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A Quantitative Risk Framework for DER-rich Power System Planning and Decision Making

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Abstract: The increased penetration of Distributed Energy Resources (DERs) within power networks is bringing challenges, an important one being the potential voltage excursions within the system that must be mitigated, as voltage must be maintained within statutory range at all times and at any node of the system by regulation. This paper proposes a scalable framework based on machine learning techniques (ML) to assess voltage excursion risks node by node and derive the related marginal probabilities in response to any net-loads under various DER penetration scenarios. The framework is then used to quantify the resulting financial impact of voltage excursion in large-scale networks. Therefore, this novel end-to-end risk framework supports decision making in the planning phase of networks in response to any intermittent DER penetration scenario. We show through simulations that the framework is both scalable to high-dimensional systems and efficient to handle vast number of scenarios. In our simulations, the use of ML technique enables to lower the computing time by a factor of 800 compared to load flow solving, while maintaining an accuracy $\geq 95\%$, enabling the assessment of vast number of scenarios.

Keywords: DER-rich Power System, Voltage Excursion, Risk Management, Machine Learning

1. INTRODUCTION

The adoption of renewable energy sources is fast increasing globally. For instance, in its global roadmap REMap to 2050, (1) predicts an increase of global electricity demand from 20.204 TWh/yr in 2015 to 41.508 TWh/yr in 2050, with a renewable share jumping from 24 % to 85% in the same period and where the solar PV capacity contribution would jump from 223 GW to 7,122 GW. Increasing the share of Distributed Energy Resources (DERs) to significant levels would create some effects on the power networks that need to be appropriately planned and managed. The intermittency of some renewable sources characterised by fluctuation and uncontrollability of the power generated can cause rapid unbalance between power generated and consumed locally. In scenarios of high penetration level of DERs within the network, the containment of voltage within statutory limits, and especially the upper limit, would become an issue, (2). Distribution Network Service Providers (DNSPs) must plan to adapt their network to control e the voltage where it is susceptible to exceed the threshold limits.

This paper presents a framework that helps the DNSP in their planning decision making in response to any scenario of DER penetration within their network. The fluctuation of generation and local imbalance of net-demand are both of stochastic nature, and therefore, so are the resulting voltage excursion risks. It is consequently appropriate to analyse and assess those phenomenons using quantitative risk management techniques that combine the likelihood and the severity of event to quantify the risk, (3). The likelihood at any node can be modelled through a marginal probability that will depend on the net-demand joint distributions at every node given a network configuration. The severity of voltage excursion event can be modelled though financial impact for the customers.

In this paper we propose a robust and scalable framework to assess the probability and financial impact of voltage risk events in response to any intermittent net-load penetration scenario. The predictive method uses *Support Vector Machine* (SVM) classifiers to assess the identified risk event's occurrence. SVM is a robust Machine Learning technique that is particularly suitable to deal with high-dimensional data, (4) and the computations involved in using trained classifiers are linear. This property enables the proposed method to assess vast numbers of scenarios in order to infer risk probabilities. The novelty of the developed approach is multiple:

- It is 'end-to-end', providing a framework that assesses the voltage risk probabilities and respective financial impacts for planning decision making
- It is fast and reliable to assess vast amounts of scenarios
- It is scalable to large-scale power networks

By using machine learning classifiers, the presented method will decouple the problem of identifying the net-loads conditions that lead to a voltage excursion at one

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node and the capability of assessing vast amounts of net-loads scenarios. The initial problem, which is connected to training the machine learning classifiers, is computationally intensive and uses traditional methods to solve the load flow equations for the system, but this is a one-off exercise per network configuration. Once the classifiers are trained and sufficiently accurate, they can be repetitively and swiftly used to assess any net-load and penetration scenario for the system. Our simulations have shown that using the classifiers is 800 times faster than solving the load flow equations. This proposed methodology opens the way to assess wide range of 'what-if' analyses for the system and derive voltage risk probabilities that can then be linked to financial impact and constitute a quantitative voltage risk assessment framework as illustrated in Fig1.

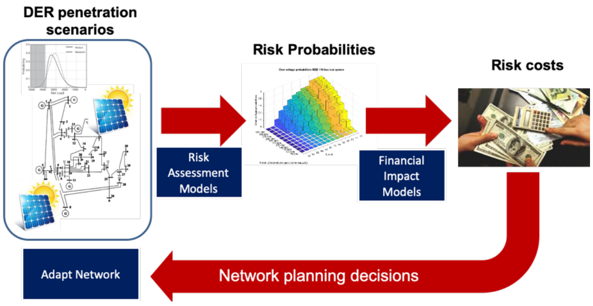

Fig. 1. 'End-to-end' decision making framework

The integration of DERs and their impact on the voltage stability has been subject to research in recent years,(5) provide an overview of the consequences of decentralised generation for typical voltage stability issues. In (6; 7), planning frameworks for distribution grids are broadly discussed, highlighting the need for new quantitative analysis tools. In (8), a probabilistic voltage risk analysis is proposed to assess the value at risk associated with decision making of installing SVC in the power system and (9) proposes a probabilistic method to evaluate the over-voltage risk in a distribution network with different PV capacity sizes under different load levels, and (10) proposed a voltage collapse risk approach. In (11), we have proposed a machine learning based approach to assess the voltage stability risk under stochastic net-loads. This paper focus on voltage statutory thresholds and complete the quantitative risk assessment framework with risk probabilities and financial impact assessment approach

2. VOLTAGE RISK ASSESSMENT FRAMEWORK

The voltage risk framework that we propose is intended to determine marginal voltage risk event probability at any selected bus of a network in response to any scenario of intermittent DER penetration and net-loads profile in the system. The net-load is defined as the consumer embedded generation minus the consumer demand. The voltage risk events and criteria that are considered for this paper are:

(1) *'Over-voltage'* at one bus (e.g. 1.1 $p.u.$ in Australia)
(2) *'Under-voltage'* at one bus (e.g. 0.94 $p.u.$ in Australia)

Those risks refer to net-load conditions that would cause the voltage to breach the upper or lower voltage statutory limit that is set according to local regulation.

To accomplish this, we firstly need a model that assesses the occurrence of voltage risk events in response to any particular net-load values within the system. Secondly, we need the ability to run the model on a vast amount of net-load values in order to determine marginal voltage risk probabilities.

The method proposed in this paper decouples the assessment of voltage risk events and the actual stochastic distribution of net-loads. This offers a framework that can be applied to any intermittent DER penetration level and net-load profile, knowing that distributions of the net-loads varies according to the geography, the time of the day/year, and are highly dependent on external factors such as weather forecast.

2.1 Model the voltage risk events

The voltage risk assessment model is an extension of the model proposed by the authors in (11) where the steady state power system is described by a set of $2B$ load-flow equations, where B is the number of buses in the system, in $2B$ algebraic variables V_i, θ_i :

$$0 = -P_i + \sum_{k=1}^{B} |V_i||V_k|(G_{ik}\cos\theta_{ik} + B_{ik}\sin\theta_{ik}) \quad (1)$$

$$0 = -Q_i + \sum_{k=1}^{B} |V_i||V_k|(G_{ik}\sin\theta_{ik} + B_{ik}\cos\theta_{ik}) \quad (2)$$

where P_i is the net injected real power (power generated minus power consumed) at bus i, