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Article

An Operational Approach to Multi-Objective Optimization of Volt-VAr Control

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Abstract: Recent research has enabled the integration of traditional Volt-VAr Control (VVC) resources, such as capacitors banks and transformer tap changers, with Distributed Energy Resources (DERs), such as photo-voltaic sources and energy storage, in order to achieve various Volt-VAr Optimization (VVO) targets, such as Conservation Voltage Reduction (CVR), minimizing VAr flow at the transformer, minimizing grid losses, minimizing asset operations and more. When more than one target function can be optimized, the question of multi-objective optimization is raised. In this work, we propose a general formulation of the multi-objective Volt-VAr optimization problem. We consider the applicability of various multi-optimization techniques and discuss the operational interpretation of these solutions. We demonstrate the methods using simulation on a test feeder.

Keywords: Volt-VAr Control; Volt-VAr Optimization; Multi-Objective optimization

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1. Introduction

Traditionally, distribution systems include Volt-VAr Control (VVC) devices that aim to maintain the voltage within allowable limits, as required by the grid code or by power quality standards such as EN 60150 [1,2]. Failure to meet these limits may result in malfunction, damage to electrical equipment or regulatory sanctions and fines.

The load fluctuates during the day as a function of various variables, such as the type of load, the type of infrastructure, geogravarphic area, local weather conditions, season, holidays etc. [3]. There are methods in which a VVC device is varying the reactive power, which as a result also changes the voltage in the system. These are called indirect VVC methods, and include devices such as shunt reactors, capacitor banks, Static VAr Compensators (SVC) and more recently, distributed generators (DG). The traditional operation of indirect voltage control is to connect and disconnect capacitor banks when the voltage exceeds a certain threshold. On the other hand, direct methods, directly change and affect the voltage and include devices such as On-load Tap Changers (OLTC), transformers and voltage regulators[4].

Up to the last decade, due to lack of telemetry at the distribution network, the methods for dynamically controlling voltage levels were very basic, mostly relying on connecting and disconnecting capacitor banks [5]. Recent smart grid technologies bring forth a vast amount of data and information to electricity utilities. On one hand, this amount of data increases the complexity of the analysis required for the decision-making process. On the other hand it allows for more sovarphisticated, dynamic and holistic methods for controlling voltage levels, a process which is usually referred to as Volt-VAr Optimization (VVO) [6–8].

Operation of the DG consumes energy resources and increases the operational age of the machine. Voltage control coordination is therefore necessary in the distribution network and has been a subject of interest in many research papers. For example, Ma et al in [9] have used the hierarchical genetic algorithm (HGA) to optimise the power and voltage control system according to the number of control actions and in [10], an integrated voltage control called Coordinated Secondary Voltage Control (CSVC)

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has been proposed for controlling the LTC positions to ensure that voltage and loading constraints are satisfied during normal and emergency conditions. Practical VVC applications must take into consideration some physical and economical aspects of the assets [11]. There is some work done on the coordination and operation of VVC assets under various conditions. Some work is focused on the coordination of DGs and LTCs [12]. In [13] the theory of coordinating the operations of switched capacitors and LTCs by approximating the problem as a constrained discrete quadratic optimization problem is discussed.

The addition VVO may add other capabilities to the system such as reduced system losses, reduced transformer losses and control of the reactive power flow up to zero or even negative VAr flow and flat voltage profiles. Recently, a holistic method based on control at a system level of the Volt/VAr assets in order to achieve one of seven possible target functions was proposed in [14]. This raises the need for multi-objective optimization, where more than one target function is optimized, and specifically, where target functions may contradict each other.

Multi-objective optimization (MOO) is a well-established field of research. Probably introduced in the 1960s with [15], its root lies in much earlier research, see historical review and extensive survey [16]. Many textbooks have been, and still are, written on the subject e.g. [17] and more recently [18].

In the last decade, following the smart-grid revolution mentioned above, some works in the VVC literature have addressed MOO aspects. The first to mention multi-objective tradeoffs were probably Turitsyn et al [19], which discuss the tradeoff between power quality, usually achieved by increasing the reactive power Q, and distribution loss reduction, which requires minimal Q. [20] also consider active power losses and voltage deviations, and use a weighing function to combine the two, without addressing the question of how to select the weights. [21] also consider loss minimization and reducing voltage variation. They propose to avoid the problem of choosing weights through a switching law that evaluates the state of the system and determines which objective function best meets the current system needs. Recently, [22] proposed an adaptive weight-sum algorithm for solving a similar problem in a robust manner. Some works have addressed more target functions. For example, in [23], power loss, voltage profile, and voltage stability are considered. A genetic algorithm is used for finding all Pareto-optimal solutions, which are then ranked using a fuzzy compromise function. In [21], the multiple objectives of the VVC problem to be minimized electrical energy losses, voltage deviations, total electrical energy costs, and total emissions of renewable energy sources and grid, and a fuzzy function is used to combine the multiple target functions. Voltage variation on pilot buses, reactive power production ratio deviation, and generator voltage deviation are minimized in [24] and [25]. In both cases, the multiple objectives are addressed using weighted-sum of Pareto optimal solutions. Note that as a general rule, the above-mentioned works focus on the very important problem of solving a specific VVC-MOO problem, but none of them propose a general framework for formulating such a problem.

