Data-Aided Offline and Online Screening for Security Constraint

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***Abstract*—Security constraint is a key component in unit commitment to guarantee reliable generator commitment. Large set of security constraints are notorious for making the problem difficult to solve. Constraint screening, i.e., filtering out non-dominating constraints, is regarded as a powerful tool to address this challenge. This work presents a security-constraint screening that can effectively integrate virtual transaction and capture changes online in real-time or look-ahead markets. The proposed approach takes advantage of both deterministic and statistical methods, which leverages mathematical modeling and historical data. Effectiveness are verified using Midcontinent Independent System Operator (MISO) data.**

***Index Terms*—Data aided, security constraint, transmission congestion, unit commitment, virtual power.**

I. Introduction

SECURITY constrained unit commitment (SCUC) is discussed extensively in the literature and well implemented in daily power system operation by independent system operators (ISO) and Regional Transmission Organizations (RTO) [1], [2]. It is a challenging task to obtain an optimal solution in an acceptable time due to the enormous size of the problem. The SCUC's objective is to maximize social welfare subject to a variety of constraints, such as generator physical constraints, power balance, reserve requirements, and transmission security constraints [3].

SCUC, by nature, is a nonconvex and large scale mixed integer optimization problem. Recent improvements in modeling, optimization solvers, and efficient algorithms enable system operators to quickly obtain optimal or near-optimal solutions. SCUC can be generally solved by Lagrangian Relaxation (LR) and Mixed Integer Linear Programming (MILP), performance comparison can be found in [3]. Midcontinent Independent System Operator (MISO) has adopted MILP approach for the Co-optimized Energy and Ancillary Service Market since 2009. Day-Ahead Market (DAM) is a financial market, and the market-clearing process requires solving SCUC problems for all planned operation periods. It is crucial to obtain a near optimal solution while meeting the time requirement.

In DAM, security constraints are defined as power flow transmission constraints for transmission lines considering the N-1 security rule according to North American Electric Reliability Corporation (NERC). There are over 15 000 security constraints formulated for MISO's DAM. Incorporating all security constraints in the model could cause computational intractability, which means optimality and solution time requirements cannot be guaranteed. Many research efforts have gone into improving SCUC computational performance [3], [4]. Decomposition approaches, such as Benders decomposition and Lagrangian decomposition, divide the original problem, which is difficult to solve, into smaller pieces; acceleration comes from solving the smaller problems in parallel. Heuristic approaches, such as warm start, gives the solver a starting node, which may help in some situations. Good quality of warm start information can help filter out inferior nodes, but a poor one may hurt more than they help. However, it is not always possible to obtain high quality of warm start information.

According to our experiences in real-world challenging cases at MISO, security constraint is one of the primary driving factors of slowing the SCUC computational performance. Models with fewer security constraints can generally reach an acceptable optimality gap with less time. Reducing non-binding hard constraints often helps reduce solution time for MILP problems. The goals of this research are to effectively reduce the size of security constraints set in both offline and online SCUC models, and to improve solution quality, while maintaining solution integrity. Only a small fraction of security constraints is binding in real-world systems. For example, MISO heuristically identifies around 200 critical security constraints each interval as "watchlist" that could be routinely binding.

The overwhelming security constraints have attracted much attention in literature. In general, approaches to tackling this problem include constraint preprocessing and constraint generation method. In constraint preprocessing approaches, researchers bring the umbrella constraint concept to SCUC problems [5], [6]. The umbrella constraints are dominating constraints defined as the minimum set of constraints that shapes the

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feasibility region of the original problem. Binding constraints are a subset of umbrella constraints, which can only be determined after solving the original MILP problem. As it involves additional Linear Programming (LP) or MILP problems, which can be time consuming and harder to apply to large systems. Authors in [7] propose an efficient numerical method to eliminate redundant constraints in SCUC, and [8], [9] further take uncertainty into consideration by leveraging the bound of the net power injection uncertainty. By considering the bound when contingency occurs, author in [10] presents how to efficiently eliminate constraints for contingencies in SCUC. Similar applications can be found in [11]–[13]. However, the eliminating rate of these approaches may not be as high as that of optimization based approaches. Constraint generation based method attempts to solve a smaller model (e.g. initially ignoring some constraints). Once a solution is obtained, security constraints will be checked. If a violation is found, the corresponding constraints will be added back to the model, as discussed in [14], [15]. Many constraints that have low probability of being binding can be skipped to avoid modeling too many redundant constraints. However, a significant drawback is that each iteration is time consuming and it is hard to know how many iterations needed for convergence. Recently, intelligent system based heuristic approaches are applied to remove potentially non-binding constraints in [16]–[18], which addresses the conservatism. The warm start and setting proper lazy constraints may improve the SCUC solution performance [19].

There are two open questions, although many efforts are put in security constraint screening. The first one is how to effectively handle virtual transactions that often account for up to 45% market capacity in real-world systems. The virtual offer or bid has a large range and poses a challenge in modeling a tight power injection interval, which is a key to conduct screening. The second open question is to find an effective screening approach for real-time or look-ahead market. A precise N-1 security screening has significant overhead in real-world systems. The system's real-time conditions, such as load level, renewable generation, and topology, are constantly changing and could be significantly different from DAM. The DAM screening may not apply to real time directly. Due to the timeliness requirement, it is difficult to conduct thorough screening in real-time or look-ahead market. Some ISOs, such as MISO, rely on after-the-fact state estimation instead of enforcing security constraints in advance.

To address these challenges, we present a two-step screening approach, an extension to [20]. Furthermore, we propose an online approach that could find a tight upper bound of power flow when more information is revealed in real-time or look-ahead market. By utilizing dual variables from the offline component, the online counterpart uses a closed-form formulation to quickly determine whether a security constraint is violated. A data-aided approach is employed to attain the confidence interval of virtual power that can be cleared in DAM. The price signal interval is integrated to reduce net power injection range, which results in fewer security constraints. Lazy constraint in optimization solver is employed as an effective last resort to avoid any violation. A lazy constraint resembles a call back function that checks constraint violations once a feasible solution is found.

The contributions of this paper are summarized as below.

