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Mid-term operational planning of pre-installed voltage regulators in distribution networks

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ABSTRACT

In this paper, a methodology is presented to maximize the effectiveness of pre-installed Voltage Regulators (VRs) in medium voltage distribution networks. While considering the daily tap operation limitation of VRs, this method contains mid-term operational planning of VRs' settings which is carried out to satisfy voltage constraints in distribution networks and reduce power losses throughout the network. The proposed approach optimizes the settings periodically, leading to Distribution System Operators (DSOs) ' financial benefit because energy losses are reduced by applying the proposed method. Using different combinations of ZIP load model coefficients in the optimization process, the importance and impacts of the load model in the optimization of VRs' settings are also investigated because the operation of a VR directly influences the consumption of voltage-dependent loads (depending on their type of voltage dependency). Due to the discrete nature of the problem, the Genetic Algorithm (GA) has been employed as a tool to attain the previously mentioned goals by optimizing the settings of VRs for forthcoming months. Numerical studies carried out for a 70-bus distribution network show that a reduction of energy loss is achieved by applying the article's proposed method.

1. Introduction

Transformers equipped with On Load Tap Changers (OLTCs)[1], Voltage Regulators (VRs), and transformers with constant tap position known as Off Load Tap Changers (OFF-LTCs) are transformer-based voltage control components being utilized in distribution networks. A distribution network's needs define where to deploy those components considering the components' features and abilities. A VR operates like an OLTC, making it possible to dynamically change the turn ratios considering the local or network state. Unlike OLTCs and VRs, OFF-LTCs lack dynamic features and operate with fixed tap ratios (i.e., tap ratios are altered manually).

As depicted in Fig. 1, an essential difference between an OLTC and a VR is that the OLTC works between two different voltage levels (e.g., High Voltage (HV) to Medium Voltage (MV)) for the sake of voltage level change (e.g., HV to MV). In contrast, a VR connects the same voltage levels (e.g., MV to MV) to regulate voltage within voltage constraints. As another difference, primary and secondary windings are magnetically coupled in OLTCs, while there is an electrical connection between common and series windings of VRs because VRs are autotransformers in nature [1].

As Distribution System Operators (DSOs) always need to maintain the network's voltage under various load levels within the acceptable limits, OLTC and VRs are precious devices for them due to their dynamic behavior. DSOs usually install OLTCs and OFF-LTCs in primary and secondary substations, respectively, as shown in Fig. 1; nevertheless, OLTCs can substitute OFF-LTCs in secondary substations because of OLTCs' dynamic voltage controllability feature. Using OLTCs in LV networks becomes more attractive when voltage variations of the LV network rise due to the high penetration of photovoltaic (PV) generation and electric vehicles (EVs) [2]. Although OLTCs can be deployed in secondary substations, OFF-LTCs are still being utilized in secondary substations because the number of secondary substations is large in distribution networks and OFF-LTCs are cheaper with lower maintenance costs than OLTCs. From a control perspective, an advanced supervisory control in the DSO control center is required to assure the proper and coordinated functioning of a large number of secondary

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[1] To favour the readability of the text, a transformer equipped with OLTC is called OLTC and a transformer with OFF-LTC is noted OFF-LTC.

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Nomenclature

V_t	Terminal voltage
i	Increment
d	Decrement
Timer i	Tap increment timer
Timer d	Tap decrement timer
Y	Yes
N	No
$Tap(\min)$	Minimum tap step
$Tap(\max)$	Maximum tap step
$V(\max)$	Maximum voltage limit
$V(\min)$	Minimum voltage limit
nPop	Number of GA population
m	Number of iterations
K	Counter
OBJ	Objective function
Δt	Delay
UP	Up set point
DP	Down set point

substation OLTCs. Therefore, some DSOs still prefer OFF-LTCs to OLTCs in secondary substations. Alternatively, to be cost-effective and to adopt a dynamic voltage control along with the medium voltage network, a few VRs can be efficiently added to MV feeders where needed. Indeed, having VRs installed along with the MV feeders, as shown in Fig. 1, the dynamic voltage controllability of OLTCs in the primary substation is accompanied by the dynamic voltage controllability of VRs along the MV feeders meaning that the voltage of the whole MV lines becomes controllable to some extent. In this way, a combination of an OLTC in the primary substation and a few VRs in MV feeders are proposed to DSOs facing voltage violations in MV or even LV networks. Since VR's settings play a vital role in VR's operation, those settings should be optimized after adding VRs to the MV network, which is this paper's topic. The point is that if VRs' settings are kept constant for the lifetime of the VRs, the maximum efficiency of VR in the distribution network cannot be harvested.

This paper aims to clarify the mid-term operational problem on how VRs' settings can be optimized and what factors influence the setting optimization of VRs. VRs with fixed settings are considered for the reference scenario. The VRs' settings are then optimized for a season ahead, assuming that all VRs have already been in use across the MV network, which means the paper deals with the mid-term operational problem, not planning (i.e., VR placement).

1.1. Literature review

The primary substations usually use the Line Drop Compensation (LDC) technique to adapt the OLTC' Automatic Voltage Regulator (AVR) reference value based on the flowing current of feeders, as shown in Fig. 1. The LDC technique used in primary substations can also be used in MV networks where VRs exist, provided that Current Transformers (CTs) are available at the VR bus to measure flowing current. VRs' settings can be optimized either through the paper's proposed approach or via the LDC technique. As LDC is one method of solving the paper's raised problem, reviewing the LDC technique's literature seems beneficial. It is worth mentioning that in Section 5, a discussion regarding the presented approach's features and the LDC technique will be offered.

By taking advantage of CTs, LDC-based solutions can adapt the reference values of VRs based on the load current. In [3], a closed-form solution for tap optimization of VRs according to the impedance and flowing current of multiple feeders has been suggested. The Branch and Bound method has been used as a solver of the integer optimization

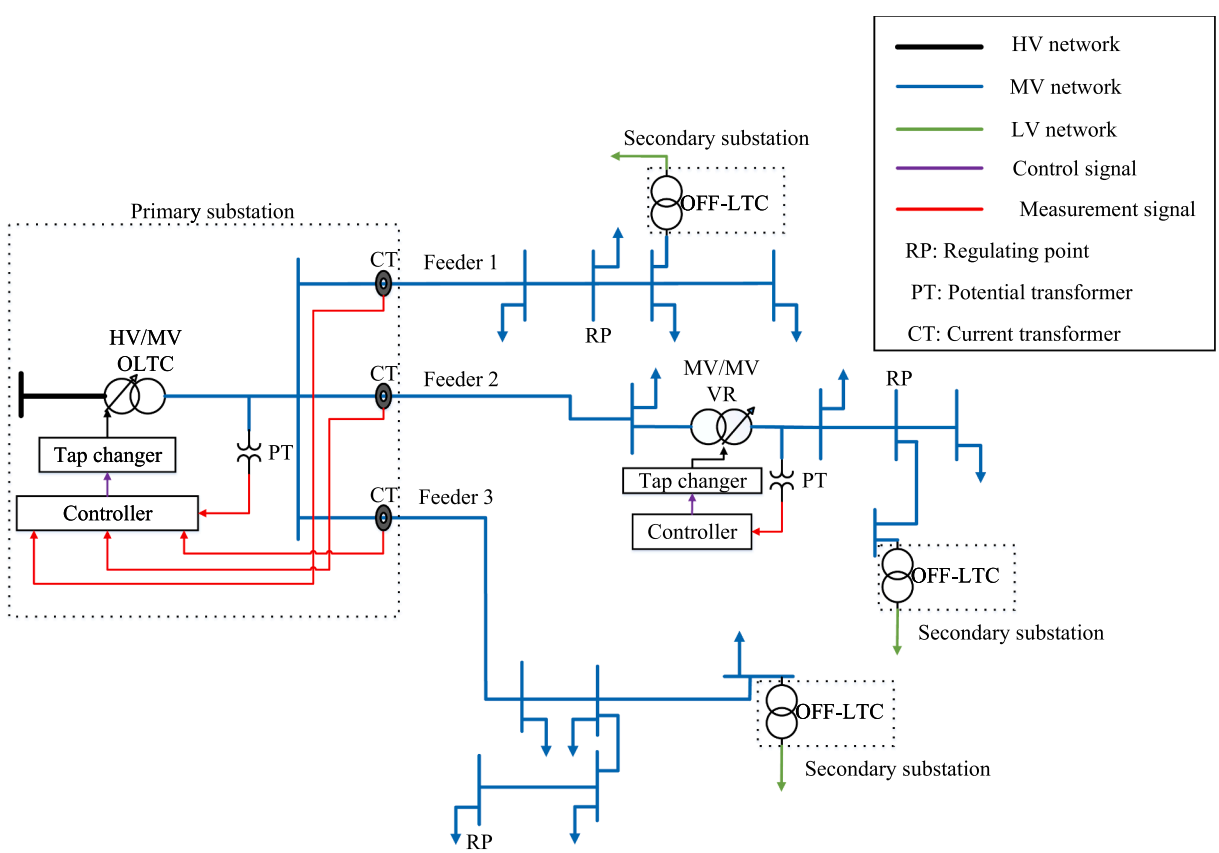

Fig. 1. One-line diagram of a symbolic radial distribution network.