While multi-objective tradeoffs are becoming common in distribution systems, and several solutions have been proposed, the adoption level of these solutions is very minor. To the best of our knowledge, no operational system exists for multi-objective optimization in distribution networks. We believe that one of the main reasons for this is lack of operational interpretation. A solution may be mathematically valid, but it will be hard to adopt without clear operational interpretation. Our contribution is therefore two-fold. First, we propose a general framework for formulating multi-objective Volt-VAr optimization problems. Second, and more importantly, we investigate simple techniques for MOO and discuss operational interpretation of each. This discussion, especially when the operational interpretation is intuitive, may lead to faster adoption of these techniques.

The structure of this paper is as follows. First, in Section 2.1, we propose a general formulation for multi-objective Volt-VAr optimization problems. This serves as the fundamental blocks for the MOO techniques we discuss in Section 2.2, providing the operational interpretation for each. We then, in Section 3, apply and demonstrate these methods on a test feeder, optimizing active power and reactive power. This is followed by conclusions in Section 4.

2. Materials and Methods

2.1. General multi-objective Volt-VAr optimization

In this section we propose a general formulation for the VVO problem. We start with a general formulation of the single-objective variant. We briefly discuss the subject of time and scenario based optimization. We then extend to the multi-objective case. This formulation is based on [14], but extends it considerably.

2.1.1. The general VVO problem

Let $k = 1, \dots, K$ be the nodes (busses) of the network and let $j = 1, \dots, J$ be the conductors (edges) of the network. Let $\{P^*_k, Q^*_k\}$ be the native active and reactive power consumption in leaf node k, with vector notation $\{\vec{P^*}, \vec{Q^*}\}$.

We will consider both indirect and direct voltage control elements. Let $a = 1, \dots, A$ be the indirect voltage control elements. We associate each control element a with decision variable $X_a \in \xi_a$ where ξ_a are the possible values of X_a, with vector notation $\vec{X}$. Note that $\vec{X}$ may be discrete, as is the case with capacitor banks, which can usually be connected or disconnected, or continuous, as is the case with smart inverters. Either way, we define a function g which associates the control vector $\vec{X}$ and the native active and reactive power vectors $\{\vec{P^*}, \vec{Q^*}\}$ with the actual active and reactive power consumption $\{\vec{P'}, \vec{Q'}\}$ as follows

$$\{\vec{P'}, \vec{Q'}\} = g(\vec{X}, \vec{P^*}, \vec{Q^*}). \tag{1}$$

Similarly, let $b = 1, \dots, B$ be the direct voltage controlled elements. We associate each controlled element b with decision variable $Y_b \in \psi_b$ where ψ_b are the possible values of Y_b, with vector notation $\vec{Y}$. Note that ψ_b are voltages, and may also be continuous or discrete. For example, an LTC is discrete, while a voltage regulator may have continuous control.

From the actual active and reactive power consumption $\{\vec{P'}, \vec{Q'}\}$ and the direct voltages controls Y we can calculate the voltages V_k and currents I_j ($\vec{V}$ and $\vec{I}$), respectively, and the total active and reactive power $\{\vec{P}, \vec{Q}\}$. This is usually done by solving the well-known power flow equations

$$P_m = Re\left[\sum_{n=1}^{K} V_m V_n^* \mathbf{Y}^*_{m,n}\right] \qquad m = 1, \dots, K \tag{2}$$

$$Q_m = Im\left[\sum_{n=1}^{K} V_m V_n^* \mathbf{Y}^*_{m,n}\right] \qquad m = 1, \dots, K \tag{3}$$

where $\mathbf{Y}$ is the admittance matrix that represents the topology, that is, $\mathbf{Y}_{m,n}$ is the admittance between busses m and n. After the equations are solved, the current can be easily calculated from the voltages and line admittances.