1) We propose an offline-online approach based on a two-step security constraint screening. The offline part identifies dominating security constraints in the case of maximum net power injection with conservative forecasted system information. The online component, which can be utilized in real time, captures latest changes, and provide fast yet accurate screening of security constraints. The online approach clears the computational barrier of guaranteeing N-1 security, which is not enforced in real-time market in MISO.
2) We develop an effective approach to managing virtual transactions in screening. Although virtual supply and demand account for a large portion of load or generation in DAM, there is few literatures reporting how to handle virtuals in security constraint screening. A challenge stemming from virtual transactions is that its interval is often very large, which could hurt the effectiveness of existing approaches. The approach proposed in this paper integrate the market-clearing price and lazy constraint so that we could effectively narrow the range of virtual power injections and reduce the size of the dominating constraints set.
3) The proposed techniques are examined in a real-world system, i.e., MISO system. Extensive numerical testing results are presented in this work. Authors argue that these world-world testing results provides some insights for other systems.

It is shown in the real-world MISO case study that the proposed method is able to eliminate 99.97% security constraints in real time. With proper offline preparation, online screening only takes 12 seconds. Incorporation the propose method, security constraint pool size has been reduced by half. DAM SCUC solution time has decreased by up to 50%.

The paper is organized as following. In section II, the deterministic two-step screening method with offline-online approach is presented. Section III introduces an approach to handle the virtual transactions. In section IV, we present the numerical testing results for MISO systems. Section V concludes the paper.

II. Offline and Online Security Screening

It is challenging to deal with large number of security constraints in real world systems. Some ISOs/RTOs develop special procedures to identify creditable security constraints and only include those constraints in the DAM SCUC model. Iterative approaches are often employed, such as standard operation procedure among DAM SCUC, Security Constraint Economic Dispatch (SCED) and Simultaneous Feasibility Test (SFT) [14]. SCUC determines generator commitments, and SCED takes finer piecewise generator bids to determine the most economical dispatch. The SFT checks for security violation, commitment, and reserve sufficiency. Any violated security constraint can be iteratively added to the model. For instance, MISO evaluates outages and other relevant information to build the watchlist, which is a much smaller subset of the full set of security constraints, and then iteratively add any violated constraint to

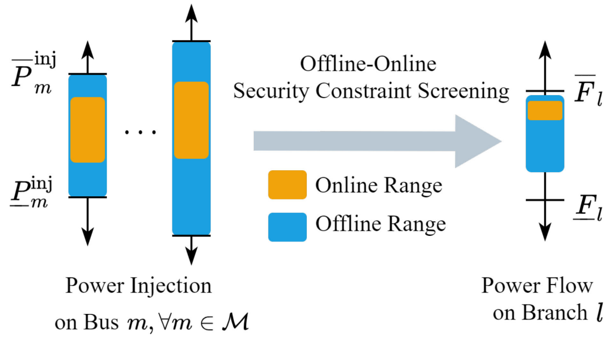

Fig. 1. From net power injection interval to power flow interval in offline-online security constraint screening.

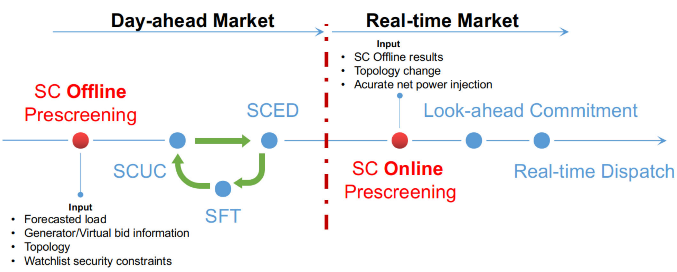

Fig. 2. Offline-online approach timeline. SCED: Security constraint economic dispatch, SFT: Simultaneous feasibility test.

the model. However, the system operator may still confront situations where optimization engine cannot find an acceptable solution within the time limit. There is an emerging and practical need to find acceleration techniques to improve the optimization performance.

It is even more challenging in real-time or look-ahead markets due to higher timeliness requirement. Instead of modeling the security constraint, ISOs use modules such as Real-Time Contingency Analysis (RTCA) to check the N-1 security. RTCA relies on state estimation and is just an after-the-fact verification tool. This may cause both economic and security issues. The proposed offline-online method provides a more robust and accurate yet fast approach. Fig. 1 shows the idea of offline-online approach, where the offline part provides a basis and the online part integrates the latest information. The closed-form equation for online screening is able to meet the timeliness requirement.

In this section, two-step security constraint screening is presented to reduce the size of security constraint set watchlist. Step-1 is a numerical method that employs necessary conditions to filter out redundant security constraints considering the uncertainty [9]. For the remaining constraints filtered by step-1, step-2 solves multiple LP problems to check constraint redundancy. Let $\mathcal{J}_1$ be the remaining security constraint set after step-1. Step-2 solves $|\mathcal{J}_1|$ LP problems (C) [20], to identify the dominating security constraint set, $\mathcal{J}_2$. In the meantime, dual variables, λ, of LP constraints are saved for the use of online method. When more information is revealed, we present a closed-form equation to attain the upper bound of the power flow. Implementation timeline is shown in Fig. 2.

A. Offline Screening

The DC power flow on line l is modeled as $f_l = \sum_m \Gamma_{l,m} P_m^{\text{inj}}$, where $\Gamma_{l,m}$ is the power transfer distribution factor (PTDF) for line l, bus m, and P_m^{inj} is the net power injection at bus m. An LP to find the largest possible power flow for line l is formulated as problem (C) below

$$(C) \quad f_l^{\text{off}} := \max_{\{P_m^{\text{inj}}\}} \sum_m \Gamma_{l,m} P_m^{\text{inj}} \tag{1}$$

$$\text{s.t.} \quad \sum_{m \in \mathcal{M}} P_m^{\text{inj}} = 0, \qquad (\lambda_l) \tag{2}$$

$$\sum_m \Gamma_{l',m} P_m^{\text{inj}} \leq F_{l'}, \quad l' \in \mathcal{J}_1 \setminus l \qquad (\alpha_{l'}) \tag{3}$$

$$\underline{P}_m^{\text{inj}} \leq P_m^{\text{inj}} \leq \overline{P}_m^{\text{inj}}, \quad m \in \mathcal{M} \qquad (\beta_m^-, \beta_m^+) \tag{4}$$

where (2) is the power balance constraint, and $\mathcal{M}$ is the set of bus indices, and (3) includes all security constraints except the one that is being tested. If optimal value of problem (C) f_l^{off} is greater than the line rating F_l, security constraint l is dominating in the positive direction. Dominating security constraints set determined by offline method (C) is $\mathcal{J}_2$. We are able to identify the security constraint dominance as long as the network topology and upper and lower bounds of net power injection are available. This feature enables a wide range of applications. Theorem 3 in [8] is also based on the net power injection model, although identification rate might not be as high as problem (C).