problem inside each VR microcontroller. Since the optimization algorithm should continuously optimize the Tap Positions (TPs), this approach is classified as a real-time solution. Not using the power flow for optimizing the TP is an advantage of the paper at the cost of not optimizing power losses because power flow is required for power loss optimization. Although the method of [3] is practical, it needs CTs in the location of VRs, which makes the solution inapplicable when CTs are not available (i.e., due to any reason). Besides, as mentioned, the distribution network's power loss is not considered while optimizing the TPs. Also, due to time limitations in real-time operations, solutions based on real-time optimization such as [3] cannot embrace a multiobjective fitness function because the search space then becomes large and impossible to deal with considering that the microcontroller in the location of VR responsible for the optimization has minimal computational power.

Control of voltage regulators in distribution networks using Neural Networks (NNs) has been addressed in [4]. The measured real power (P) and reactive power (Q), as well as voltage amplitude at selected buses, are the inputs of the NNs. In [4], a voltage regulation method with dispersed storage and generation (DSG) has been presented. The TP of the OLTC is the optimized variable. Accessing active and reactive power at each node as inputs of the optimization algorithm is one of the assumptions of [4,5], which disables those approaches in some distribution networks where data exchange is impossible or at least very limited.

Reference [6] attempts to achieve a power loss reduction by selecting the primary substation's transformer settings. An equivalent T-shaped network has been considered to obtain compensation impedance of feeders to be used by the LDC technique. Power loss depends on the Regulating Point (RP) voltage, which has shown those observing it that by increasing the regulating point voltage, the power losses will be increased and vice versa. It could be added that the mentioned correlation between power losses and regulating point voltage is valid if the load model maintains constant impedance.

Distributed Generation (DG) penetration has been increased during recent decades due to the power system restructuring process. These DGs remarkably impact voltage control approaches in distribution systems. These impacts have generally have been investigated in [7]. [8] has mainly studied unbalanced PV-based DGs' challenges in low voltage distribution systems from the viewpoint of voltage control methods. Also, some solutions have been presented by this reference to overcoming these difficulties. To maximize the benefit of these DGs as well as minimize their harmful effects, some studies have concentrated on Volt/Var optimization in traditional distribution systems [9,10] and restructured distribution systems [11]. To increase the expandability and flexibility of systems, distributed control architectures have been the center of attention. In this way, [12] has focused on distributed control of Modular Multilevel Converter (MMC) system.

Control parameters of VRs, including reference voltage, dead band, and delay of the tap changer, have been optimized in [13]. The control variables of multiple VRs across the MV lines are optimized through a central control system every 15 Min; however, it is not clear the used optimization algorithm in the control center. The proposed method in [13] is communication dependant; therefore, it might not work for distribution networks without communication infrastructure or with a limited communication possibility. The point is that a proposed solution for setting optimization of VRs should be able to handle the situation when communication is limited (i.e., remote areas) or wholly lost (e.g., failure).

Taking the aforementioned into consideration, in line with the distributed voltage control architecture, an attempt has been made in this paper to maximize the applicability of VRs by optimizing their settings by an offline method where communication is not needed. Offline refers to the procedure that entails optimizing the VRs' settings seasonally, unlike online methods where optimization is required continuously (i.e., every few minutes) when the state of the network changes.

Without loss of generality, the following assumptions should be made when assessing this paper:

- The DSO can forecast the medium-term data (time-series of consumption, load model) across the network.
- The network information, including location, number, and rating of pre-installed VRs, are available.
- The distribution network is traditional in the sense that communication infrastructures do not exist.

1.2. Motivations and innovative contributions

Fewer inclinations for electricity suppliers to use VRs can be seen from various standpoints. Apart from the higher price of VRs than OFF-LTCs, expectations of a DSO regarding the voltage quality improvement and reduction of power losses are not usually fully satisfied by VR utilization. Those two reasons mainly actuate DSOs to explore other alternatives (e.g., using OLTCs in secondary substations). Nevertheless, suppose VRs are used efficiently with proper settings. In that case, their effects on voltage improvement and power loss reduction are substantial because the tap changing of VRs has an immediate impact on voltage and power losses.

This paper will establish the following innovative contributions:

- A new and practical method of voltage control based on offline settings optimization.
- The importance of the optimization of the settings of VRs in the mid-term operation of distribution networks.
- The impact of load models in VRs' setting optimization.
- The impact of load model prediction error on the VRs' settings optimization and performance of the distribution network.

It is worth mentioning that this paper is subsequent research of the reference [14].

1.3. Paper's approach

It seems beneficial to explain how the offline approach of the paper is realized in practice for DSOs. The approach involves optimizing the VRs' settings for a fixed period (a season ahead) which in this paper is called an offline solution. Indeed, settings are optimized for three months planning horizon, meaning that setting optimization is repeated seasonally, according to Fig. 2. Every time, once the new settings are found through optimization, these new settings are applied to the controllers [14] of each VR by a field crew team from the DSO because it is assumed that communication infrastructure does not exist to apply new settings to VRs remotely. This is the basic concept of this work which is explained further with more details in the following sections.

With the availability of communication infrastructure at the location of all VRs, the real-time approach based on real-time optimization could

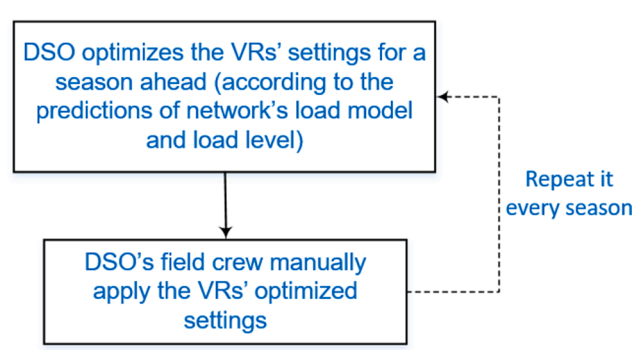

Fig. 2. General workflow of the proposed approach.

be more beneficial than the offline approach. Nonetheless, this paper assumes that communication is not available for the under-study distribution network because, in reality, many distribution networks still lack a reliable communication infrastructure. Another use case of the presented approach can be when a VR that relies on the communication system loses its communication channel (due to any reason), so the settings based on this paper's offline approach can be used as back-up/default settings. Therefore, to avoid an arbitrary behavior of VRs, solving what to do when a VR is in stand-alone mode without access to a communication system is valuable.

1.4. Paper's structure

The structure of the paper is comprised of 6 sections. The introduction containing the literature review and motivations was described in Section 1. The problem is introduced in Section 2. In Section 3, the problem is formulated, constraints are stated, and the optimization algorithm is presented. Numerical studies and discussions about achieved results are shown in Section 4. A discussion regarding the setting optimization approaches and their features is provided in Section 5. The conclusion is provided in Section 6.

2. Problem description

VRs are mainly used as a remedy to voltage quality issues in distribution networks as well as to reduce power losses. The operation of a VR is dependent on time, delay, and the type of tap movement (step up or step down), considering that these factors influence the achieved efficiency of a VR in a distribution network. An explanation will be provided here to understand the operational mechanism of a VR and to clarify how a VR affects the voltage profile.

Autotransformers' applications vary from a starter of induction and synchronous motors to voltage stabilizers and regulators. The autotransformer useful in distribution networks is named voltage regulator (VR). Fig. 3 illustrates how a VR can regulate the voltage of its secondary side by its tap changer. Equation (1), a and b explain the operation of a VR on increment and decrement mode, respectively where $V1$ and $V2$ are representative of primary and secondary voltages and N_c and N_s stand for turns of common and serial windings, respectively [15]. If the VR is in increment mode, the number of secondary-side winding turns becomes larger than the primary-side winding turns, leading to voltage rise and vice versa.

$$\frac{V_1}{V_2} = \frac{N_c + k_1 N_s}{N_c + k_2 N_s} \quad \begin{array}{l} k_1 = 0, k_2 = 1 \text{(a} \\ k_1 = 1, k_2 = 0 \text{(b} \end{array} \tag{1}$$

At each VR bus, a Potential Transformer (PT) exists to measure voltage magnitude, according to Fig. 4. The controller continuously monitors the measured voltage of a PT (the red signal called Vt in the figure) because the controller is responsible for keeping that voltage at acceptable limits. In other words, the controller acts as the VR's brain. The controller's decision is made according to an algorithm considering Vt magnitude. In the control algorithm, as shown in Fig. 3, the VR settings, including the Up setpoint (UP) and Down setpoint (DP) are defined for the controller (i.e., through an optimization process) so that the controller attempt to maintain the voltage between these boundaries. Based on the algorithm, if Vt is larger than the UP, tap decrement is needed, whereas for a Vt smaller than the DP, tap increment is necessary. No tap movement is required when Vt is between the DP and the UP.

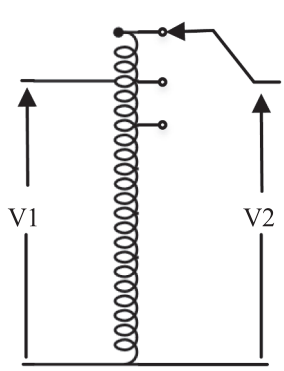

Fig. 3. Voltage regulator (autotransformer).

To better understand how the controller behaves, a tap increment example is pointed out based on the control algorithm in Fig. 3 as follows (some blocks in Fig. 3 have been numbered):

1. Let's assume that $V_t < DP$ based on block number 1.
2. Tap decrement timer (Timer d) resets based on block number 2.
3. Tap increment timer (Timer i) starts counting based on block number 3.
4. In block number 4, if the value of "Timer i" is larger than a pre-specified delay (e.g., 10 s), block number 5 is triggered.
5. In block number 5, if at least one tap step exists for tap increment, block number 6 is triggered.
6. Block number 6 sends the tap increment command (purple signal) to the tap changer for execution.

The controller in Fig. 4 can perform a similar action when Vt is larger than UP, leading to tap decrement. It is worth mentioning that a timer and delay have been embedded in the controller decision-making process to avoid unnecessary tap changes due to the voltage transients because the tap changer is supposed to only react to permanent voltage changes.

Regarding the setpoints, some considerations such as equation (2) should be taken into account.

$$|DB| = (UP - DP) > V_{step} \tag{2}$$

where V_{step} represents the voltage corresponding to one tap step. The Dead Band (DB) should be larger than one tap step voltage to avoid an endless tap changer attempt (hunting). As no action is required when the voltage stays inside the DB, it has also been termed an insensible area [16].

Fig. 5 is a practical example of VR's operation during under-voltage situations. It should be emphasized that VR set points (UP and DP), as depicted in Fig. 5, are always between the maximum and minimum permissible voltage limits.

As illustrated in Fig. 4, the red signal (Vt) is compared to the DP and UP's value for tap movement decision. The problem is figuring out what UP, and DP's optimum values are, which will be discussed in Section 3.4.

3. Problem formulation

In this section, the Objective function (OBJ), constraints, and the optimization algorithm will be presented.

3.1. Objective function

The OBJ is comprised of two terms: Total Energy Losses Reduction Benefit (TELRB) and Total Cost of Field Implementation (TCFI). The subtraction of these two terms forms the OBJ, which is introduced as a maximization problem.

The power losses under two different conditions are calculated. The first is the power losses from the distribution network under the condition that the settings (UP and DP) of VRs have not been optimized and the same for all the pre-installed VRs (fixed values of 1.01 and 1.04p.u. are used for DP and UP respectively). Secondly, by applying the presented approach and optimizing the UPs and DPs for all the pre-installed

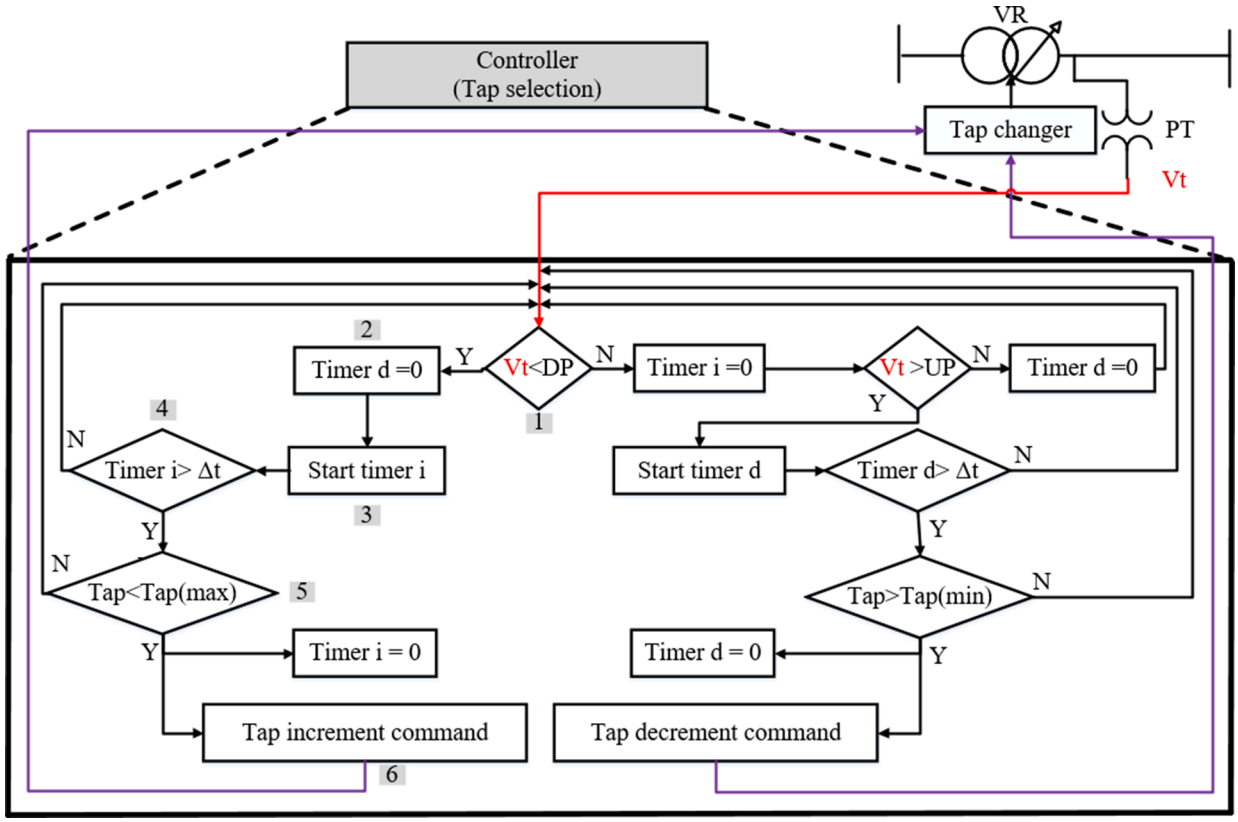

Fig. 4. The control algorithm of VR.

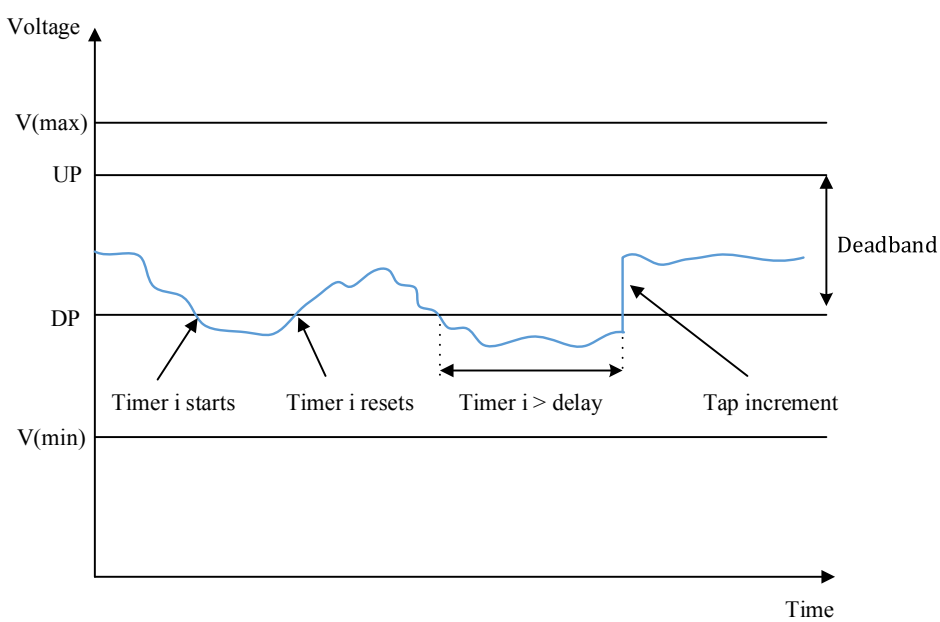

Fig. 5. Operation of a VR.

VRs by using the GA, the network's power losses are calculated. The subtraction of these two terms (power losses) for every hour of operation throughout the network will provide the energy loss difference between the two conditions according to Eq. (3):

$$TELRB = \sum_{n=1}^{N_D}\left(\sum_{j=1}^{N_L} K_e T_j \left(P_{lossB}^{j,n} - P_{lossA}^{j,n}\right)\right) \quad (3)$$

where N_L is the number of load levels; K_e is the rate of benefit for power loss reduction in $\frac{€}{kWh}$; $P_{lossB}^{j,n}$ is the power losses of jth load level in the nth before the VRs' settings optimization in terms ofkW while $P_{lossA}^{j,n}$ is the power losses of jth load level in the nth day after the VRs' settings optimization in terms ofkW. N_D is the mid-term operation horizon length (day) and T_j is the duration of j^{th}load level per hour. To calculate the network's power losses ($P_{lossB}^{j,n}$, $P_{lossA}^{j,n}$), backward-forward sweep power

flow [17–20] has been used, taking into consideration that any other valid power flow method could be substituted.

As the operational problem has been solved in this paper, the paper also regards the implementation costs to the distribution companies that wish to apply the presented solution to demonstrate that the proposed approach is a practical, real-world solution. Distribution companies should change the settings of the pre-installed VRs according to the optimized settings of this paper. Therefore, the cost of an execution team from a DSO is regarded as TCFI. Indeed, the TCFI is affected by factors such as the execution team's wage, transportation cost (fuel, vehicle, etc.), length of the feeder (traveling time), the density of the population (traffic), and time of the settings adjustment, etc. Therefore, for each DSO, the TCFI can be different.

$$TCFI = N^{*}Cost_{FI} \tag{4}$$

In Eq. (4), N is the number of pre-installed VRs that need setting adjustment and $Cost_{FI}$ represents the Cost of Field Implementation per VR. In other words, $Cost_{FI}$ covers all the implementation costs paid by a DSO to dispatch a field crew to a VR setting for the settings adjustment. Finally, by subtracting TCFI from TELRB, the OBJ can be achieved, as it is shown in (5).

$$OBJ = TELRB - TCFI \tag{5}$$

One of this paper's contributions is the consideration and investigation of the effects of the load model in optimizing the settings of VRs; hence, the ZIP load model has been taken into account. Since the voltage is always changing because of the tap movements of VRs, the drawn power of loads might be affected based on their load model, which is calculated by (6) [21].

$$P = P_o\left[Z_p\left(\frac{V}{V_o}\right)^2 + I_p\left(\frac{V}{V_o}\right) + P_p\right] \tag{6}$$

where $Z_p, I_p, and P_p$ denotes constant impedance, current, and power coefficients, respectively. V_o and V represent the reference and generic voltage of the load, respectively. The corresponding power of V_o is called P_o and power calculated under the new generic voltage of V is P.

3.2. Problem constraints

3.2.1. Bus voltage constraints

The Eq. (7) is applied to the voltage of buses:

$$V^{min} \le V_{i,j,n} \le V^{max} \tag{7}$$

$$\forall i \in \{1, 2, \cdots, N_{bus}\}, \forall j \in \{1, 2, \cdots, N_L\}, \forall n \in \{1, 2, \cdots, N_D\}$$

where V^{min} and V^{max} are lower and upper allowable limits of voltage; $V_{i,j,n}$ is the voltage magnitude of ith bus in j^{th}load level and in n^{th} day; N_{bus} is the total number of buses.

3.2.2. Line current constraints

The next constraint is Eq. (8) for the current of branches.

$$I_{b,j,n} \le I_i^{max} \tag{8}$$

$$\forall b \in \{1, 2, \cdots, N_{branch}\}, \forall j \in \{1, 2, \cdots, N_L\}, \forall n \in \{1, 2, \cdots, N_D\}$$

$I_{b,j,n}$ is the magnitude of the current flowing over the bth branch in j^{th}load level and in n^{th} day. I_i^{max} is the maximum allowable current of the bth branch. N_{branch} represents the total number of branches in the distribution network.

3.2.3. VR related technical constraints

The following voltage-related constraints should be abided.

$$V^{min} = 0.95, V^{max} = 1.05 \tag{9}$$

$$UP - DP \ge 0.02 \tag{10}$$

$$0.98 \le UP \le V^{max} - 0.01 \tag{11}$$

$$V^{min} + 0.01 \le DP \le 1.02 \tag{12}$$

Constraint (9) contains two equalities representing the minimum and maximum allowable voltage of the network. Constraint (10) shows that the minimum value of the DB is 0.02 p.u. Constraint (11) defines a 0.01 p.u. margin between V^{max} and UP. Without this margin for the time durations when the voltage is more than UP, the network experiences a voltage violation because the tap changing operation has a certain delay, as shown in Fig. 4 (Δt). This delay is needed to make sure that the voltage rise is permanent. With a similar mechanism; (12) specifies a margin between V^{min} and DP to avoid under-voltage situations when Timer i is counting.

3.2.4. Current constraint of VRs

To avoid a situation where too much current flows through a VR, Eq. (13) should be obeyed:

$$I_{k,j,n}^{reg} \le I_k^{\max(reg)} \tag{13}$$

$$\forall k \in \{1, 2, \cdots, N_{VR}\}, \forall j \in \{1, 2, \cdots, N_L\}, \forall n \in \{1, 2, \cdots, N_D\}$$

where $I_{k,j,n}^{reg}$ represents the magnitude of the flowing current through the kth voltage regulator in j^{th}load level and in n^{th} day, $I_k^{\max(reg)}$ is the maximum allowable current of the kth voltage regulator. N_{VR} represents the total number of pre-installed VRs in the distribution network.

3.2.5. Tap operation constraint

It is an undeniable fact that the number of tap operations per day is a confining factor affecting the maintenance costs of VRs. Therefore, the following constraint [10,22] should be satisfied for each of the pre-installed VRs while optimizing their settings by the GA.

$$\sum_{h=1}^{24} |Tap_h - Tap_{h-1}| \langle Tap_{max} \tag{14}$$

where Tap is the tap position of each VR in hour h. As long as the accumulative daily tap operations for each VR is less than Tap_{max} (30 in this case), the constraint is obeyed.

It is worth mentioning that the given constraints are considered hard constraints; therefore, the final optimization solution must obey them. Solutions violating constraints (7–14) are heavily penalized for reducing their fitness. Consequently, they become less eligible to be transferred to the next generation, leading them to extinct. Indeed, the penalization technique helps the GA exploring fully obedient solutions. Therefore, the GA's global optima (in the last iteration) fully obey (7–14); otherwise, it is not considered the solution.

3.3. Genetic algorithm

Since the problem is identified in this section so far, a methodology to solve the raised problem should be discussed. This problem is introduced as an optimization task for GA to find the best set points (UP and DP) of pre-installed VRs in a distribution network. The GA accurately matches discrete problems [23], suitable for a more significant number of variables, and also appropriate for nonlinear objective functions (i.e., power loss reduction) [24]. The GA has some benefits for this specific problem; nevertheless, it can be replaced by other metaheuristic search methods such as Particle Swarm Optimization (PSO) [25,26] or Tabu Search (TS) [27] because it is deployed as a tool, and there is no claim over the merit of optimization algorithms in this study. It should be noted that tunning the GA parameters such as the probability of single-point, double-point, and uniform cross over as well as population size

(*nPop*), the number of iterations (*m*) and the mutation ratio have been done using the trial and error method.

The selection of crossover type has been made using Roulette Wheel (RW) selection method. The probability of using single-point, double point, and uniform crossover are 0.1, 0.2, and 0.7, respectively. Also, the mutation ratio is considered to be 0.03.

