3 | 10 | 2 | 0 | 399.23 | 4697.43 | 2023.45 |
| 4 | 27 | 2 | 1 | 412.32 | 5613.23 | 3174.09 |
| 5 | 14 | 5 | 0 | 417.23 | 4609.74 | 2355.48 |

# ON MATLAB VERSION 7.11 AND WITH I7-3.4 GHZ / 8 GB RAM

primary substations. The total network demand is 427 MW + 127 MVAr. The setting of the GA parameters also based on the TABLE 1. The number of tap operation and the error percentage of the active power reduction is analyzed with different load active power reduction requirement. The GA method has considered 28 substation transformers, i.e. $N = 28$ and the load power reduction error is again set to < 1%.

### 1) COMPUTATION TIME

The studies used the same 24-hour load profile as shown in Figure 6. Table 2 shows (i) the number of violations of the load power reduction requirement, i.e. errors $e_{limit}$ exceeding 1%, over the 24 hours period for three different $P_{required}$ of 3MW, 4MW and 5MW, respectively, and (ii) the computation time for the 24-h optimization studies.

As can be seen from Table 3, the GA method has the least number of violations among all the testing results. The rule-based method shows the most numbers of violations, i.e. error of $e_{limit}$ exceeding 1% setting. In contrast, the GA method shows no violations exceeding 1%. The studies confirm that the GA approach can achieve accurate and robust control of the tap changing operation under different load power reduction targets and at various load levels.

As can also been seen from Table 3, although the rule-based method can provide much faster control than both branch-and-bound and GA approach, it deeply relies on the fixed-sequence selection of tap changers. Results show many violations over 24 hours optimization studies. Both branch-and-bound and GA methods show smaller violations, but GA has the least violations. By comparing the computational time for 24 hours optimization studies between GA and the branch-and-bound, GA has the faster solution computation time than the branch-and-round method. The search solution speed change from the fact that the search space in 222-bus system is $5^{28}$ for the GA, which is significantly less than the $2^{112}$ of the branch-and-bound method. In this case, the GA approach shows more efficiency in determining the optimal solution in a large distribution system.

### 2) GA PERFORMANCE WITH 10% LOAD VARIATIONS

In order to study the impact of load variation on the performance of GA method, the original 24 hours load profile is randomly changing by 10% variations. There are total 50
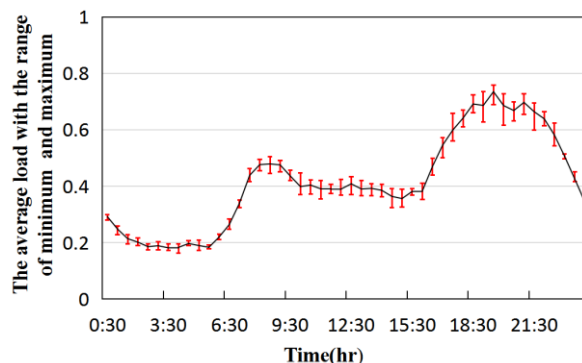


(a) load profile changing range
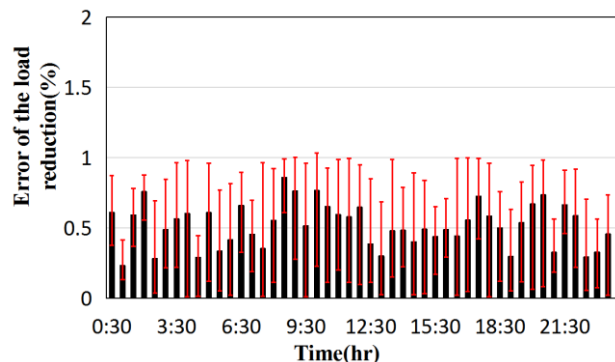


(b) Percentage difference between $P_{required}$ and $P_{actual}$

**FIGURE 8.** Load changing range and error range of the GA approach.
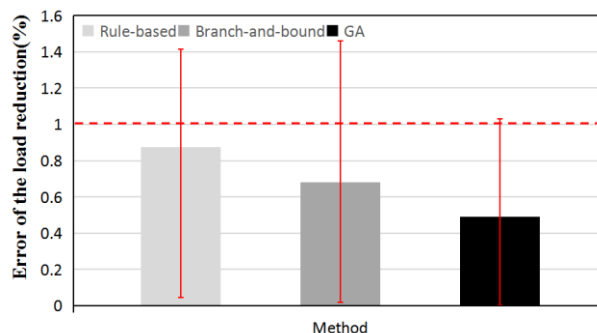


**FIGURE 9.** Average of load reduction errors of 3 control methods over 24-hours optimization studies.

randomly generated load profiles used in this case study. And the corresponding average, maximum and minimum active power reduction error, $e_{limit}$, over the 24-hours period is shown in Figure 8(a).

Since 222 buses network can provide more than 10MW load demand reduction based on the measured ZIP load models, in this study assuming a required power reduction of $P_{required}$ is set at 10MW. The corresponding average, maximum and minimum load demand reduction error over the 24-hours period is shown in Figure 8(b). The error range shows in the Figure 8(b) could keep below 1% (error limitation) when the load is changing randomly within 10%.

The results confirm that the GA method can still maintain the load power reduction accuracy within 1% under different load level and load variation. This is because GA uses 1% of $e_{limit}$ as one of search solution targets.

By taking the average of errors over 24-hours optimization studies based on the results in Figure 8(b), the average, maximum and minimum load power reduction average error of GA over 24-hours optimization studies is shown in Fig.9. Similarly, results of both rue-based and branch-and-around methods over 24-hours optimization studies are also calculated and shown in Figure 9.

As shown in Figure 9, the GA method can satisfy the load power reduction target within the 1% tolerance throughout the 24-hours period. However, the other two methods exist violations of the load power reduction response requirement.

## V. CONCLUSION
This paper has presented the use of Genetic Algorithm (GA) to optimize voltage-led customer load active service in distribution networks. Two practical 102 buses and 222 buses UK distribution networks based on real data are modelled and used to test the effectiveness of the GA-based tap changer optimal control strategy under different operating conditions. The performances of the proposed method are also compared with both the rule-based and the branch-and-bound methods.

Under the small 102-bus system studies, GA approach takes longer time to find the solution than both rule-based and the branch-and-bound methods. However, GA method has achieved the required accuracy of less than 1% for all cases. Under the large 222-bus system studies, GA can find the solution not only faster, but also more accuracy than both the rule-based and branch-and-bound control methods

In summary, the studies confirm the proposed GA optimal control approach is more effective by achieving more accuracy and a faster solution for a large distribution network than other two methods. Thus, the proposed method satisfies the fast reserve service requirements in term of the accuracy for the load demand reduction delivery of less than 1% within 2 minutes in the studies.

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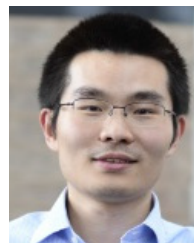
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