Denote $\mathcal{G}_m, \mathcal{V}_m, \mathcal{N}_m$, and $\mathcal{F}_m$ as sets of generator, virtual, fixed demand, and price-sensitive demand, respectively. Let i, k, n and f be indices for generator, virtual, fixed demand, and price-sensitive demand, respectively. The net power injection P_m^{inj} can be expressed as

$$P_m^{\text{inj}} = \sum_{i \in \mathcal{G}_m} P_i + \sum_{k \in \mathcal{V}_m} P_k^v - \sum_{n \in \mathcal{N}_m} D_n - \sum_{f \in \mathcal{F}_m} D_f^{\text{flex}}, \tag{5}$$

where P_i is output from generator i, P_k^v is virtual bid/offer, D_n is the fixed demand, D_f^{flex} is the price-sensitive demand.

As a side note, one could improve the solution time by converting the optimization problem (C) into a feasibility checking problem. More specifically, we can replace equation (1) with 0 and add constraint

$$\sum_m \Gamma_{l,m} P_m^{\text{inj}} \geq F_l \tag{6}$$

in problem (C).

B. Online Screening

The online identification is performed based on closed form equations without solving optimization problem, and the offline part includes tasks of solving LP problems. At the offline optimization stage, load/net power injection information is assumed not precise. In contrast, more information will be available at the online calculation stage in real time. In the following section, we present online screening methods capturing both net power interval change and network topology update.

1) Updated Net Power Injection Interval: In the real-time market, many uncertainties are materialized. The load forecast for next hours is more accurate than that in DAM. The predication of renewable generation is also with smaller errors. Furthermore, ON/OFF status for many generators are already known for next hours. This information can be utilized to narrow the net power injection. More specifically, $\underline{P}_m^{\text{inj}}$ and $\overline{P}_m^{\text{inj}}$ in equation (4) will be updated to capture the materialized information.

Instead of solving another LP problem with updated constraint, we present a computationally efficient way to find the new largest power flow. Offline method requires solving problem (C) for each security constraint, which gives the maximized power flow f_l^{off}, optimal net power injection $P_m^{\text{inj}*}$ and, dual variables, i.e., $\lambda_l^*, \alpha_{l'}^*, \beta_m^{-*}, \beta_m^{+*}$. In fact, most modern optimization solver will provide dual values after solving problem (C). To show how to utilize dual values, we formulate dual problem (D) of (C) below and denote its optimal value as $f_l^d(\underline{\mathbf{P}}^{\text{inj}}, \overline{\mathbf{P}}^{\text{inj}})$.

$$
\begin{aligned}
&f_l^{\text{d}}(\underline{\mathbf{P}}^{\text{inj}}, \overline{\mathbf{P}}^{\text{inj}}) := \\
&\qquad \max_{\left\{\substack{\lambda_l, \alpha_{l'}, \\ \boldsymbol{\beta}^-, \boldsymbol{\beta}^+}\right\}} -\sum_{l'} F_{l'}\alpha_{l'} + \sum_m (\underline{P}_m^{\text{inj}}\beta_m^- - \overline{P}_m^{\text{inj}}\beta_m^+) \\
(D) \qquad &\text{s.t.} \quad \lambda_l + \sum_{l' \in \mathcal{J}_1 \backslash l} \Gamma_{l,'m}\alpha_{l'} - \beta_m^- + \beta_m^+ = \Gamma_{l,m}, \\
&\qquad\qquad\qquad\qquad\qquad\qquad m \in \mathcal{M} \\
&\qquad \beta_m^+, \beta_m^- \geq 0, m \in \mathcal{M} \\
&\qquad \alpha_l \geq 0,
\end{aligned}
$$

where $\underline{\mathbf{P}}^{\text{inj}}, \overline{\mathbf{P}}^{\text{inj}}$ are lower and upper bound vectors for all net power injections. It is noticed that $f_l^d(\underline{\mathbf{P}}^{\text{inj}}, \overline{\mathbf{P}}^{\text{inj}})$ is a function of $\underline{\mathbf{P}}^{\text{inj}}$ and $\overline{\mathbf{P}}^{\text{inj}}$.

It is observed that optimal dual values of (C), i.e. $\lambda_l^*, \alpha_{l'}^*, \beta_m^{-*}, \beta_m^{+*}$ are always feasible in (D) no matter what upper and lower bounds of net power injections are. Denote the updated upper and lower bounds as $\hat{\underline{P}}_m^{\text{inj}}$ and $\hat{\overline{P}}_m^{\text{inj}}$, respectively. We define f_l^{on} as

$$
f_l^{\text{on}} := -\sum_{l'} F_{l'}\alpha_{l'}^* + \sum_m \hat{\underline{P}}_m^{\text{inj}}\beta_m^{*-} - \sum_m \hat{\overline{P}}_m^{\text{inj}} * \beta_m^{*+}. \tag{7}
$$

According to duality theory,

$$
f_l^{\text{on}} \geq f_l^{\text{d}}(\hat{\underline{\mathbf{P}}}^{\text{inj}}, \hat{\overline{\mathbf{P}}}^{\text{inj}}) = f_l^{\text{off}}
$$

holds. Therefore, f_l^{on} is an upper bound of power flow on line l. In other words, we can determine the upper bound of the maximal power flow using the closed-form equation (7). According to our experience, this upper bound is tight enough to remove the majority of industrious constraints in real-world systems.

