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Multi-Objective Aspects of Distribution Network Volt-VAr Optimization

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SUMMARY

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 photovoltaic farms and batteries, 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. In this case, where more than one target function is involved, the question of multi-objective optimization is raised. In this work, we demonstrate various methods in which such optimization can be performed in practice and we discuss the various operational considerations that are involved with each method. We demonstrate the methods using simulation on a test feeder.

KEYWORDS

Volt-VAR Control, Volt-VAR Optimization, Multi-Objective optimization

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Introduction

Traditionally, distribution systems include 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, geographic area, local weather, season, holidays etc. [3]. There are methods in which a VVC device is varying the reactive power (for example), which as a result also changes the voltage in the system. These are called indirect methods which include devices such as distributed generation (DG), shunt reactors/capacitor banks, Static VAR Compensators (SVC), etc. 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 (LTC), transformers, regulators and smart inverters [4].

Up to the last decade, due to luck of telemetry at the distribution, the methods for controlling voltage levels were very basic ones [5]. New 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, and on the other hand it allows for more sophisticated as well as more holistic methods for controlling the voltage levels as in VVC and VVO [6-8].

Operation of the DG consumes energy resources and increases the operational age of the machine. The voltage control coordination is therefore necessary in the distribution network and has been a subject of interest in many research papers. Ma et al in [3] have used the hierarchical genetic algorithm (HGA) to optimise the power and voltage control system according to the number of control actions. In [4], an integrated voltage control called Coordinated Secondary Voltage Control (CSVC) has been proposed for controlling the LTC positions to ensure that voltage and loading constraints are satisfied during normal and emergency conditions. In [5] optimizing the sending voltages using the Least Square method is used. The work in [6] coordinates the operations of switched capacitors and LTCs in a radial distribution system by approximating the problem as a constrained discrete quadratic optimization. In [7], a coordination method for operating DG and step voltage regulators, for improved voltage regulation, has been presented.

The addition of VAr control 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. However, practical VVC applications must take into consideration some physical and economical aspects of the assets [9]. 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 [10]. In [11] the theory of coordinating the operations of switched capacitors and LTCs by approximating the problem as a constrained discrete quadratic optimization problem is discussed. More 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 [12].

While multi-objective optimization [13-16] is mentioned in some of these works, none of them considered the matter of multi-objective optimization in VVO in a methodical manner, especially not considering the operational aspects involved.

Our purpose in this work is not to offer solution methods or algorithms but to consider the formulation of multi-objective optimization in the context of VVO, and to consider the operational aspects involved.

1. The general VVO problem

Let us consider a general VVO problem, with both direct and indirect voltage control elements. Let $k = 1, \dots, K$ be the nodes 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 $\{\boldsymbol{P}, \boldsymbol{Q}\}$. Let $a = 1, \dots, A$ be the indirect voltage controlled elements. We associate each controlled element a with decision variable $X_a \in \chi_a$ where χ_a are the possible values of X_a, with vector notation $\boldsymbol{X}$. Thus in the most generic way, we can defined a function g which associates the control vector $\boldsymbol{X}$ and the native active and reactive power vectors $\{\boldsymbol{P}, \boldsymbol{Q}\}$ with the actual active and reactive power consumption $\{\boldsymbol{P}', \boldsymbol{Q}'\}$ as follows: $\{\boldsymbol{P}', \boldsymbol{Q}'\} = g(\boldsymbol{X}, \boldsymbol{P}, \boldsymbol{Q}\}$.

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 $\boldsymbol{Y}$. Note that ψ_b are voltages, and may be continuous or discrete.

From the actual active and reactive power consumption $\{\boldsymbol{P}', \boldsymbol{Q}'\}$ and the direct voltages controls $\boldsymbol{Y}$ we can calculate the voltages V_k and currents I_j ($\boldsymbol{V}$ and $\boldsymbol{I}$) respectively and the total active and reactive power $\{\boldsymbol{P}^*, \boldsymbol{Q}^*\}$. This is usually done through power flow software (see e.g. [12]),

$$\{\boldsymbol{V}, \boldsymbol{I}, \boldsymbol{P}^*, \boldsymbol{Q}^*\} = PF(\boldsymbol{P}', \boldsymbol{Q}', \boldsymbol{Y})$$

We can now finally define the VVO problem. In the most general way, as a problem for minimizing some target functions, under voltage constraints:

$$\begin{aligned} &\text{minimize } f(\boldsymbol{V}, \boldsymbol{I}, \boldsymbol{P}^*, \boldsymbol{Q}^*, \boldsymbol{X}, \boldsymbol{Y}) \\ &s.t. \qquad \boldsymbol{V}_{min} \le \boldsymbol{V} \le \boldsymbol{V}_{max}, \end{aligned}$$

where $\boldsymbol{V}_{min}, \boldsymbol{V}_{max}$ are the minimum and maximum allowed voltages. Note that other constraints may easily be added such as minimum and maximum power etc. In the rest of this work, we omit the constraints for brevity. We will use the shortened notation $f(\cdot)$ to denote the target function.

Some target functions which are proposed at [12] include:

- Target voltage: $f(\cdot) = |\boldsymbol{V} - \boldsymbol{V}^*|$ where $|\cdot|$ is a norm and $\boldsymbol{V}^*$ is some nominal target voltage. For example, for CVR we have $\boldsymbol{V}^* = \boldsymbol{V}_{min}$.
- Minimize losses: $f(\cdot) = \boldsymbol{I}^2\boldsymbol{R}$ where $\boldsymbol{R}$ is the line resistances vector
- Minimize root power factor: $f(\cdot) = \frac{P_1^*}{\sqrt{(P_1^*)^2 + (Q_1^*)^2}}$
- Minimize root active power: $f(\cdot) = P_1^*$
- Minimize root reactive power: $f(\cdot) = Q_1^*$
- Minimize the cost of controls: $f(\cdot) = h(\boldsymbol{X}, \boldsymbol{Y})$, where h is a generic function deriving the cost of controls from the control vectors $\boldsymbol{X}, \boldsymbol{Y}$.

2. The test feeder

For demonstrating the various techniques, we simulate a test feeder from [17], as seen in Figure 1. The feeder is an 11kV distribution feeder. The total load is around 2.5MW and 0.8MVAr. About half of the loads are resistive and half have work under constant power factor regime. This was selected in order to demonstrate a situation where various types of loads exist in the network.

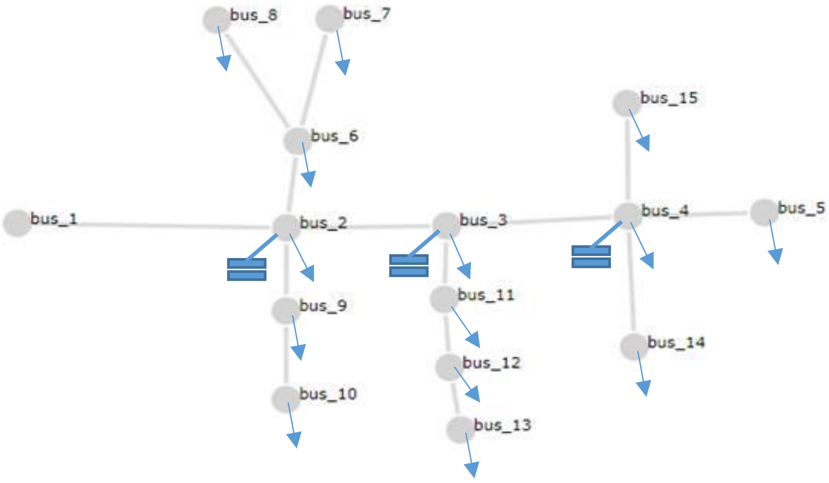

Figure 1: Test feeder from [17]

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 250KVAr. The solar farm supplies 1MW with controllable power factor in the interval of 0.8 and 1 with increments of 0.02. This supplies $2 \times 2 \times 2 \times 8 = 88$ controllable states.

3. 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 $f_1(\cdot), f_2(\cdot)$, ... we select one target function $f_p(\cdot)$ and we can write the problem as

$$\text{minimize } f_p(\cdot)$$
$$s.t. \quad f_i(\cdot) \leq e_i \qquad i \neq p,$$

where e_i are the reservation levels. Common practice is to first run individual optimizations for each of the target functions and derive $Z_i^{min} = \min f_i(\cdot)$, where $i \neq p$, and then set $e_i = (1 + \delta_i) Z_i^{min}$, where δ_i is the reservation proportion for the target function $f_i(\cdot)$. Note that this method strongly depends on the range of values and other operational concerns. 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 [16, chapter 3].

In order to demonstrate this technique, consider minimizing two objectives, i.e. the active power P and the reactive power Q. In Figure 2,**Error! Reference source not found.** the 88 control points for the test feeder are plotted, as described in section 2. For each capacitor bank state $\{X_1, X_2, X_3\}$ we plot the eleven inverter control points.

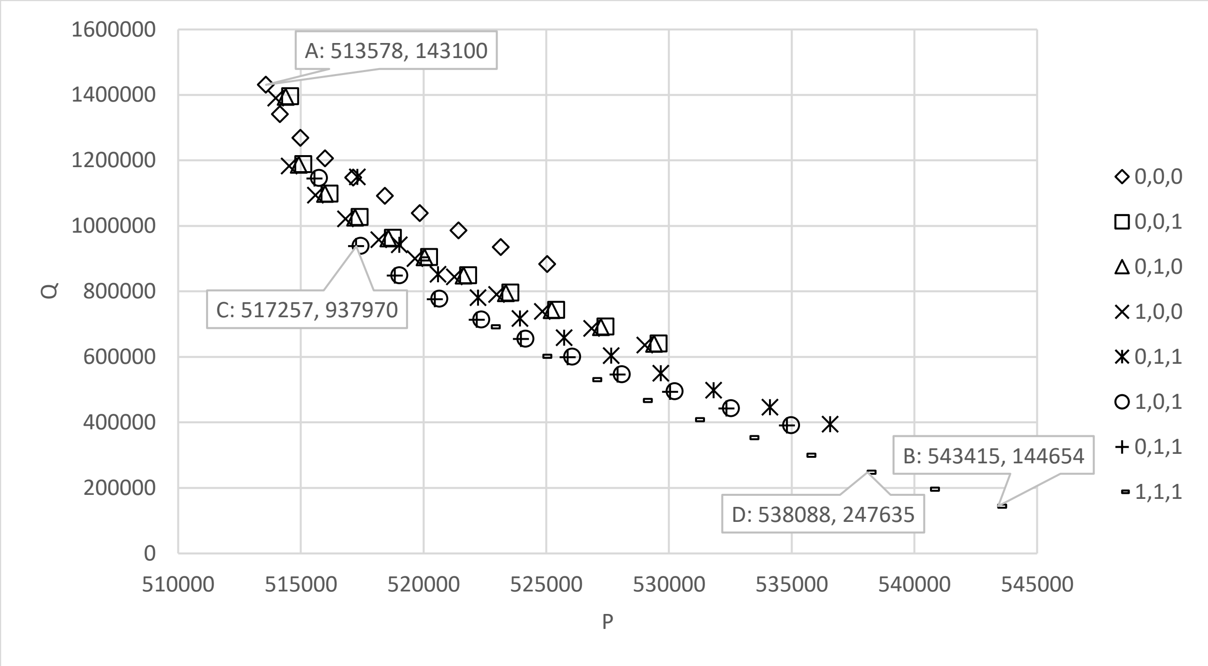

Figure 2: Calculated active power (P) and reactive power (Q) for all control points in the test feeder, with highlighted points of interest

Minimizing for P we get working point A with $P_{min} \cong 514\text{kW}$ and $Q_{P_{min}} \cong 1431\text{kVAr}$. Minimizing for Q we get working point B with $Q_{min} \cong 145\text{kVAr}$ and $P_{Q_{min}} \cong 543\text{kW}$.

In the multi-objective optimization case, if we optimize for Q as the preferred objective, the range we can set to $\delta_P = 1\%$ we get the reservation point $e_P = 519\text{kW}$. This leads to the optimal working point C in which $P_C \cong 517\text{kW}$ and $Q_C \cong 938\text{kVAr}$. The benefit of this method of reservation selection is that it has a significant operational meaning: for loss of optimality of 1% in active power, we gain $1431 - 938 = 493\text{kVAr}$, which is a gain of 34%.

Using this reservation selection method for optimizing P makes negligible operational sense due to the range of values of Q, so we base e_Q on the range $(Q_{min}, Q_{P_{min}})$ as follows: $e_Q = Q_{min} + \gamma\left(Q_{P_{min}} - Q_{min}\right)$, where γ stands for the range of values we allow. Selecting $\gamma = 10\%$ we get $e_Q = 273\text{kVAr}$, and optimizing for P, we get the working point D with $P_D \cong 538\text{kW}$ and $Q_D \cong 247\text{kVAr}$. Operationally speaking, for a loss of 10% of the range, we get a gain of $543 - 538 = 5\text{kW}$ which is 18% of the range $(P_{min}, P_{Q_{min}})$.

4. The weighted-sum technique

In the weighted-sum technique, we assign weighting coefficients to each of the objective values. For target functions $f_1(\cdot), f_2(\cdot), \ldots$ we can write the problem as

$$\text{minimize} \sum_i a_i f_i(\cdot),$$

where a_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.

One special case of the technique is the *monetization* method, in which pricing per unit is available for the different objectives, and can be used as the obvious weighting coefficient. However, in most cases these values are very rough estimations. In fact, from the target functions listed in section 1, only the cost of energy and the cost of losses are easily monetized.