Fig. 6 illustrates the chromosome's structure. To fill the chromosome's arrays, the corresponding arrays of the top and bottom rows where a VR is deployed are then filled with a randomly selected value subject to $0.98 \leq UP \leq 1.04$ and $0.96 \leq DP \leq 1.02$, respectively.

After knowing the chromosome structure, now Fig. 7 illustrates how the GA optimizes the UP and DP. As shown in the initial stage, the UP and DP are randomly chosen by the GA. Afterward, power flow is used to obtain the voltage magnitude of VR buses. The grey block (tap selection) is used to change the VRs' tap (based on the voltages and random settings) to put the voltage in the acceptable limit (if voltage violation exists) according to what was explain in Fig. 4. If the tap changer operates, then power flow should be executed again to update the voltages. Suppose tap changers of any of the VRs do not operate. In that case, the chromosome will be evaluated according to Objective Function (OBJ) terms, and the chromosome is considered a solution candidate in the initial population. The chromosome creation is continued until reaching the desired number of population (nPop). Once the first generation is built, the crossover and mutation operators will create offsprings and mutants and form the new generation population. Afterward, members of the new population are evaluated individually. Subsequently, once the whole new population is evaluated, then they are merged to be sorted out according to their OBJ values. Solution candidates with a better objective function value create the next generation population (become parents of the next generation), and the rest of the solution candidates are truncated because the GA functions based on elitism. The process continues unless reaching the maximum number of iterations. When the maximum iteration number is reached, the first solution candidate of the population (with the best OBJ value) is identified as the answer of GA to the UP and DP optimization problem.

One of the advantages of offline setting optimization is that the optimization process can be repeated several times to avoid local optima since there is no time restriction in the offline approach, unlike online approaches that reaching the optimum solution should be done as quickly as possible otherwise, the control system may behave unexpectedly. Therefore, in the presented method, the optimization of VRs' settings has been repeated several times to ensure the optimization process's maturity. Nevertheless, none of the optimization algorithms, namely GA, Particle Swarm Optimization (PSO), etc., cannot safely claim to find the global optima keeping in mind that the merits of optimization algorithms are not the topic of the paper.

4. Numerical studies

A reference scenario followed by three main scenarios will constitute the numerical studies in this section. The first case study aims to show the reference scenario where VRs' settings are fixed (before setting optimization). In the second case study, the VRs' settings are optimized, and setting optimization impacts power loss reduction is assessed. The third case study aims to discover how the variety of load types affects the settings optimization results of VRs. In the fourth case study, a carefully defined scenario demonstrates whether an inaccurate load model (ZIP) prediction affects the network operation. It is worth mentioning that all simulations of the article have been carried out in MATLAB R2017b environment using a laptop with 1.3 GHz (core i3) CPU and 4 GB RAM (DDR3). The computational time of each scenario was around 45 min.

UP of VR No.1	UP of VR No.2	…	UP of VR No. N-1	UP of VR No. N
DP of VR No.1	DP of VR No.2	…	DP of VR No. N-1	DP of VR No. N

Fig. 6. Chromosome's structure of the Genetic Algorithm.

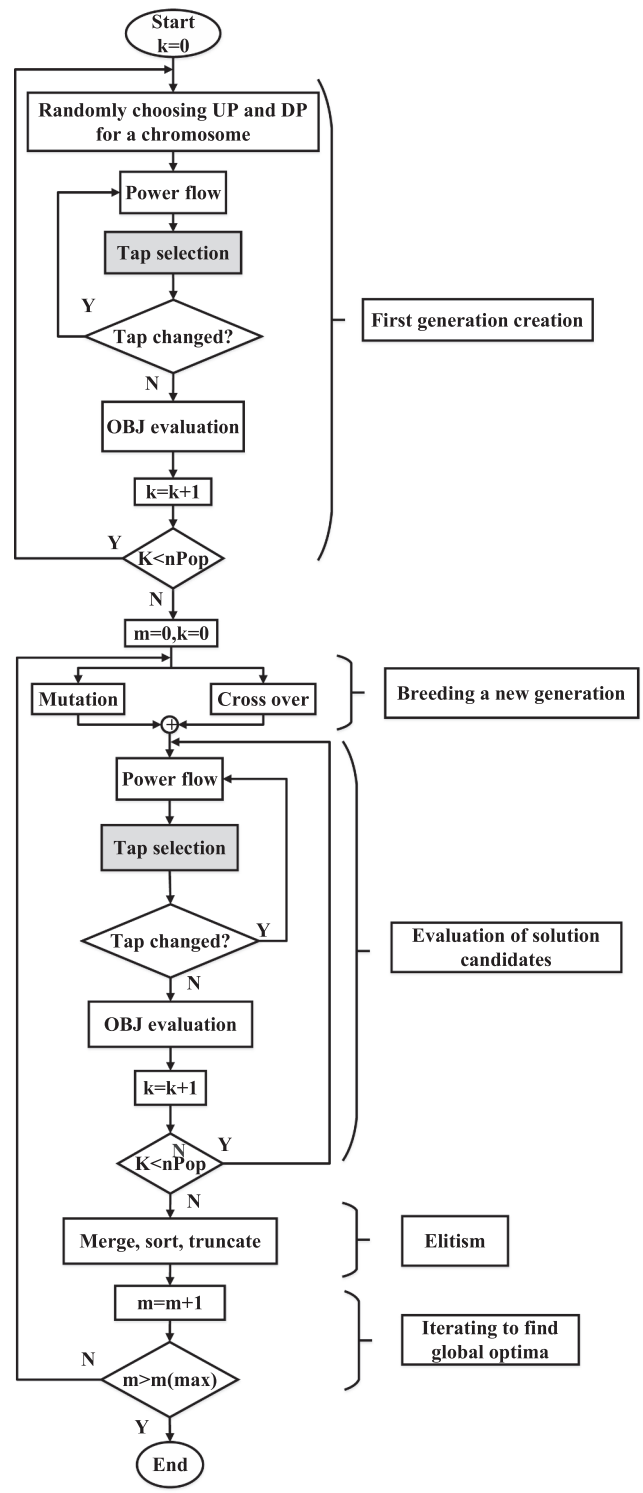

Fig. 7. The genetic algorithm optimization process of the proposed approach.

As illustrated in Fig. 8, a 70-bus distribution network is considered the understudy network of this paper in that the detailed data of line impedances and loads are available [28]. Since this article is the subsequent research of the reference [14], the previous study's experience was used to select the number and location of VRs so that voltage violation across the network is prevented. Therefore, based on the acquired experience, it is assumed that five VRs have already been

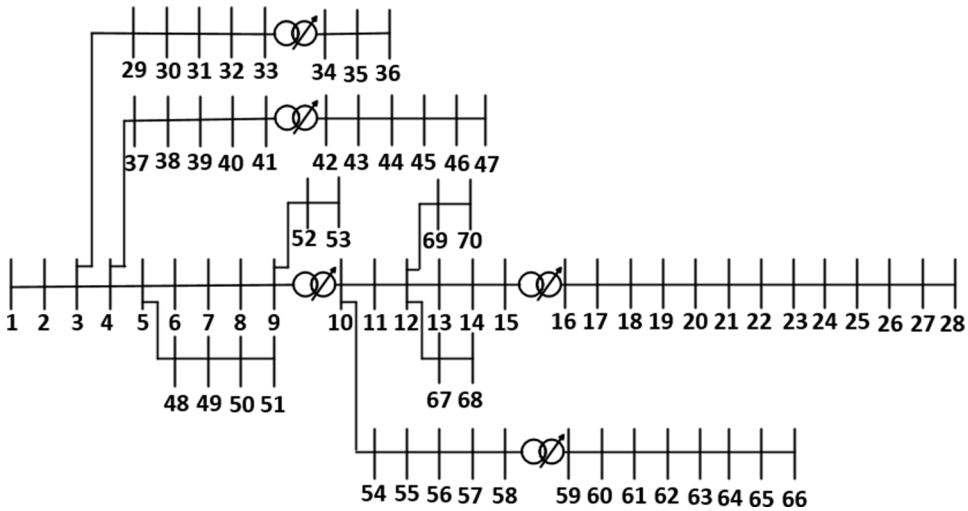

Fig. 8. Understudy distribution network.

installed at buses 10, 16, 34, 42, and 59. It should be noted that a VR has 11 tap positions between tap ratio 0.95 to 1.05 with a 0.01 tap step.

A 24 h time-series has been used to model the network's loading, as shown in table 1, emphasizing that the nominal consumption of the distribution network is 20.8 MVA. As setting optimization should consider a season ahead (next 90 days), it has been assumed that the mentioned time-series will adopt three different load levels (light, nominal, and peak) with different durations, based on Table 2, to examine the presented approach in different loading conditions.