2) Updated Network Topology: The method aforementioned works when there is no topology change. In this part, our goal is to quickly determine whether post line contingency power flow will cause congestion. Line outage distribution factor $\mathbf{LODF}_{ml\rightarrow ol}$ can be quickly calculated as shown in [21], where $ml \rightarrow ol$ represents monitored lines to outage lines. Pre/post contingency power flow, $f_{ml}^{\text{base}} \backslash f_{ml}^{\text{ctg}}$, must respect branch flow limits, F_{ml}. They are typically modeled as

$$
\begin{cases}
f_{ml}^{\text{ctg}} = f_{ml}^{\text{base}} + \mathbf{LODF}_{ml\rightarrow ol} f_{ol}^{\text{base}} \\
\quad -F_{ml} \leq f_{ml}^{\text{ctg}} \leq F_{ml}
\end{cases} \tag{8}
$$

where $f_{ml}^{\text{base}} = \mathbf{\Gamma}_{ml} P_m^{\text{inj}*}$ is obtained from the base case.

The traditional approach calculates post-contingency power flow from pre-contingency power flow. The proposed approach verifies congestion potential of monitored lines over an injection range, $\Delta P_m^{\text{inj}*}$. Denote the pre-contingency net power injection as $P_m^{\text{inj}*}$, $\Delta P_m^{\text{inj}*}$ can be calculated around $P_m^{\text{inj}*}$ by factoring in topology change, load forecasting error, generator ramping rates and participation below

$$
P_m^{\text{inj}*} - \sum_{i \in \mathcal{G}_m} R_i + \underline{d} \leq \Delta P_m^{\text{inj}*} \leq P_m^{\text{inj}*} + \sum_{i \in \mathcal{G}_m} R_i + \overline{d}, \tag{9}
$$

where R_i is ramping rate. Consider post-contingency power flow change due to $\Delta P_m^{\text{inj}^*}$

$$
\Delta f_{ml} = (\mathbf{\Gamma}_{ml} + \mathbf{LODF}_{ml\rightarrow ol}\mathbf{\Gamma}_{ol})\Delta P_m^{\text{inj}*}, \tag{10}
$$

where $\mathbf{\Gamma}_{ol}$ is outage lines' shift factors extracted from base case. The new power flow is

$$
f_{ml}^{\text{ctg}} + \Delta f_{ml}. \tag{11}
$$

Together with

$$
-F_{ml} - f_{ml}^{\text{ctg}} \leq \mathbf{\Gamma}_{ml}^{\text{ctg}} \Delta P_m^{\text{inj}*} \leq F_{ml} - f_{ml}^{\text{ctg}},
$$

we can directly apply the proposed two-step screening to determine potential dominating security constraints in post contingency situation.

III. Modeling Virtual Transactions

Experience with MISO DAM data shows that virtual power accounts for 35-45% of market capacity in DAM. These virtual transactions make it difficult to find tight net power injection in the security constraint screening. A loose net power injection could significantly decrease the screening performance. Observing only about half of virtual transactions are cleared in reality, we propose to tighten the range of virtual offer and bid based on historical market-clearing prices.

A. Virtual Transaction Aggregation and Predication

From equation (5), we observe that the net power injection at bus m can be decomposed into non-virtual component (P_i, D_n, D_f^{flex}) and virtual component (P_k^{v}). Due to its large volume, virtual component heavily affects the net power injection interval. In this subsection, a statistical approach is proposed to narrow down the power injection intervals caused by virtual transactions. screening is thus able to produce a tighter dominating security constraint set.

At any given bus m, multiple virtual bid/offer Price Quantity Pairs (PQP) can exist. Bid/offer quantities are cleared under Locational Marginal Price (LMP), say π_m. Virtual supply and demand help bridge the gap between DAM and Real-time Market (RTM). Generation non-convexity due to minimal output limit is mitigated by the available virtual bids. The price signal of highest virtual bid cleared at a node can be a better representation

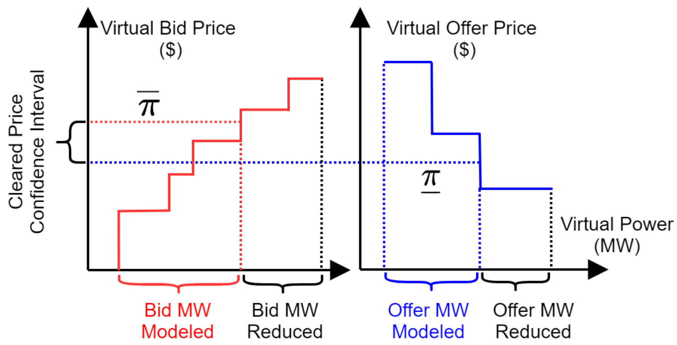

Fig. 3. Virtual power cleared on bus m, bid/offer curves were built on aggregated PQPs submitted by virtual power plants.

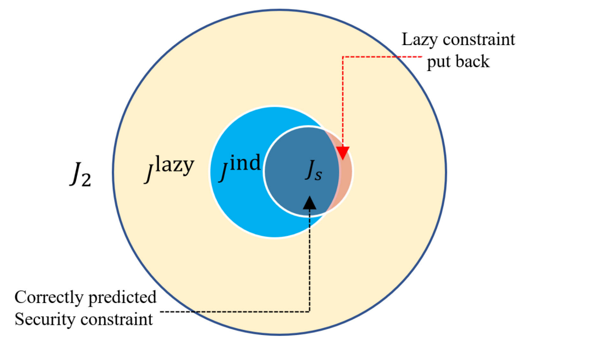

Fig. 4. Relationship between industrious constraints J^{ind}, lazy constraints J^{lazy} and supporting constraints J_s.

of marginal unit than the most expensive generation cleared. The cleared quantity of virtual transaction is a function of LMP. We approximate it as

$$P_m^{\text{v, inj}} = \overline{P}_m^{\text{v}} - \underline{P}_m^{\text{v}} = C(\overline{\pi}_m) - C(\underline{\pi}_m), \tag{12}$$

where $\overline{\pi}$ and $\underline{\pi}$ represents the 95% virtual price confidence interval (VPCI) estimated from quantiles of historical LMPs. Fig. 3 illustrates the general idea. As shown in Fig. 3, $\overline{\pi}$ cuts off the most expensive bids, and $\underline{\pi}$ cuts off the lowest offers.

B. Integration With Lazy Constraint

Denote all security constraints supporting the optimal point as $\mathcal{J}_S$. When predication of virtual transactions is involved, we cannot guarantee complete inclusion of $\mathcal{J}_S$. This issue can be addressed by employing *lazy constraint*, which is designed in optimization solver to incorporate user confidence to improve solution quality. Constraints that believed to be less probable to violated at the optimal point can be marked as lazy. The model is initially optimized without any lazy constraints. Once a solution is found, lazy constraints are checked with the current solution. If any lazy constraints are violated, they will be added back to the model. Optimization process continues till an optimal point is found without any lazy constraint violations. The key is to exercise best judgment regarding lazy constraints, as they are intended to shrink constraints set and optimize a smaller and easier model. However, if set inappropriately, it may result in more iterations to put back the lazy constraints and solution time may suffer.

In contrast to lazy constraint, the constraint directly built to the model is called industrious constraint in this work. We separate $\mathcal{J}_2$, i.e., set of remaining security constraint after Step-2, into industrious constraint pool, $\mathcal{J}^{\text{ind}}$, and lazy constraint pool, $\mathcal{J}^{\text{lazy}}$. Illustrated in Fig. 4, $\mathcal{J}^{\text{ind}} \cup \mathcal{J}^{\text{lazy}} = \mathcal{J}_2$ and $\mathcal{J}^{\text{ind}} \cap \mathcal{J}^{\text{lazy}} = \emptyset$. Industrious constraints are highly likely to bind at the optimal solution, and lazy constraints are less likely to bind at the optimal solution. If the active pool is over-conservative, $\mathcal{J}^{\text{ind}} \approx \mathcal{J}_2$, performance improvement would be negligible. If the pool is over-optimistic, $\mathcal{J}_S \backslash \mathcal{J}^{\text{ind}} \subseteq \mathcal{J}^{\text{lazy}}$ is large, more constraints are added back in the MILP searching process, which may increase solution time.

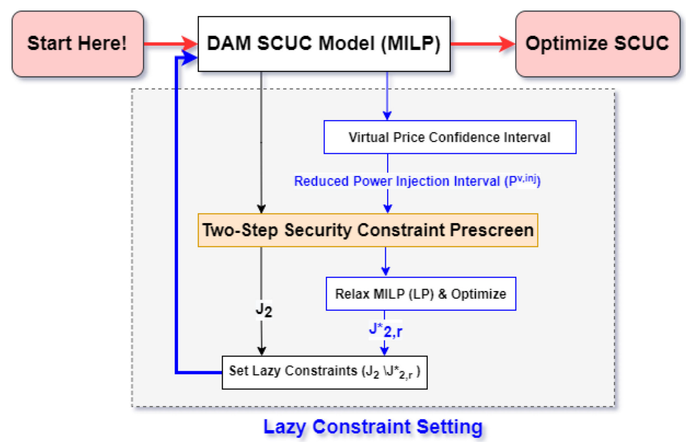

Fig. 5. Incorporating virtual price confidence interval and lazy constraint setting in DAM SCUC.

We develop a procedure to separate $\mathcal{J}_2$ into $\mathcal{J}^{\text{ind}}$ and $\mathcal{J}^{\text{lazy}}$, as shown in Fig. 5. Firstly, apply two-step screening in the SCUC model and get dominating constraints set $\mathcal{J}_2$. Secondly, relax integer variables in the SCUC model, use virtual price confidence interval to cut off more expensive virtual injection bands in a relaxed model (LP). Thirdly, optimize LP and get a relaxed power flow f_l^{r*}. Given power flow limit F_l and threshold γ, if

$$\frac{f_l^{r*}}{F_l} \geq \gamma, \qquad l \in \mathcal{J}_2 \tag{13}$$

holds, security constraint for line l is considered as potentially binding, it is put to the Industrious constraint set $\mathcal{J}^{\text{ind}}$. Otherwise, this constraint is set as lazy, $\mathcal{J}^{\text{lazy}} = \mathcal{J}_2 \backslash \mathcal{J}^{\text{ind}}$. Lastly, optimize the SCUC model with redundant constraints removed and lazy constraints identified.

IV. Case Study

The proposed offline-online security constraint screening is applied to medium size system such as IEEE 118-bus system [8] and RTS-GMLC [22], and a large size system i.e. MISO. We also show the impact of different formulations of security constraint on the solution performance. Experiment results are presented in section IV-A and IV-B respectively with following implementations,

- *Offline Screening:* apply offline component to the test cases, while making conservative assumption that net power injection intervals cover relatively wide uncertainty bounds. Consider all creditable contingencies. Identify dominating security constraints and extract dual variables.
- *Online Screening:* apply online component in real-time or look-ahead markets. At this stage, uncertainty is (partially) materialized. The uncertainty includes the load, renewable generation, UC, and network topology change. We determine potentially dominating security constraints by utilizing dual variables from Offline Screening. Real-time power injection data is simulated from uniform distribution that is bounded by intervals used in offline.
- *Verification:* Verify the dominating constraints in real time without considering the timeliness requirement.

Comparison between power flow upper bounds in Online Screening and Verification is determined by,

$$\frac{f_l^{\text{Online Screening}} - f_l^{\text{Verification}}}{f_l^{\text{Verification}}} \tag{14}$$

Case study presents dominating security constraints detection rate, power flow upper bounds difference, computation time and SCUC solution quality improvements with proposed methods. Numerical simulations are carried out with MISO HIPPO [23], using Gurobi 7.5 in Centos with Intel Xeon E5@3.50 GHz, 64 GB RAM [24].

A. RTS-GMLC and IEEE 118-Bus System

1) Test Setup: Proposed offline-online approach is applied to the RTS-GMLC and IEEE 118-bus system to demonstrate dominating constraint detection and algorithm efficiency for N-1 contingency. In RTS-GMLC test case, 28 800 (=120*2+119*120*2) power flow constraints are considered per time interval. We first apply the Offline Screening to one specific period to determine the dominating security constraints and dual variables, 10% load side uncertainty is considered. Secondly, use the updated real-time data (5 minutes interval, 12 data sets for the specific hour) and Online Screening to determine the power flow upper bound and power flow violations. Lastly, apply the Verification step to the 12 sets of real-time data to determine the true dominating constraints and power flow upper bounds. In IEEE 118-bus test case, 69 192 (=186*2+185*186*2) power flow constraints are considered per time interval. Three wind farms are added to bus 36, 77, and 69. We use wind generator ratings, and 10% load side uncertainty in Offline Screening to account for net power injection uncertainty. Online Screening is applied to 12 sets of simulated wind generation and load profiles. Detailed data is available at http://poweree.github.io/118BusPrescreening.zip and https://github.com/GridMod/RTS-GMLC.

2) Offline and Online Results: Table I shows the performance of proposed offline-online security constraints method on RTS-GMLC system and IEEE 118-bus system. In Offline Screening stage, step-1 finds 20% of the security constraints potentially binding in RTS-GMLC system and 15% in IEEE 118-bus system. The computation time is 0.18 seconds and 1.12 seconds, respectively. Step-2 solves 5685 LPs and further determines only 106 are dominating constraint, which accounts for 0.37% (=106/28 800) of N-1 security constraints in RTS-GMLC system. For IEEE 118-bus system, the dominating constraints rate is 0.15%. The LP calculations took 165 and 332 seconds respectively.Note that we applied the modified step 2 method, feasibility check, mentioned in II-A. On RTS-GMLC system, the feasibility check performed on 5685 constraints is 165.12 seconds, 106 constraints have the potential of becoming dominating, perform LP calculation 106 times takes 0.338 seconds. However, if we solve the LP directly 5685 times, it will take 1035.03 seconds. It is observed that the significant computation burden of step-2, even for a relatively small size system, calls for a more efficient method real-time security constraint monitoring.

TABLE I
RTS-GMLC/IEEE 118-Bus System Security Constraint Screening Results

	Dominating Constraint Detection		Time (Seconds)	
Test Case	RTS-GMLC	IEEE118	RTS-GMLC	IEEE118
Original[1]	28,800	69,492	-	-
Step-1[2]	5,685	9,643	0.18	1.12
Step-2[3]	106	101	165	332
Online[4]	99	69	0.0025	0.0024
Verification[5]	91	53	147	326

[1] N-1 security constraints modeled.
[2] Apply step-1 to the test system.
[3] Apply step-2 offline screening including uncertainty.
[4] Apply step-2 online screening with real-time data.
[5] Verify the results by applying step-2 offline method with real-time data.

Online Screening is then applied with real-time net power injection. Online method is based on the closed-form equation (7). It takes 2.5 ms and 2.4 ms to finish the calculation on RTS-GMLC system and IEEE 118-bus system, respectively. Compared with 165 and 332 seconds for offline screening, the online version shows significant advantage in processing time. When the uncertainty is materialized, the online screening finds 99 out of 106 security constraints are potentially dominating in RTS-GMLC, and 69 out of 101 in IEEE 118-bus system. Apply Verification to same data set used in Online Screening, 91 out of 99 constraints are truly dominating in RTS-GMLC system, and 53 out of 69 in IEEE 118-bus system. It shows that the online component has relatively accurate predication of the dominating constraints. The comparison between the two medium size test system shows that the proposed method is consistent in terms of dominating constraint detection and computational performance.

3) Power Flow Upper Bound Comparison: Power flow upper bounds determined in Online Screening and Verification are compared as (14). For RTS-GMLC test case, it is normally distributed with mean of 0.002, variance 0.00 008, 95% of the data points resides between -0.7% and 2.4%. For IEEE 118-bus test case, it is normally distributed with mean of 0.0032, variance 0.0028, 95% of the data points resides between -15.6% and 16.2%.

TABLE II
WATCHLIST SECURITY CONSTRAINT SCREENING RESULT

Case#	Watchlist[1]	Step-1[2]	Step-2[3]	Time1[4]	Time2[5]	Time[6]
2	6,732	3,653	3,231	2.88	8.83	11.72
13	6,910	4,040	2,418	5.8	10.98	16.78
26	5,902	3,506	3,162	1.45	8.24	9.68
41	7,974	4,551	4,047	3.33	10.41	13.75
62	11,618	6,203	2,722	3.54	20.20	23.74
Average[7]	7,782	4,103	3,492	2.86	10.17	13.03

[1]Watchlist security constraints modeled.
[2]Number of potentially dominating constraints detected by step-1.
[3]Number of dominating constraints detected by step-2.
[4]Step-1 time, in seconds.
[5]Step-2 time, in seconds.
[6]Offline screening total time, in seconds.
[7]Average over 78 MISO cases.

B. MISO Systems

1) Screening for Watchlist: In MISO, "watchlist" is heuristically selected from N-1 security constraints. It is noted that the amount of "watchlist" is significantly smaller than that of N-1 security constraints. On average, there are 216 (=7782/36) security constraints per time interval (MISO uses 36 planned periods for DAM cases). System topology varies in each time interval, usually around 3000 buses are present in the topology, it can be aggregated into 1000 buses after inspecting the PTDF matrix. The objective of this part is to model the least amount of security constraints in DAM SCUC model that is necessary to maintain solution integrity. Two-step security constraint screening helps achieve that. Apply Offline Screening, dominating constraint detection rate and processing time are shown in Table II. On average, 45% (=3492/7782) of watchlist constraints are identified as dominating, processing time is 13.03 seconds by feasibility checking in step-2. It means that we could eliminate half of watchlist in MISO's current SCUC engine.