Monetizing voltage profiles, reactive power or the cost of operations is usually done by speculation.
The common solution for this is to supply an "efficient curve" which includes the solutions for every possible combination of coefficients. A common variant of this is the so-called "α:(1-α)" method. This involves normalizing each objective value by its range of possible values, and then optimizing with weighting coefficients that sum to one. Namely, the optimization is to minimize $\sum_i a_i \frac{f_i(\cdot)}{N_i}$, where N_i are the normalizing factors and $\sum_i a_i = 1$.
In order to demonstrate this technique, we consider the same scenario as in section 3. Figure 3 shows the same 88 control points, highlighting the 14 control points that belong to the efficient curve, with the maximum value of α corresponding to each one.

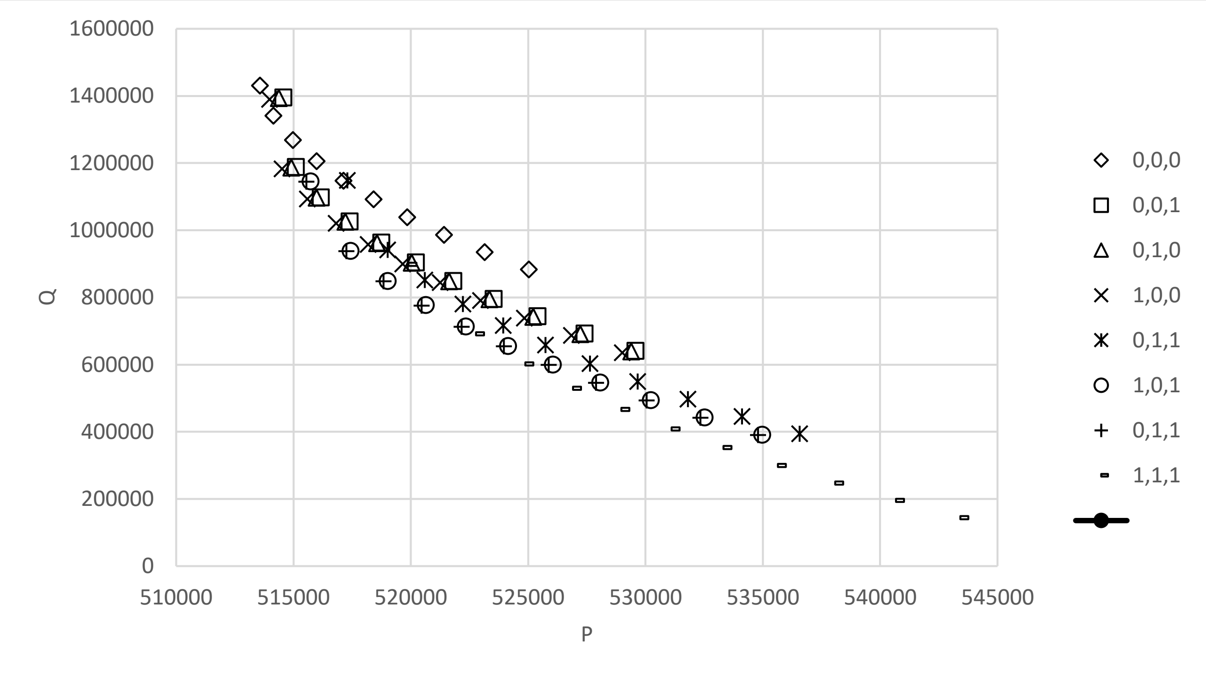

Figure 3: Active power (P) and reactive power (Q) on test feeder with efficient curve highlighted and α values

Operationally speaking, it only makes sense to select working points that belong to the efficient curve. While it can be observed that in this case all the working points that were considered by the *e-constraint* technique belong to the efficient curve, it should be noted that this is not always the case. For example, selecting $e_P = 522786$W yields a working point (522786W, 691811VAr), which is inefficient.
While this technique seems to provide the most freedom to the decision maker, it can be argued that it does not supply the operator with any meaningful method to select the actual working point. In our experience, operators find it confusing, and would rather have clear operational meaning for their choices.

5. Conclusions

In this work, we methodically applied the common multi-objective techniques to VVO. We demonstrated that in many case there is strong contradiction between selecting different objectives. Monetization of the objective functions is usually not straightforward. We showed that while the weighted-sum technique gives the operator the most freedom, it does not supply a ready operational explanation to make the final choice. The e-constraint seems to supply such

an explanation, and may be more appropriate in many cases, as long as the reservation values are meaningful.
A family of techniques that we did not consider are the *reference point* techniques, in which a distance function to a reference point (e.g., an ideal solution) is minimized. In our experience, these methods are two cumbersome to be used in the VVO context, as they typically require both weighting and selecting a reference point.
Another set of methods that we did not consider are interactive methods similar to the computer package TOMMIX [18]. Most of these methods were designed for mixed linear programming, while our problem is obviously non-linear. We are unaware of a ready-made too which enables such tools and leave this subject to future research.

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