The planning horizon for optimizing the VRs' settings is one season meaning that every three months (if needed), settings should be optimized again considering the predicted level and type of the coming season's loads. The seasonal VRs' setting optimization has been chosen because it is a common practice in distribution networks that settings are set seasonally but not in shorter time intervals (i.e., daily) due to practical difficulties. Besides, based on [29], load types of costumers (constant current, constant impedance, constant power) often experience seasonal variations, which further accredit the chosen time interval (three months) for VRs' settings optimization. It should be noted that neither load modeling [18,30] nor production and load forecast methods [31–33] are not the topics of this paper and will not be investigated in this article.

4.1. Reference scenario- before setting optimization

In this case study, the reference scenario is presented to clarify the network's condition before VRs' setting optimization. Table 3 contains the VRs' UP and DP in this scenario that are considered according to experience, not through an optimization process. Since this paper is the subsequent research of the reference [14], the experience of authors has been used to adjust the settings in a way that voltage does not violate at any loading condition because, in the reference scenario, it is assumed that VRs are under operation already and the DSO obtains knowledge of appropriate settings by experience. Consequently, the DP has been adopted a relatively high value of 1.01 p.u. to assure not causing under voltage situation at the tale of feeders since the under-study distribution network is lengthy.

Table 2
Load levels and durations.

Type of load level	Duration (day)
light (0.9)	60
nominal (1)	24
peak (1.05)	6
Total duration	90 (one season)

Table 3
Unoptimized settings (Fixed DP and UP).

Bus number	DP	UP
10	1.01	1.04
16	1.01	1.04
34	1.01	1.04
42	1.01	1.04
59	1.01	1.04

Fig. 9 represents the distribution network's voltage profile when VRs' settings are not optimized. As shown, the voltage profile does not represent any voltage violation as expected because it is assumed that the DSO that already uses the VRs has experience on how to set the setpoints nearly optimal without using optimization algorithms, therefore, the network's state considering all the constraints (7–14) is acceptable in the reference scenario.

4.2. Scenario 1- after setting optimization

Once the voltage regulators settings are optimized by the GA, as shown in Table 4, the settings are then applied to the VRs after that, the

Table 1
Time-series of consumption for three load levels.

Time (AM)	1	2	3	4	5	6	7	8	9	10	11	12
Light 0.9 (p.u.)	0.56	0.57	0.58	0.54	0.58	0.81	0.83	0.86	0.85	0.86	0.82	0.72
Nominal 1 (p.u.)	0.63	0.64	0.65	0.6	0.65	0.9	0.93	0.96	0.95	0.96	0.92	0.8
Peak 1.05 (p.u.)	0.66	0.67	0.68	0.63	0.68	0.94	0.97	1	0.99	1	0.96	0.84
Time (PM)	1	2	3	4	5	6	7	8	9	10	11	12
Light 0.9 (p.u.)	0.49	0.45	0.42	0.41	0.42	0.43	0.45	0.45	0.47	0.49	0.51	0.5
Nominal 1 (p.u.)	0.55	0.5	0.47	0.46	0.47	0.48	0.50	0.51	0.53	0.55	0.57	0.56
Peak 1.05 (p.u.)	0.57	0.52	0.49	0.48	0.49	0.5	0.52	0.53	0.55	0.57	0.59	0.58

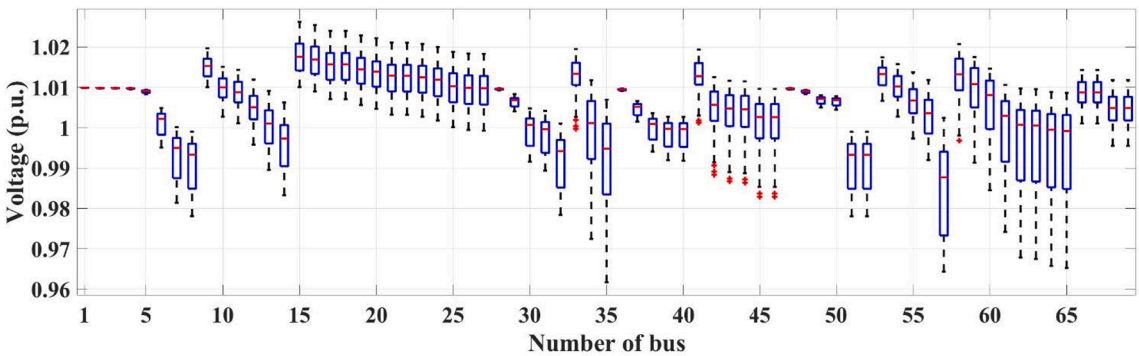

Fig. 9. Voltage profile of network before setting optimization. Note: Redline in the middle of each box shows the sample median of voltages for each bus, considering that it may not place in the center due to sample skewness. The bottom and top of each box are 25th and 75th percentiles of voltage samples, respectively. Extending whiskers above and below each box are drawn from the ends of the interquartile ranges to the furthest observations within the whisker length. The outlier (red + sign) represents the value that is more than 1.5 times the interquartile range away from the box's top or bottom.

Table 4
Optimized set points (DP and UP).

Bus number	DP	UP
10	1.01	1.04
16	0.96	1
34	0.98	1.02
42	0.96	0.98
59	0.96	0.99

voltage of each bus is acquired, as illustrated by Fig. 10. Like the previous scenario, as shown in Fig. 10, no voltage violation is observed. Table 5 shows that the benefit of loss reduction for three months is €1260 (according to Finland's average electricity price in 2019 [34]). €500 should be paid to the execution team to apply new VRs' settings. Therefore, €760 is the DSO's benefit due to setpoint optimization within three months compared to the reference scenario. It is worth mentioning that the three months' energy losses of the whole distribution network are equal to 643.54 MWh, which is decreased as much as 28.62 MWh (4.45%) by the proposed method. The question is how power loss has been reduced in scenario one compared to the reference scenario. The comparison of UP and DP values of Tables 3 and 4 indicates that settings have been slightly lowered in scenario one compared to the reference scenario. The reason is that the optimization attempts to lower the voltage levels of the whole distribution network by reducing VRs' setting values because the load model used in the load profile is mainly assumed to be a constant impedance type. In constant impedance loads, voltage and current changes are proportional; therefore, voltage reduction contributes to current reduction and less power loss in the distribution network. To further understand the impact of the load model in setting optimization, scenario 2 will be presented.

Table 5
Profit and Costs of Setting optimization.

Function	Value (€)
TELRB	1260
TCFI	500
OBJ	760

Table 6 provides data regarding the number of tap operations per VR within three months because the restriction in the number of tap operations needs to be considered in every feasible solution. Adopting the setting optimization method has increased the number of tap operations compared to the reference scenario; however, the maximum number of tap movements defined in equation (14) has been abided by the proposed approaches of scenario 1. Therefore, in terms of the tap operation of VRs, scenario one's results are acceptable.

As mentioned, the next case study aims to investigate the impact of

Table 6
Number of tap operation of VRs.

	After setting optimization (scenario 1)		Before setting optimization (reference scenario)	
VR bus	Number of tap operations within three months	Average of tap operations per day	Number of tap operations within three months	Average of tap operations per day
9	294	3.26	294	3.26
15	684	7.6	342	3.8
33	438	4.86	102	1.13
41	390	4.33	240	2.66
58	876	9.73	552	6.13

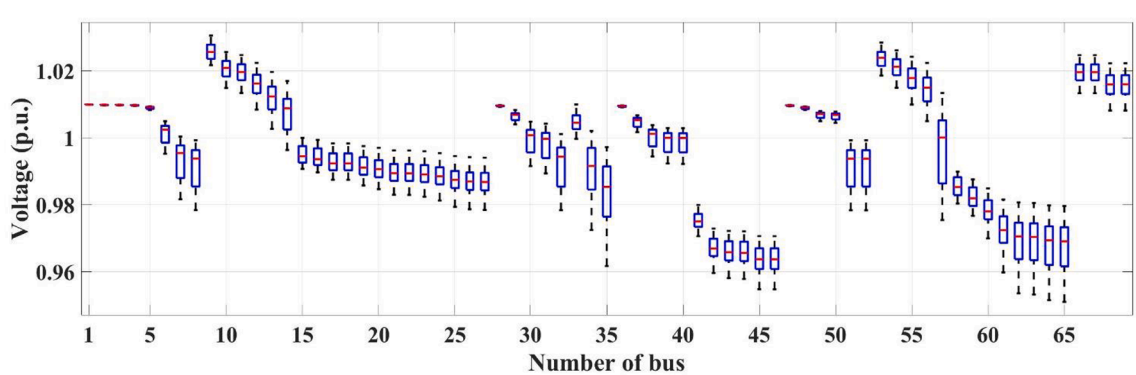

Fig. 10. Voltage profile of network with optimized settings of VRs (presented method).

voltage dependency of load models on VRs' setting optimization.