We denote this process $\mathbb{PF}$:

$$\{\vec{V}, \vec{I}, \vec{P}, \vec{Q}\} = \mathbb{PF}(\vec{P'}, \vec{Q'}, \vec{Y}). \tag{4}$$

Note that we use the term "power flow", but this does not necessarily need to be so, and any other form of voltage, current and power evaluation will suffice. For example, in some works about balanced networks, approximations are used.

For simplicity and without loss of generality, the general single-objective VVO problem is defined as a minimization problem of a function f, under constraints:

$$\begin{aligned} \min \quad & f(\vec{V}, \vec{I}, \vec{P}, \vec{Q}, \vec{X}, \vec{Y}) \\ \text{s.t.} \quad & \vec{h}(\vec{V}, \vec{I}, \vec{P}, \vec{Q}, \vec{X}, \vec{Y}) \leq 0 \end{aligned} \tag{5}$$

where $\vec{h}$ represents any set of constraints. For examples, the most common constraint is the voltage constraint $\vec{V_{min}} \leq \vec{V} \leq \vec{V_{max}}$, where $\vec{V_{min}}$, $\vec{V_{max}}$ are vectors of the minimum and maximum allowed voltages. In the rest of this work we will use the shortened notation $f(\cdot)$ and $\vec{h}(\cdot)$ to denote the target function and the constraints.

2.1.2. Example target functions

Using this notation, many target functions can be easily expressed. Some common examples follow.

- Target voltage and Conservation Voltage Reduction (CVR): For nominal voltages v_k^{nom}, the deviation function is the sum of differences, under some norm function $|\cdot|$:

$$f(\cdot) = \sum_k |V_k - V_k^{nom}| \,. \tag{6}$$

  Specifically for CVR, we have $V_k^{nom} = V_{min}$, where V_{min} is a regulatory set minimum voltage.

  Alternatively, especially when the nominal values vary considerably, the voltage deviation can be normalized (see e.g. [21,22]), resulting in

$$f(\cdot) = \sum_k \left| \frac{V_k - V_k^{nom}}{V_k^{nom}} \right| . \tag{7}$$

- Feeder voltage deviation: This can be seen as a variant of target voltage. To express this function we use a re-indexing such that $V_{m,n}$ is the voltage at element n of feeder m. We use the index $n = 0$ to represent the feeder head. The voltage deviation is defined as $V_{m,n} - V_{m,0}$. Typically (see e.g. [20]), the maximum deviation in each feeder is maximized:

$$f(\cdot) = \sum_m \max_n \left[V_{m,n} - V_{m,0} \right] . \tag{8}$$

  In the case of a radial network, Eq. (8) can be expressed in terms of the power as follows (see [19,20]):

$$f(\cdot) = \sum_m \max_n \left[\frac{r_{m,n} P_{m,n} + x_{m,n} Q_{m,n}}{V_{m,0}} \right] , \tag{9}$$

  where $r_{m,n}$ and $x_{m,n}$ are the resistance and the reactance of the conductor between node n and $n+1$ of feeder m, respectively.
- Losses: The total losses due to energy dissipation can be written in the most general case as

$$f(\cdot) = \sum_j I_j^2 r_j , \tag{10}$$

  where r_j is the resistance the conductor j. This formulation is used, for example, by [21,23]. In the radial case, Eq. (10) can be expressed in terms of the power as follows (see [19,20,22]):

$$f(\cdot) = \sum_m \sum_n r_{m,n} \frac{P_{m,n}^2 + Q_{m,n}^2}{V_{m,0}^2} . \tag{11}$$

- Root power factor: typically, the power factor is important at the root of the network, that is, the point where the network is fed. Using the index 1 for that node, we can write

$$f(\cdot) = \frac{P_1}{\sqrt{P_1^2 + Q_1^2}} . \tag{12}$$

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- Root active power: The root active power is the total power the network consumes. It is simple to express it as:

$$f(\cdot) = P_1. \tag{13}$$

- Root reactive power: In a similar way, the root reactive power is:

$$f(\cdot) = Q_1. \tag{14}$$

- Cost of controls: In the most generic way, the cost of control can be expressed as

$$f(\cdot) = h(\vec{X}, \vec{Y}), \tag{15}$$

where h is a generic function deriving the cost of controls from the control vectors $\vec{X}$, $\vec{Y}$. As a simple example lets look at photo-voltaic generation curtailment. In that case X_a is the amount of generation curtailed by the installation a, and a simple target function may be to minimize the total curtailment:

$$f(\cdot) = \sum_a X_a. \tag{16}$$

2.1.3. Time and scenario based optimization

In this section we discuss two desired extensions of the model are presented, relating to time and scenario based optimization.

In time based optimization (e.g. [22,23]), the optimization is performed over multiple time-slots, not necessarily of equal duration. For example, optimization may be carried over 24 hours, in order to take into account different load profiles at different hours. For time-slots $t = 1, \ldots, T$ we define $V_k^t, I_j^t, P_k^t, Q_k^t, X_a^t, Y_b^t$, the respective voltage, current, active power, reactive power, indirect controls and direct controls at time-slot t. The target functions defined in Section 2.1.2 can then be extended to include this additional dimension, by summation, averaging or maximization. For example, in [22], Eq. (7) becomes

$$f(\cdot) = \sum_t \sum_k \left| \frac{V_k^t - V_k^{nom}}{V_k^{nom}} \right| / T, \tag{17}$$

averaging over the number of time-slots. For unequally sized time-slots with slot duration of Δ_t, Eq. (17) becomes

$$f(\cdot) = \frac{\sum_t \Delta_t \sum_k \left| \frac{V_k^t - V_k^{nom}}{V_k^{nom}} \right|}{\sum_t \Delta_t}, \tag{18}$$

i.e. a weighed average over the slot duration. Such treatment can be seen for example in [21].

In scenario based optimization (e.g. [20,21]), the model is further extended to take into account multiple scenarios. For example, the model can look at the operation for a 24-hour period, where the scenarios represent days with various cloud levels, from completely sunny to complete cloud coverage. For scenarios $s = 1, \ldots, S$ we define $V_k^{s,t}, I_j^{s,t}, P_k^{s,t}, Q_k^{s,t}, X_a^{s,t}, Y_b^{s,t}$, the respective voltage, current, active power, reactive power, indirect controls and direct controls at time-slot t of scenario s. The target functions defined in Section 2.1.2 can then be further extended to include this additional dimension, typically through taking the expected value over the scenarios, which we denote with $\underset{s}{\mathbb{E}}$. For example, in [20], Eq. (11) becomes

$$f(\cdot) = \underset{s}{\mathbb{E}} \left[\sum_t \sum_m \sum_n r_{m,n} \frac{(P_{m,n}^{s,t})^2 + (Q_{m,n}^{s,t})^2}{(V_{m,0}^{s,t})^2} \right], \tag{19}$$

i.e. the expected value over the scenarios of the total over time of the total losses over the network.

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2.1.4. The multi-objective VVO problem

Having defined a general single-objective VVO problem, the multi-objective problem for N objectives becomes simply:

$$\begin{aligned} \min \quad & f_1(\cdot), f_2(\cdot), \ldots, f_N(\cdot) \\ \text{s.t.} \quad & \vec{h}(\cdot) \leq 0. \end{aligned} \tag{20}$$

In the next section we will propose several manners in which the target functions can be mathematically combined.

2.2. Techniques for multi-objective optimization

Having defined the general MOO problem, in this section we discuss two common techniques in which multiple target function can be mathematically combined, namely the weighted-sum technique and the e-constraint technique.

2.2.1. The weighted-sum technique and the efficient curve

The *weighted-sum technique* is probably the most widely used MOO technique in the industry. For example, it is used in [20,22,24,25].

In the weighted-sum technique, we assign weighting coefficients to each of the objective values, thus transforming the multiple objectives into one objective. For target functions $f_1(\cdot), f_2(\cdot), \ldots, f_N(\cdot)$ we write the problem as:

$$\begin{aligned} \min \quad & \sum_i^N \lambda_i f_i(\cdot) \\ \text{s.t.} \quad & \vec{h}(\cdot) \leq 0, \end{aligned} \tag{21}$$

where λ_i are the weighting coefficients.

The major disadvantage of this method is that the weighting coefficients may have negligible operational sense, and therefore selecting them is not straightforward. We will now discuss several manners in which the coefficients may be intuitively selected.

One special case of the technique is the monetization method, in which price-per-unit is available for the different objectives, and can be used as the obvious weighting coefficient. For example, from the VVO target functions listed in Section 2.1.1, the cost of energy and the cost of losses can typically be monetized. However, objectively monetizing voltage profiles, reactive power or the effects of equipment operation is not a trivial task, and may result in very large discrepancies (cf. the large discrepancies evaluation of "social cost" of $CO2$ emissions, see e.g. [26]).

A common variant which attempts to give the weighting coefficients a more intuitive meaning is what one may call the $\alpha : (1-\alpha)$ method. This involves normalizing each objective value by its range of possible values, i.e., defining

$$\hat{f}_i(\cdot) \triangleq \frac{f_i(\cdot) - \min f_i(\cdot)}{\max f_i(\cdot) - \min f_i(\cdot)} \quad , \tag{22}$$

thus $0 \leq \hat{f}_i(\cdot) \leq 1$. Now, optimization is done with weighting coefficients that sum to one. Namely, the optimization is to minimize $\sum_i^N \lambda_i \hat{f}_i(\cdot)$ where $\sum_i^N \lambda_i = 1$. In the case of two target functions, $n = 2$, this can be written as $\alpha \hat{f}_1(\cdot) + (1-\alpha)\hat{f}_2(\cdot)$, hence the $\alpha : (1-\alpha)$ method.

