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Computational Impacts of SVCs on Optimal Power Flow using Approximated Active-Set Interior Point Algorithm

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Abstract—Interior point methods (IPMs) are popular and powerful methods for solving large-scale nonlinear and nonconvex optimization problems, such as AC optimal power flow (ACOPF). There are various ways to model ACOPF, depending on the objective and the physical components that need to be optimized. This paper models shunt flexible AC transmission systems (FACTS). Shunt FACTS devices such as static VAR compensators (SVCs) are sources for reactive power compensations and addressing voltage stability issues. The co-optimization of SVCs with power dispatch can impact the computational performance of ACOPF. In this paper, we evaluate the performance of different ACOPF formulations with approximated active-set interior point (AASIP) algorithm and co-optimization of SVC set points alongside other decision variables. Our numerical results suggest that both AASIP and SVCs alone improves the computation performance of almost all formulations. The gain in performance, however, depends on the sparsity of the formulation. The most sparsely formulated, such as branch power flow rectangular voltages (BPFVR), shows the highest gain in performance. In the event of co-optimizing SVCs with power dispatch using AASIP, the performance gain is minimal. Finally, the results are verified using various test cases ranging from 500-bus systems to 9591-bus systems.

Index Terms—SVC, FACTS devices, IPM, ACOPF, approximated active-sets, AASIP

I. INTRODUCTION

Flexible AC transmission system (FACTS) devices are power electronic network controllers [1] with capabilities of adjusting a variety of power system parameters. They are, thus, deployed for a wide range of applications. FACTS technology is key to enhance the efficiency, controllability [2], and stability [3], [4] of the existing power grid. When the available transfer capability (ATC) of power system is limited and an upgrade is needed to relieve congestion, installation of FACTS devices provides a more efficient alternative to the lengthy and expensive process of new transmission line construction [5]. Moreover, FACTS technology is an important approach to facilitating the power grid to accommodate the increasing renewable generation penetration. Currently, the United States has an ambitious goal of completely eliminating carbon emissions from its power grid by 2035. With power flow control and voltage control capabilities, FACTS devices,

such as the thyristor controlled series compensator (TCSC) and the static VAR compensator (SVC), have been shown to be beneficial in enhancing the utilization of renewable generation [6]–[8].

In industry applications, FACTS technology has been deployed by various regional transmission organizations. Transmission owners, at PJM's direction, invested over \$1.3 billion in reactors and static VAR compensators (SVCs) between 2008 and 2018 aiming to reduce high-voltage system conditions [9]. FACTS devices including the static synchronous compensator (STATCOM) and the SVC has been deployed in ISO-NE in multiple locations from 2017 to 2019 for dynamic voltage control and dynamic support to the transmission system [10]. Across the globe, General Electric (GE) has developed and installed 380 SVC systems in a variety of projects for various applications [11]. Furthermore, modular and mobile design of FACTS devices have emerged to further provide flexibility. The SmartValve™ [12] developed by Smart Wires Inc., which is a modular static synchronous series compensator (M-SSSC), and the relocatable SVC (RSVC) [13] from ABB both allow mobile deployment and fast installation.

Among the various types of FACTS devices, shunt devices, including SVCs and STATCOMs, are widely deployed for voltage support [3] and reactive power compensation [1]. They provide an important approach for enhancing voltage stability [3] and improving power quality [14]. Furthermore, shunt FACTS devices are applied to help power systems accommodate growing renewable energy penetration. SVC and STATCOM devices provide dynamic voltage control capabilities that can help alleviate the impact of large-scale wind farm integration on voltage stability [15]. Given the significance and benefits of shunt devices to the power grid, in this paper, we focus on the SVC, which has been deployed on transmission level since the 1970s [1]. Details of SVC modeling are presented in Section II.

Incorporating FACTS into power system operation and planning models, such as the optimal power flow (OPF), is imperative to exploit the aforementioned benefits of the technology. Such models are key approaches to determining

optimal FACTS placement, sizing, and dispatch. However, the inclusion of FACTS has significant impact on operation and planning models. Notably, for instance, FACTS devices further increase the complexity of models that may already be computationally demanding. Many recent studies have focused on OPF models with FACTS included, aiming at a variety of objectives. In addition, because of the inherent non-linearity and non-convexity of ACOPF models, techniques to help improve computational efficiency, such as relaxation and linearization, are desirable. In following subsection, we provide a literature review covering both aforementioned topics.