4.3. Scenario 2- load model considerations for settings optimization

VRs are mainly in use to mitigate voltage violation problems in the network and reduce power losses. From the voltage regulation perspective, a VR is a vital piece of equipment to control voltage levels by taking advantage of its tap-changing capabilities. Consequently, voltage-dependent loads according to their voltage dependency consume differently while experiencing a voltage change. Indeed, the consumed power of loads (e.g., households, schools, shopping centers, industries, etc.) cannot be assumed constant under voltage variations caused by VRs' tap operations. To study, the ZIP load model has been regarded to understand how different load types consume power when tap movement of VRs changes their voltages.

The problem that needs to be addressed here is whether a load model should be included in settings optimization studies. If so, it is necessary to find out how load models influence optimized settings results of VRs.

$$Z_p + I_p + P_p = 1 \tag{15}$$

Z_p, I_p and P_p stand for constant impedance, current, and power coefficients, respectively [35]. In (15), the summation of load coefficients is equaled to unity, meaning that a load according to its features can adopt different coefficients provided that the summation always remains unity. Table 7 provides useful information about how different load coefficients affect VRs' setting optimization. Three different load models, including $(0, 0, 1)$, $(0.5, 0, 0.5)$ and $(1, 0, 0)$ have been regarded as the vector (P_p, I_p, Z_p). The reason for choosing a zero constant current coefficient for all the load models is that the dynamics of optimized DP and UP are more evident when two extremes of the load model (constant power and impedance) are compared.

Concerning Table 7, by comparing the information for three different load combinations, three conclusions are made. Firstly, optimized VRs' settings are influenced by load models, which means that load model consideration is essential. Therefore, the load model of customers should be estimated before VRs' settings optimization. Secondly, by increasing the constant power coefficient's weight, the value of optimized settings becomes higher. The reason is that higher settings result in higher voltage levels. Higher voltage creates less current for constant power loads; therefore, power losses of the grid can be reduced as less current is flowing through the grid. Thirdly, by comparing the value of OBJ, the benefit of DSO from setting optimization is dependent on the load model. For instance, in this case, DSO can expect more financial benefits when the constant impedance coefficient is heavier. Concerning the voltage violation issue, Figs. 11–13 demonstrates no voltage violation in the distribution network, meaning that the difference between the load types can only impact the financial aspects.

As an example, if it is assumed that a few VRs have been installed throughout the distribution network and their settings want to be optimized for a planning horizon of 3 months, we need to know that there is a difference in the VRs' settings depending on the load type coefficients.

Table 7
Optimized settings of VRs and monetary values for three different load model of customers.

Location of VRs	Load coefficients $(0, 0, 1)$		Load coefficients $(0.5, 0, 0.5)$		Load coefficients $(1, 0, 0)$	
	DP	UP	DP	UP	DP	UP
10	1	1.03	1.02	1.04	1.02	1.04
16	0.96	1	0.98	1	1.01	1.04
34	0.96	1.01	0.99	1.04	1.02	1.04
42	0.98	1.03	0.97	1.03	1	1.04
59	0.96	0.99	0.96	1.03	1.01	1.04
TELRB	2241		1200		194	
OBJ	1741		700		−306	

Consequently, if load types are not considered when optimizing a VR setting, then this negligent behavior could lead to improper VR settings and therefore increase the probability of voltage violation and rise of energy losses. This situation will be discussed in the following section.

4.4. Scenario 3- adverse impact of load model error

The previous section analyzed the importance of load models and their effects on the settings of VRs. It was found that knowing the load model of customers is a prerequisite of setting optimization studies. A question remains: What would be the proposed approach's performance whether the load model (ZIP) is neglected or it contains a significant amount of prediction error? The raised question is also associated with the uncertainty issue in decision-making problems [36]. To answer the question, an example is made here.

As an example, it is predicted that the vector $(0.1, 0.1, 0.8)$ represents the customers' load type as (P_p, I_p, Z_p). Table 8 provides data on the optimized VRs' settings. Fig. 13. illustrates the distribution network's voltage profile after applying the settings provided that there is no mismatch between the predicted and realized load model. Now, a load with a different vector than predicted $(0.8, 0.1, 0.1)$ is applied to the network to observe the network's voltage profile, as shown in Fig. 15. By comparing Figs. 14 and 15, it is obvious that buses including 42, 43, 44, 45, 46, 62, 63, 64, and 65 experience a minor voltage violation (less than 0.95 p.u.) for peak hours because of the incongruence of the predicted load model and the applied load model to the network. Therefore, it is concluded that load model consideration is needed to avoid voltage violation in VRs' setting optimization.

It should be mentioned that in this case study, VRs' settings were optimized based on the vector $(0.1, 0.1, 0.8)$ whereas the loading combination $(0.8, 0.1, 0.1)$ was applied to the network. The point is that the first vector is highly voltage-dependent, whereas the applied vector has much less voltage dependency. The predicted and applied vectors reflect two extremes of voltage dependency of loads to enable us to highlight the impact of the load model. This level of mismatch may not happen in practice but to stress the load model's importance.

5. Discussion

This section satisfies a need to discuss a relevant set of aspects associated with VR operational planning. The discussions aim to positively influence future research in this area and provide a clearer picture to DSOs about VRs' settings optimization approaches.

The paper's proposed approach named the offline method, besides the LDC technique, can be seen as two major setting optimization solutions. A discussion concerning the features of those approaches is presented here.

LDC approach is a practical solution for tap selection of VRs. Nevertheless, it has certain disadvantages. For instance, if three branches are fed through a VR in a radial distribution network, then the total measured current at the VR location does not specify the current of each branch leading to arbitrary tap operation or voltage violation in a worst-case scenario. The said problem can be solved by installing three CTs at the beginning of each branch and then sending the signals to the VR's location. Nevertheless, extra costs are associated with the solution, and communication is required in this case.

LDC method should consider network reconfiguration that DSOs often use for congestion management. Adapting the LDC approach to perform optimally under network reconfiguration is recommended for future research in this area. Regarding the network reconfiguration and the proposed method of the paper, the situation falls into two categories. If network reconfiguration is used in real-time control, the offline approach does not work. Suppose the network reconfiguration is done periodically, for instance, once a month depending on the load level changes. In that case, the setting optimization planning horizon can be

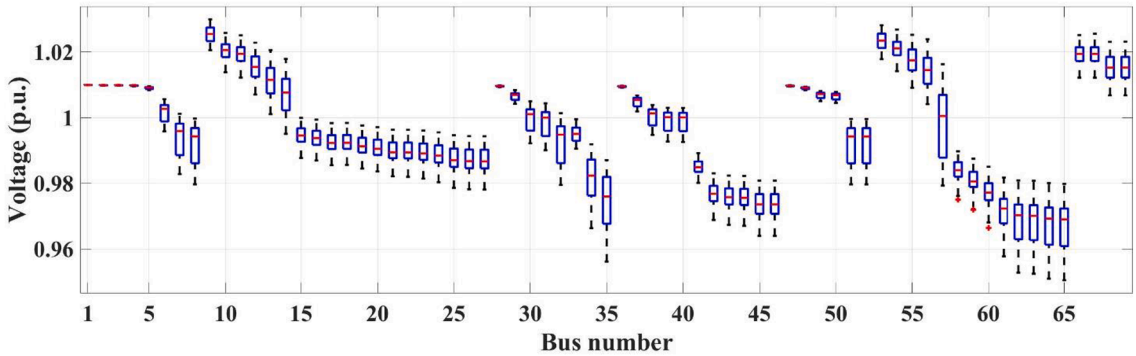

Fig. 11. Voltage profile of network with optimized settings of VRs with load coefficients (0,0,1).