The normalized variant in Eq. (22) clearly makes more operational sense, and it provides a simple intuitive meaning for the weighing coefficients, as percentiles of the overall target function. However, it still does not provide any practical way of choosing the coefficients.

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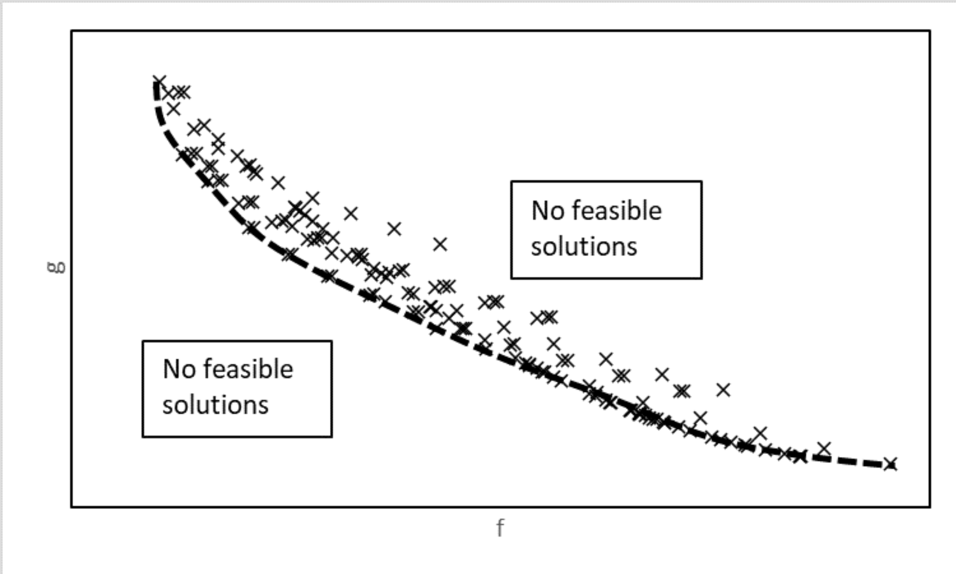

Figure 1. Efficient curve example. Each plot is a feasible solution, the efficient curve is shown as a dashed line.

The common solution to the problem of choosing the coefficients is to involve a decision-maker in the process of selecting the most preferable solution. Typically, this is done by first finding the "efficient curve", that is, the set of solutions that are optimal for some combination of coefficients. A demonstration of this concept for two objective functions, f and g, is shown in Figure 1. Each plot on this graph is projection into the objective space of a feasible solution and the efficient curve is shown as a dashed line. No feasible solutions exist "below" the efficient curve. Solutions above the efficient curve are inefficient. Thus, the efficient curve represents the set of viable and efficient solutions.

This concept is closely related with the concept of "Pareto front", that is, the set of solutions which are Pareto optimal, or non-dominated. The Pareto front includes solutions where there is no feasible solution that is better in all objectives, but a set of solutions with different trade-offs among the conflicting objectives. Selecting between these solutions is done by imposing a set of weighing coefficients. Many methods have been proposed for finding the Pareto front, a subject which is outside the scope of this work. In any case, the decision-maker can then analyze the set of solutions and select the most preferable solution. Several tools and methodologies are available in order to facilitate the decision-making stage e.g., [27–30], and also see taxonomy in [31].

While the efficient curve method seems to provide the most freedom to the decision-maker, in our experience, operators find the visualization tools confusing, and would rather have clearer operational meaning for their choices.

2.2.2. The e-constraint technique

In the *e-constraint technique*, one of the objective functions to be optimized is selected, and the other objectives are considered as constraints, by specifying inferior reservation levels that are acceptable in some sense. For target functions $f_1(\cdot), f_2(\cdot), \ldots, f_N(\cdot)$, we select one target function to be optimized, $f_p(\cdot)$, and we set reservation levels $e_i, i \neq p$ for the other target functions. The optimization problem is written as

$$\begin{aligned} \min \quad & f_p(\cdot) \\ \text{s.t.} \quad & f_i(\cdot) \leq e_i \quad i \neq p \\ & \vec{h}(\cdot) \leq 0. \end{aligned} \tag{23}$$