If we use LP problem (C) directly in step-2, then the processing time is 53.28 seconds on average. This fact motivates us to use a slightly modified step-2 to extract dual values for Offline Screening study. Firstly, perform feasibility check on the remaining constraints from step-1, and then solve problem (C) on the dominating constraints detected previously. For example, row "Average" in Table II shows 611 (=4103-3492) constraints are identified as redundant, and we would like to use feasibility check rather than solving problem (C) to identify them. The modified step-2 reduced solution time and memory usage tremendously, particularly for N-1 security constraints. The disproportional relationship of security constraints rates between the two experiments is due to MISO watchlist is a small but creditable subset of the security constraints, while IEEE 118-bus test case contains all N-1 security constraints.

2) Offline-Online to All N-1 Security Constraints: The offline-online simulation is conducted in this part. The system contains 9498 branches and 3306 buses (can be aggregated into 1100 buses by inspecting the PTDF matrix) in base case topology and 805 line outage contingencies are regarded as creditable (i.e. not limited to N-1 contingency). There are totally 15 291 780 security constraints per time interval. It is emphasized that this study includes all creditable security constraints, while watchlist is a very small subset heuristically determined. Experiment results are presented in Fig. 6 and 7. In this case, 20% wind generation and 10% load side uncertainties are included during Offline Screening while considering all creditable security constraints. Test data is generated from uniform distribution to simulate real-time power injection, they are bounded by offline net power injection intervals, used in Online Screening.

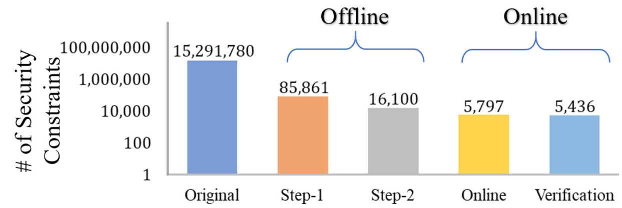

Fig. 6. Screening performance on MISO case 11.

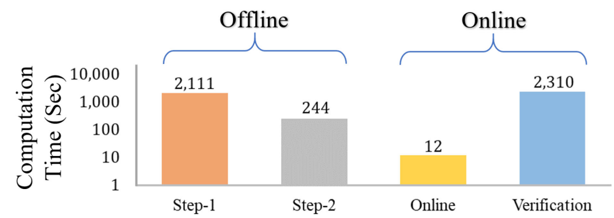

Fig. 7. Screening computation time on MISO case 11.

In Offline Screening stage, 16 100 security constraints are identified as dominating, it is 0.1% (=16 100/15 291 780) of the original constraints. In Online Screening stage, uncertainty is materialized and 5797 out of 16 100 constraints are identified as dominating. Verification shows 5436 out of 16 100 constraints are determined to be truly dominating. Verification constraint set is a subset of Online Screening's. According to Fig. 6, 94% (=5436/5797) security constraints discovered in Online Screening are truly dominating constraints given simulated real-time data.

From Fig. 7, we see that Offline Screening takes 2355 (=2111+244) seconds to screen all the creditable contingencies. On the other hand, Online Screening only takes 11.57 seconds to attain the upper bounds of power flow for all the potentially dominating security constraints. If we use offline method, which is used in Verification, then the processing takes 2310 seconds. Power flow upper bounds determine in Online Screening and Verification are compared in Fig. 8. The difference determined by equation (14) is normally distributed with mean of 0.0066, variance 0.0002, 95% of the data points reside between -2.14% and 3.46%. It shows the online method is not just fast but also accurate enough in real world applications. It is worth noting that by implementing the feasibility check in step-2, memory usage and calculation speed can be drastically improved. Offline method requires to save dual variables from step-1. Without using feasibility check, 85 861 sets of dual variables would need to be stored. With feasibility check, only 16 100 sets of the dual variables remains. Memory usage reduction is at least 81% [=(85 861-16 100)/85 861].

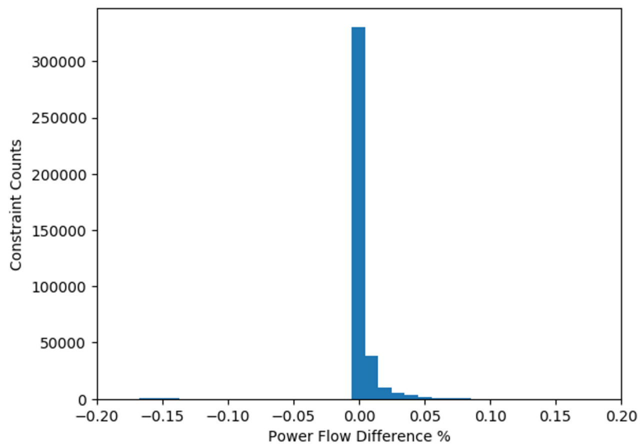

Fig. 8. Power flow upper bound difference between online screening and verification (IEEE 118-bus system test case).

TABLE III
MISO DAM SCUC SOLUTION SUMMARY

Case#	Methods	Time[1]	Gap[2]	$\mathcal{J}^{\text{ind}3}$	$\mathcal{J}^{\text{lazy}4}$	$\mathcal{J}^{\text{PB}5}$
2	S0	1,047	0.069%	6,732	-	-
	S1	734	0.067%	3,231	-	-
	S2	**207**	0.072%	1,057	2,174	32
13	S0	481	0.050%	6,910	-	-
	S1	111	0.072%	2,418	-	-
	S2	**86**	0.096%	893	1,525	10
26	S0	1,204	1.214%	5,902	-	-
	S1	1,200	0.524%	3,162	-	-
	S2	1,201	**0.404%**	1,101	2,061	8
41	S0	1,204	0.120%	7,974	-	-
	S1	**711**	0.095%	4,047	-	-
	S2	803	0.084%	812	3,235	29
62	S0	1,205	0.181%	11,618	-	-
	S1	379	0.054%	2,722	-	-
	S2	**280**	0.072%	691	2,031	7

[1]SCUC optimization time, in seconds.
[2]MIP gap of SCUC when optimization has completed, in percent.
[3]Active security constraints present in the current model.
[4]Lazy security constraints set in the current model.
[5]Lazy security constraints that deems to be active after optimization (put back to the Industrious constraint pool).