A. Literature Review

Several recent studies, as mentioned previously, aim to find optimal allocation of FACTS devices through formulating and solving OPF models. In [16], the FACTS allocation problem is formulated as a sparsity-constrained ACOPF model, and is solved using an algorithm that combines the alternating direction method of multipliers (ADMM), the interior point method (IPM), and the shrinkage-thresholding operators (STO). To determine the optimal STATCOM placement, the particle swarm optimization (PSO) is applied in [17] to solve an OPF model with the objective of minimizing power losses. The authors of [5] present a multi-objective optimization method, in which the probabilistic OPF problems are solved, to find optimal allocation and sizing of TCSC and SVC devices with the consideration of wind generation uncertainties. In addition, transient stability constrained OPF (TSC-OPF) is used for SVC planning and operation in order to ensure better voltage stability performance [18].

Through solving OPF models, the benefits of FACTS devices in improving renewable integration are revealed. The work in [8] and [6] both focus on how FACTS devices can improve wind power utilization. The authors in [8] propose a probabilistic method, which is realized with the help of two sequential Monte Carlo Simulation (SMCS) procedures that use the OPF. In [6], the proposed OPF model with FACTS included is formulated using a two-stage stochastic programming problem. Both aforementioned studied present promising results on FACTS helping improve wind energy integration. It is also worth noting that the combination of FACTS and other emerging technologies, including dynamic line rating (DLR) and real-time thermal ratings (RTTR), are also studied in [5], [8].

The significance of the computational challenge in OPF models with FACTS is reflected in previous research. Several studies use relatively smaller test systems that have no more than 30 buses to conduct numerical studies on their proposed models [5], [6], [8], [19]. In [6], the authors acknowledge that their proposed model may suffer from computational intractability for larger systems, and suggest that techniques such as parallelization and decomposition may be needed for improving computational efficiency. Some studies apply linearization techniques for computational efficiency improvement. A linearized ACOPF model which includes optimal dispatch of both TCSC and SVC devices is proposed in

[20]. The results show that the proposed model ensure better accuracy than DCOPF.

Other studies on ACOPF, although not involving FACTS, have also focused on relaxations [21]. In the domain of ACOPF, many methods have been proposed over the past few decades including a variety of convex relaxation, approximations, and nonlinear programming techniques (e.g., [22]–[34]) to solve the ACOPF problems. While other techniques have scalability challenges, approximations are currently the practical solution widely used for OPF. However, inefficient and suboptimal solutions of power dispatch are likely consequences of rough reactive power flow and voltage approximations. Moreover, the influence of formulations and the significant counter-intuitive impact of SVC incorporation on the computational efficiency performance of ACOPF, especially when tackling large-scale problems, has been overlooked in many of the various studies on convex relaxation and nonlinear programming techniques. To study the impact of formulations, the authors in [35] perform a numerical analysis on the performance of three different ACOPF formulations. The limitation, however, is that only branch flow models are included in the analysis, thus not allowing varieties based on structural sparsity of different ACOPF formulations.

B. Contributions

In this paper, we solve ACOPF with shunt FACTS devices such as the SVC using the interior point method (IPM). According to [36], IPM algorithms are one of the most powerful nonlinear methods to solve large-scale nonlinear nonconvex problems. We analyze the performance of different ACOPF formulations, encompassing different varieties of ACOPF formulations ranging from sparse formulations to least sparse ones. We also present approximated active-set interior point (AASIP) algorithm, a new algorithm that is significantly faster than the ACOPF solved using general IPM algorithms. We evaluate the improvement in the performance of ACOPF by the SVC devices and AASIP algorithm, and compare its performance with fully constrained a general IPM method.

The contributions of this paper can be summarized as follows:

- 1) Evaluation of the computational impacts of SVC devices on different ACOPF formations using the IPM;
- 2) Implementation of the approximated active-set IPM algorithm for improving the performance of different ACOPF formations while incorporating SVC devices;
- 3) Using different analysis identifying the best scalable ACOPF formulations with respect to scalability, different voltage models, and sparsity structures.

Different algorithms can have different performance behavior corresponding to the SVC modeled with different ACOPF formulations and approximated active-set approach. The convergence pattern might change when used in other methods. Thus, as a future work it is worth investigating the performance of these models using different algorithms.

The rest of the paper is organized as follows. Section II introduces co-optimization of the SVC in ACOPF. Sections

III provides an overview of interior point method and approximated active-set algorithm. Section IV presents the numerical experiments for evaluation of the computational performance of co-optimization of SVCs in different ACOPF formulations using the approximated active-set IPM. Section V summarizes the conclusions of the study.

II. CO-OPTIMIZATION OF SVCs IN ACOPF

An optimal power flow constitutes the core of power system operations. It is an optimization extension of the power flow analysis [37], where in addition to feasibility, an optimal dispatch is also desired. In this paper, we consider the objective function to serve the customers at the minimum cost, taking into consideration the physical constraints of the system.

Fig. 1 shows the classification of different ACOPF formulations that we consider in this work. We model SVC devices in these ACOPF formulations, notating the models as SVC-ACOPF, based on π -representation of transmission branches and the formulations described in [38], [39].

Fig. 1: Classification of different ACOPF formulations as shown in [38].

Fig. 2(a) [1] presents a typical configuration of the SVC, which consists of a fixed capacitor and a thyristor controlled reactor (TCR). Based on this structure, an SVC can be modeled as a variable shunt susceptance. This model is a commonly used representation of SVC devices in ACOPF [20], [40], [41]. The variable shunt susceptance model of the SVC is shown in Fig. 2(b) [40].

The variable shunt susceptance at bus i , b_i^{SVC} , is subject to the bounds defined in the following constraint:

$$b_i^{\min} \leq b_i^{\text{SVC}} \leq b_i^{\max}. \quad (1)$$

The reactive power compensation Q_i^{SVC} can be calculated based on the voltage model used in the ACOPF formulations and added as an injection source to the reactive power nodal balance equations. For polar voltages the Q_i^{SVC} can be calculated as:

$$Q_i^{\text{SVC}} = b_i^{\text{SVC}} \cdot V_i^2, \quad (2)$$

Similarly, for rectangular voltages and W -models Q_i^{SVC} can be calculated as (3) and (4) respectively.

$$Q_i^{\text{SVC}} = b_i^{\text{SVC}} \cdot [(v_i^r)^2 + (v_i^i)^2] \quad (3)$$

Fig. 2: (a) SVC configuration [1] (b) SVC variable shunt susceptance modeling [40].

$$Q_i^{\text{SVC}} = b_i^{\text{SVC}} \cdot W_i^d \quad (4)$$

where V_i is the nodal voltage of bus i . Note that our results still hold for other shunt devices that the variable shunt susceptance modeling can be applied on.

III. INTERIOR POINT METHOD (IPM)

The interior point method (IPM) has shown great deal of success in nonlinear programming domain as it has in linear programming. It is considered one of the most practical and substantial methods for solving non-convex nonlinear optimization problems [36]. Let's assume eq. (5) represents a nonlinear problem.

$$\min_x f(x) \quad (5a)$$

$$\text{s.t. } c_i(x) = 0, \quad i \in \mathcal{E} \quad (5b)$$

$$c_i(x) \geq 0, \quad i \in \mathcal{I} \quad (5c)$$

The inequality constraints in (5) which can be converted to equality constraints as shown in (6).

$$\min_x f(x) \quad (6a)$$

$$\text{s.t. } c_i(x) = 0, \quad i \in \mathcal{E} \quad (6b)$$

$$c_i(x) - s_i = 0, \quad i \in \mathcal{I} \quad (6c)$$

$$s_i(x) \geq 0, \quad i \in \mathcal{I} \quad (6d)$$

Using a logarithmic barrier framework described in [42] with subproblems of the form shown in (7)

$$\min_{x \in \mathcal{R}^n} \varphi^\mu := f(x) - \mu \sum_{j=1}^n \log s_i^{(j)} \quad (7a)$$

$$\text{s.t. } c(x) = 0 \quad (7b)$$

where $\mu > 0$ is the barrier parameter and $s_i^{(j)}$ is the j th entry of vector s . We consider a framework that approximately solves a sequence of barrier problems (7) using Newton's method and drives the barrier parameter μ monotonically to zero. A filter method can be used to determine whether a step is productive and acceptable [36].

Fig. 3: The performance profile comparing the performance of fully-constrained ACOPF formulations with approximated active-set ACOPF formulations. (Note: No SVC is included in this plot).