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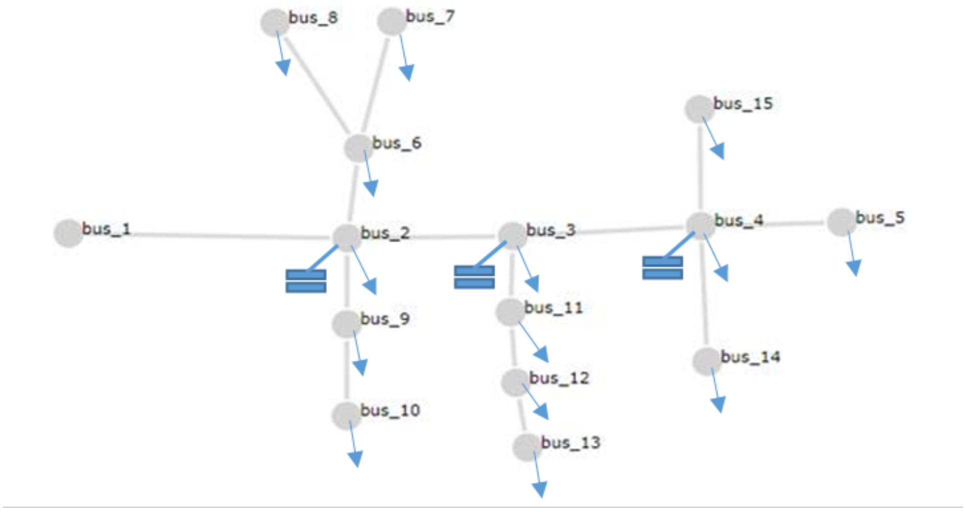

Figure 2. Schematic of the test feeder based on [32] with the addition of capacitor banks.

Note that in order to achieve strong efficient solutions we usually replace $f_p(\cdot)$ with $f_p(\cdot) + \sum_{i \neq p} \rho_i f_i(\cdot)$ with small $\rho_i > 0$, see [18, chapter 3].

Common practice is to first run individual optimizations for each of the target functions, and then derive the reservation levels based on the optimal target values. One typical way is to use a proportion reservation levels, or a percentile reservation levels, through $e_i = (1 + \delta_i) \min f_i(\cdot)$, where δ_i is the reservation proportion for the target function $f_i(\cdot)$. The advantage of this is that it has a very clear and intuitive operational interpretation, as follows. If one first sets $\delta_i = 0$ for $i \neq p$, and derives $\min f_p(\cdot)$, then δ_i is the percentile increase of $f_i(\cdot)$, that one is willing to sacrifice in order to get a better $f_p(\cdot)$. For example, if by sacrificing 1% of one target function, another target function is increased by 30%, then this increase is operationally sensible.

Alternatively, e_i can be based on the range as follows: $e_i = \min f_i(\cdot) + \gamma_i(\max f_i(\cdot) - \min f_i(\cdot))$, where $0 \leq \gamma_i \leq 1, i \neq p$. The operational interpretation of γ_i is the portion of the range sacrificed. An additive reservation level, $e_i = \min f_i(\cdot) + \Delta_i$, may also make operational sense, especially if Δ_i is in the order of magnitude of the errors in the system.

3. Simulation Results

In this section we demonstrate the MOO techniques discussed in Section 2.2 when optimizing active power and reactive power on a test feeder. We first describe the test feeder, and then demonstrate each of the methods discussed.

3.1. The test feeder

The feeder we use is a test feeder from [32], as seen in Figure 2. The feeder is an 11 kV distribution feeder. The total load is around 2.5 MW active power and 0.8 MVAr reactive power. About half of the loads are resistive and half of the loads work under a constant power factor regime. In addition, a large reactive load is present at bus 1. The controllable assets are three capacitor banks located at busses 2, 3 and 4 and a solar farm with a controllable inverter located at bus 6. The capacitor banks are on/off switchable rated at 250 kVAr. The solar farm supplies 1 MW with controllable power factor in the interval of $0.8 \leq \cos\varphi \leq 1$, with increments of 0.02. This provides $2 \times 2 \times 2 \times 11 = 88$ controllable states.