3) Modeling Virtual Transactions: The termination criteria for MISO DAM SCUC (MILP) Optimization are either MILP gap reaches 0.1% or solving time passes 1200 seconds. The following techniques are applied to MISO DAM SCUC model to help solve the MILP problem.

- *Scenario 0 (S0):* The MILP model is optimized directly without any acceleration technique, and its result serves as the baseline for benchmark.
- *Scenario 1 (S1):* SCUC model is optimized after removing redundant security constraints by two-step screening offline method.
- *Scenario 2 (S2):* It uses methods presented in Section III-B, i.e. integrating lazy constraints into the two-step screening. γ is set to 0.8.

Table III presents detailed in formation for five typical cases, including optimization time, MILP gap, constraint reduction, and lazy constraint counts. For easy cases, i.e., case 2 and case 13, we are mainly interested in solution time improvements by aforementioned approaches. In case 2, S1 improves SCUC solution time by 313 (=1047 - 734) seconds with 52% security constraint reduction. S2 has the least optimization time, it finds 2174 out of 3231 constraints are lazy constraints, and at the end of optimization, 32 constraints are deemed to be active and put back to the MILP model. The overall time saving is 840 seconds. Similarly, overall SCUC solution time is reduced by $\frac{5}{6}$ in case 13.

In the meantime, Table III shows the details for three hard cases, i.e. Case 26, 41, and 62. In case 26, none of them is able to get a solution with gap smaller than 0.1%. However, S2 provides smallest MILP gap, i.e., 0.404%, while S0 and S1 finds gap of 1.214% and 0.524%, respectively. As shown in Table III, S2 helps reach the targeted MILP gap in case 41 and 62. In case 41, the original approach, i.e., S0, get a MILP gap of 0.12% after 1200 seconds. S2 is able to reduce the MILP gap to 0.084% in 803 seconds. Case 64 shows even more promising results. S2 gets a solution with MILP gap of 0.072% in 280 seconds. It is noted that S1 performs slightly better than S2 in Case 41. That is partly because some lazy constraints are put as industrious ones. According to our experiments on MISO cases, S2 outperforms S1 most of the time. However, we also see S1 outperforms S2 in some cases. In real-world production systems, we suggest use multiple servers to solve the SCUC problem using various screening techniques.

Fig. 9 illustrates the SCUC optimization time comparison for 43 cases where the solution time is over 300 seconds by S0 among 78 cases. The red bars are the solution time of the current MISO SCUC engine and the blue bars illustrate that of S2. It is observed that the proposed approach outperforms the original approach for all cases except Case 44. The improvement is either from solution time or solution quality. The first 11 cases are hard cases, which S0 cannot reach 0.1% MILP gap in 1200 seconds. As shown in Fig. 9, S2 is able to reach the desired gap for nine of 11 cases. The difference of the objective value of SCUC is as large as \$70 000 for hard cases. For the remaining two cases, i.e., Case 26 and 64, the proposed approach is not able to reach the desired gap neither. However, S2 is able to improve the solution quality, i.e. get a smaller MILP gap. The proposed approach typically removes over 50% of the watchlist constraints selected by MISO. It generally reduces solution time by 50% in easy cases.

In real-world systems, operators have to heuristically select credit security constraints, meeting timeliness requirement. In the MISO case studies, it is about 150-200 per time interval. The proposed offline approach can screen 600 constraints every second. Considering up to 50% constraints are redundant, constraint screening helps systematically include security constraints when building the model. The accuracy of power flow upper bounds determined by the two-step approach depends on the upper/lower bounds of the net power injection interval. Typically, ISOs run multiply DAM models to estimate the discrepancy between DAM and RTM. We can apply the offline approach to all these cases, i.e. save dual variables (∼200 MB per case). To check real-time system security, we can apply the

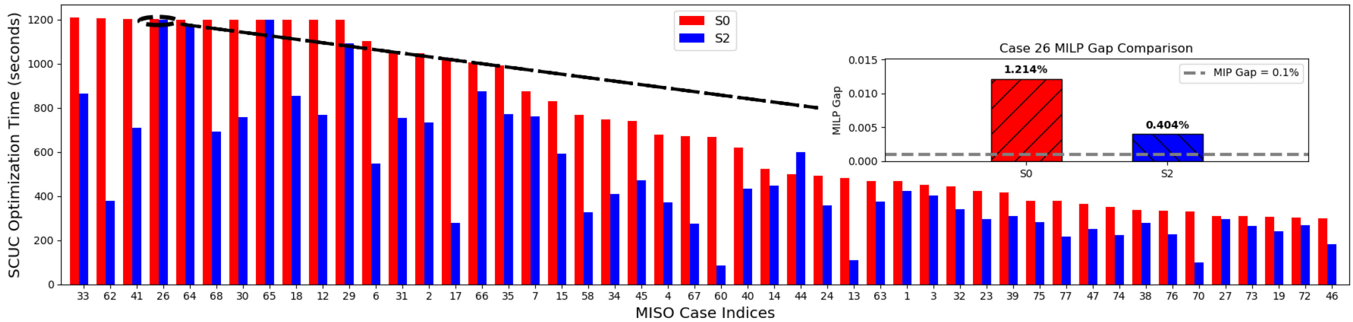

Fig. 9. Comparison of solution time with and without proposed screening. MIP gaps for case 26 are compared.

online approach by re-using dual variables from the case that is closest to the real-time situation. From our experience, S1 (without setting lazy constraint) can serve as a bottom line, and it generally offers a satisfiable solution within time limit.

V. Conclusion

In this paper, we propose a security constraint screening method that effectively integrates the virtual transactions and captures system changes in real time. Virtual supply and demand often account for a large portion of market. In the meantime, the system is constantly changing in real time. The proposed approach integrates dual information from offline method, historical price information, and lazy constraint in optimization engine to tackle open questions in security constraint screening. The numerical studies on MISO's real-world cases show significant performance improvement of the proposed approach. It typically removes over 50% of the watchlist constraints selected by MISO and reduces solution time by 50% in easy cases and improves the solution quality in hard cases. With a closed-form equation, the proposed online method clears the computational barrier of enforcing N-1 security constraints in real-time or look-ahead markets.

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