Approximated Active-Set

The active set $A(x)$ at any feasible x consists of the equality constraint indices from $\mathcal{E}$ together with the indices of the inequality constraints i for which $c_i(x) = 0$; that is,

$$\mathcal{A}(x) = \mathcal{E} \cup \{i \in \mathcal{I} | c_i(x) = 0\}.$$

At a feasible point x , the inequality constraint $i \in \mathcal{I}$ is said to be *active* if $c_i(x) = 0$ and *inactive* if the strict inequality $c_i(x) > 0$ is satisfied. In the approximated active-set approach we try to obtain an approximation of the $\mathcal{A}(x)$, notated as $\mathcal{A}'(x)$ and solve the IPM only for the $\mathcal{A}'(x)$. This will significantly reduce the computation complexity of the method for large-scale problems.

For ACOPF, we first solve DCOPF. The advantage of this approach is that DCOPF and linear solvers are readily available in the existing energy management system (EMS) and can be used to create an approximated active-set $\mathcal{A}'(x)$. The approximated active-set will significantly improve the computation times of the IPM algorithm.

Fig. 4: The box plot shows the percentage of change in real power loss and objective value using SVC. The negative values indicate the reduction in loss/objective value with the addition of SVCs.

IV. NUMERICAL EXPERIMENTS

All numerical experiments were performed on an 8-core Intel(R) i9-9980HK CPU @ 2.40 GHz with 32 GB RAM system. The programming for numerical experiments are implemented in Julia v1.5.3 using Gurobi v9.1.2, KNITRO 12.4, and JuMP v0.21.5 in a Linux Ubuntu operating system. The numerical experiments were conducted on the U.S. Department of State's Grid Optimization Competition Challenge I test cases ranging from 500-bus systems to 9591-bus systems [43].

Fig. 4 shows the percentage of change in real power losses and objective value as a result of connection SVCs. The plot shows that for the majority of the cases the real power losses are reduced by up to almost 6%. It can also slightly reduce the objective value.

The performance profile of different ACOPF formulations comparing the impact of approximated active-set with fully-constrained models (excluding SVCs) are shown in Fig. 3. The performance profile shows a significant improvement in computation time when approximated active-set is employed. The numerical experiments on a wide range of test cases has verified the effectiveness of approximated active-sets. A possible violations due to exclusion of non-binding constraints in approximated active-set approach was also monitored during the numerical experiments, which remained consistently below $1.0e^{-6}$ for all test cases.

Similarly, the performance profile in Fig. 5 compares the performance of fully-constrained ACOPF formulations with fully-constrained SVC-ACOPF formulations. The reduction in computation time due to SVCs is directly related the sparsity of formulations. The least sparse formulations such as nodal injection polar admittance polar voltages (NIPAPV) and nodal injection rectangular admittance polar voltages (NIRAPV) formulations have shown smallest gains in terms of computation time, where as the most sparse formulations such as BPFRV has yielded the largest gain. This pattern is common among

Fig. 5: The Performance profile comparing the performance of fully-constrained ACOF formulations with fully-constrained SVC-ACOF formulations.

Fig. 6: The Performance profile comparing the performance of approximated active-set ACOF formulations with approximated active-set SVC-ACOF formulations.

second-order nonlinear programming methods, where the co-optimization of SVCs and ACOF usually ends up in the better computation performance compared to the ACOF problem alone.

Finally, Fig. 6 compares the performance of ACOF formulations (approximated active-set) with SVC-ACOF formulations (approximated active-set). The plot shows the change in the performance of ACOF formulations with the addition of SVCs are minimal and negligible.

V. CONCLUSION

This paper investigated the co-optimization of generator dispatch and SVC set point in an ACOF model using an interior point method. We introduced approximated active-set interior point (AASIP) algorithm to solve different ACOF models.

The fully-constrained ACOF using an IPM is compared with the AASIP algorithm and co-optimization of SVCs and generator dispatch using different ACOF formulations. In our numerical experiments, we have used seven different ACOF formulations with various sparsity structures to examine the computational impacts of SVCs and performance gain as a result of eliminating non-binding inequality constraints using an approach called AASIP. Our numerical results found that the AASIP algorithm significantly improves the computation performance of all formulations, especially the relatively sparse formulation such as branch power flow rectangular voltages (BPFRV) formulation. Similarly, counter to the intuition, the co-optimization of SVCs with generator cost reduced the computation time compared to optimising generator cost alone. This comes in addition to the slight improvement in

the objective value and the total real power losses for the majority of the test cases. Finally, the co-optimization of SVCs and generator cost using AASIP has a minimal computational impact on the performance of the majority of the formulations.

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