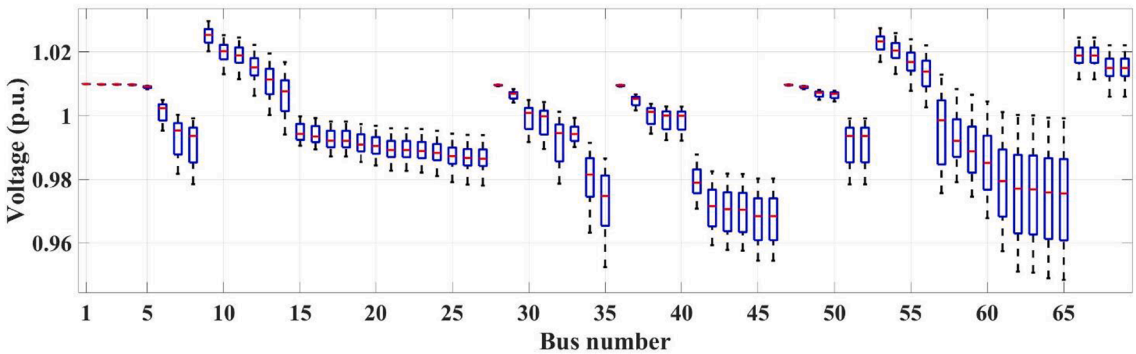

Fig. 12. Voltage profile of network with optimized settings of VRs for load coefficients (0.5,0,0.5).

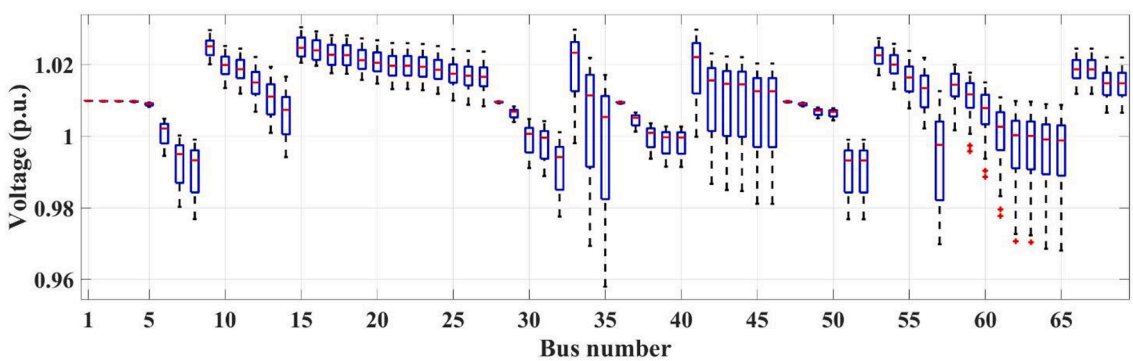

Fig. 13. Voltage profile of network with optimized settings of VRs for load coefficients (1,0,0).

Table 8
Optimized settings.

Bus number	DP	UP
10	1.01	1.03
16	0.97	1.03
34	0.99	1.02
42	0.95	0.98
59	0.96	0.99

synchronized with the network reconfiguration leading to combining two methods. As another advantage when both methods are synchronized, the implementation costs are reduced because applying new VRs' settings and network reconfiguration can happen simultaneously.

Concerning the mentioned voltage control methods' performance in the presence of distributed generations (DGs), both methods should deal with the increasing trend of DG penetration. They can smoothly perform when DGs are connected to the network unless DG penetration is high, leading to reverse power flow. The VR control system's design in distribution networks with high DGs' share requires changes to the LDC and offline approach of the paper. Reference [37] has raised the argument and can be used for future research in this area. An extensive time-domain study focusing on distribution network voltage control in the presence of multiple series VRs and DGs similar to the idea in [13] can be carried out in the future.

6. Conclusion

The mid-term operational planning of VRs in distribution networks has been targeted in this paper. Settings optimization of VRs to regulated medium voltage distribution networks and to reduce power losses have been the primary target of this paper. Also, to achieve the targets, load models' impact on VRs' setting optimization has been analyzed.

In the reference scenario where VRs' settings are not optimized, the

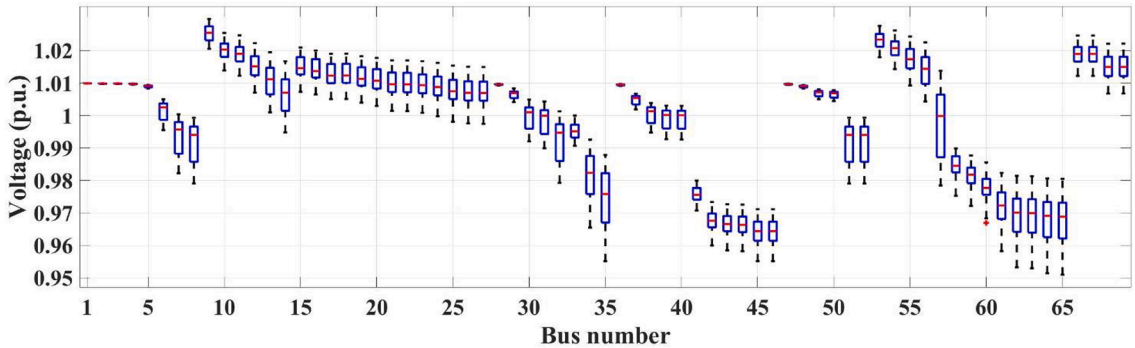

Fig. 14. Voltage profile of network with optimized settings for.$(0.1, 0.1, 0.8)$

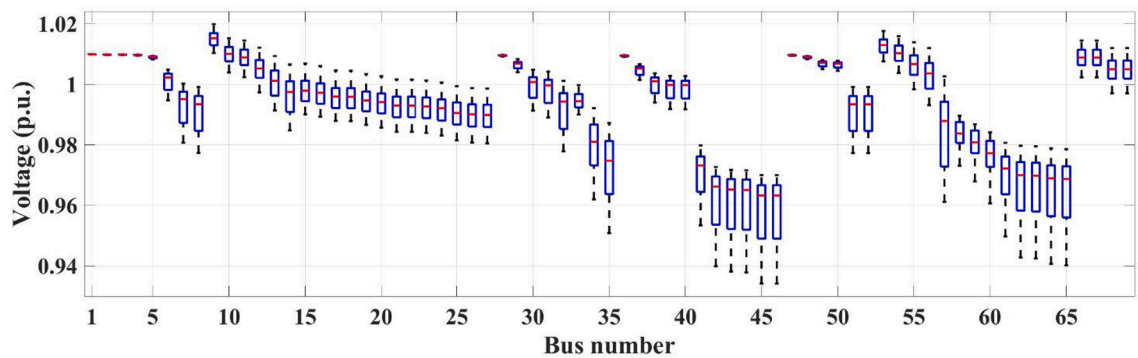

Fig. 15. Voltage profile of the network when a load with vector $(0.8, 0.1, 0.1)$ is applied whereas settings had been optimized for the vecto $(0.1, 0.1, 0.8)$r.

aim was to clarify the network's state before applying the paper's proposed approach. The power flow carried out for the upcoming season did not violate the network's constraints because we assume that the DSO has set the settings manually such that no violation occurs. The result was expected because the DSO has already deployed the VRs to prevent violations, especially voltage type, in the first place.

In scenario 1, it was shown that VRs' settings optimization reduces network's power losses; however, the network's state that was already in the acceptable range in the reference scenario did not experience further improvement in scenario 1. Within three months, 4.45% of the distribution network's total energy loss was reduced by using the paper's proposed method. Since VRs affect the voltage levels, it was concluded that the network's power loss reduction depends on the voltage dependency of loads. To further analyze the impacts of loads' voltage dependency (dependant on their load model) on VR setting optimization, scenario 2 and 3 was designed.

In scenario 2, it was established that the ZIP load model should be regarded in the setting optimization process in a sense that we cannot assume that all of the loads are a constant type, for instance, constant power type. How various load model combinations affect the optimized settings of VRs has been analyzed as well. It was proved that load model consideration influences the optimized VRs' settings. The impact is such that with an increase of constant power weight (P_p), the DP and UP's optimized value becomes larger because it managed to maintain a higher voltage, less flowing current, less power loss along the lines, and finally, more profit for DSO. In contrast, since lower voltage levels cause lower power losses for constant impedance loads (Z_p), with an increase of constant impedance weight, the optimized value of the DP and UP become smaller to keep the voltage as low as possible (without voltage violation). It was also proved that DSO's benefit associated with VR's setting optimization is dependent on the load model of customers.

In scenario 3, it was concluded that in the case of a load model's (ZIP) negligence, the voltage profile might have minor violations. Therefore, DSOs require an acceptable prediction of customers' load model, which can be acquired by looking at the category of customers [29] (residential, commercial, and Industrial). Indeed, customers' load model should be estimated accurately enough to make sure that the VRs' settings match the load type of consumers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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