The particulars of the feeder were chosen carefully in order to demonstrate the trade-off between minimizing active power at the head bus (Eq. (13), $f_p(\cdot) = P_1$) and minimizing reactive power at the head bus (Eq. (14), $f_q(\cdot) = Q_1$). Figure 3 shows the calculated active power and reactive power for

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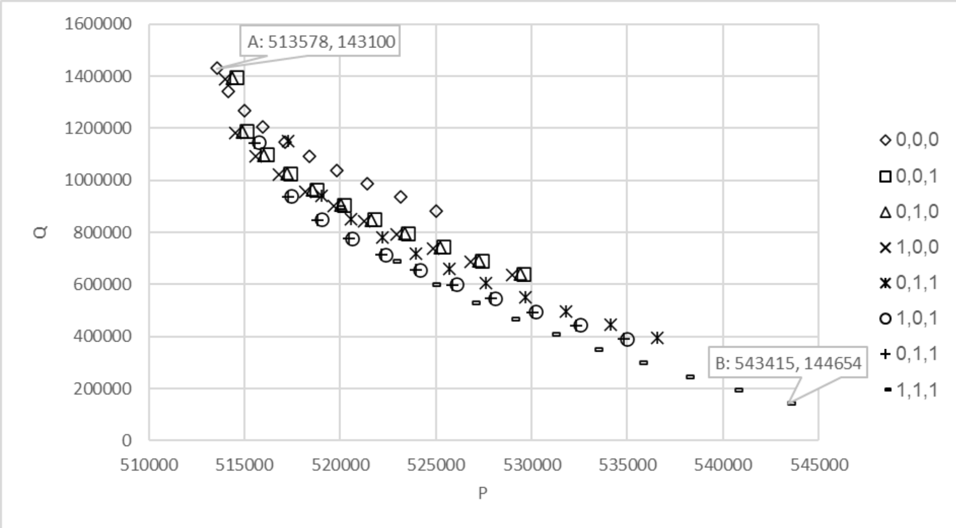

Figure 3. Calculated active power (P) and reactive power (Q) for all control points in the test feeder, with highlighted extreme points.

the 88 controllable states. For each capacitor bank state X_1, X_2, X_3 we plot the value of (P_1, Q_1) for the eleven inverter control points. This clearly demonstrates the trade-off between active power and reactive power, as follows.

At one extreme, at the P-optimal point, the reactive power is maximized, since no capacitor bank is engaged and the solar farm works at $\cos\varphi = 1$. This results in operating point A with $P_{min} \cong 513\,\text{kW}$ and $Q_{P_{min}} \cong 1431\,\text{kVAr}$. Engaging capacitor banks and changing $\cos\varphi$ reduces Q, but it also increases the voltage, which due to the resistive loads, also increases the active power P. Minimizing Q by engaging all capacitor banks and setting $\cos\varphi = 0.8$, yields operating point B with $Q_{min} \cong 145\,\text{kVAr}$ and $P_{Q_{min}} \cong 543\,\text{kW}$.

3.2. Applying the weighted-sum technique for active and reactive power optimization

The weighted-sum technique with the $\alpha : (1-\alpha)$ method was applied on the feeder described above. Both active power and reactive power were normalized, and efficient points for every value of α were calculated. The resulting efficient frontier is shown in Figure 4. Of the possible 88 operating points, 14 operating points belong to the efficient curve, and the maximum value of α corresponding to each point is also shown.

In a practical setting, these 14 possible control points are to be shown to the decision-maker and a choice is made. This provides the decision-maker with the most operational freedom, but it does not provide an intuitive operational interpretation of the decision, other than that it is "efficient".

3.3. Applying the e-constraint technique for active and reactive power optimization

The e-constraint technique was applied on the feeder described above, and the results are shown in Figure 5.

We start by optimizing Q, with a reservation level on P as a constraint. We use the percentile reservation level, setting $\delta_P = 1\%$ which yields the reservation point $e_P = 519\,\text{kW}$. This leads to the optimal operating point C, where $P_C \cong 517\,\text{kW}$ and $Q_C \cong 938\,\text{kVAr}$. The operational interpretation is very clear: for loss of optimality of 1% in active power, we gain 938 kVAr, a gain of 34%. Alternatively, this can be seen as additive reservation level, where $\Delta_P = 5\,\text{kW}$. The interpretation of this would be that we gain 938 kVAr for a loss of 5 kW.

For optimizing Q with a reservation level on P as constraint, we use a range reservation level. Selecting $\gamma = 10\%$ yields the reservation level $e_Q = 273\,\text{kVAr}$. Optimizing for P, we get the operating

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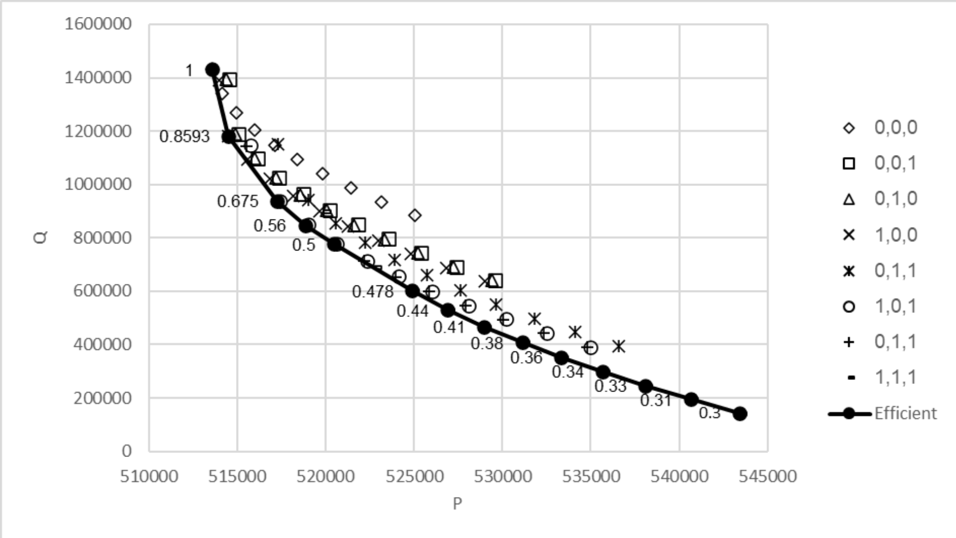

Figure 4. Active power (P) and reactive power (Q) on test feeder with efficient curve highlighted and α values.

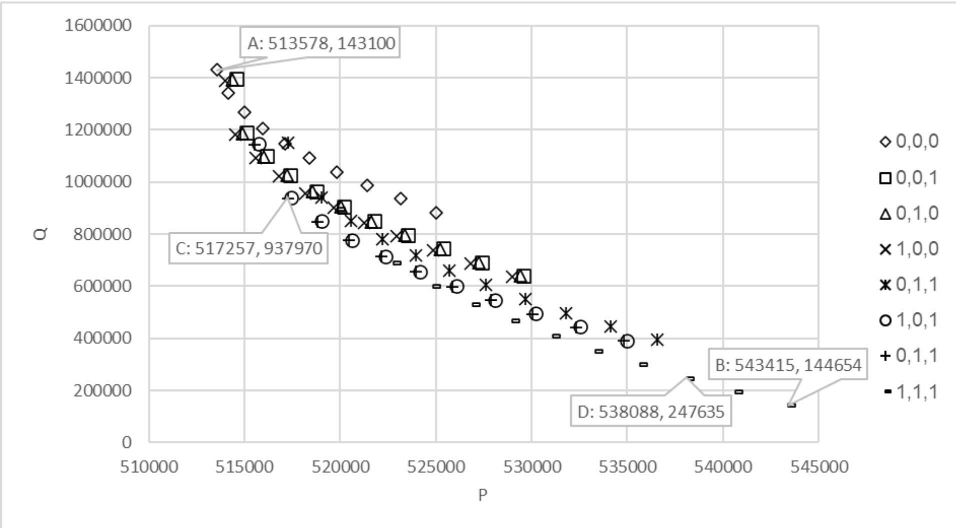

Figure 5. Calculated active power (P) and reactive power (Q) for all control points in the test feeder, with highlighted points of interest.

point D with $P_D \cong 538\,\text{kW}$ and $Q_C \cong 247\,\text{kVAr}$. Operationally speaking, for a loss of 10% of the range in Q, we gained 5 kW which is 18% of the range of P.

4. Discussion and conclusions

In this work we investigated an operational approach to multi-objective optimization of volt-VAr control. We presented a general formulation of this multi-objective problem, by first defining a general single-objection optimization, including time and scenario based optimization. We then extending it to the multi-objective case.

In this context, we discussed two general techniques for multi-objective optimization, namely the weighted-sum technique, which is many times combined with an efficient/Pareto optimal curve, and the e-constraint technique, which can be used with various reservation level-setting methods. We discussed the operational interpretation of the solutions achieved by these techniques. We then demonstrated both techniques with a simulation on a test feeder. The results clearly demonstrate that a trade-off can exist between multiple objectives. For the weighted-sum technique, the simulation

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demonstrated the existence of an efficient curve, and the way a choice can be presented for the decision-maker. For the e-constraint technique, the simulation showed how solutions with clear operational interpretation can be achieved, by using various reservation level setting methods.

It is worth mentioning that there are of course many other techniques for multi-objective optimization. For example, variants of fuzzy compromise functions are used in [21,23]. Our aim was not to review every such technique, but to focus on the most widely used ones, and especially ones which may yield to operational interpretation. In a field which is less researched, but seems to have vast operational benefits, we believe that the fundamentals provided, and especially the intuitive operational interpretation, may facilitate faster adoption of multi-objective volt-VAr optimization solutions.

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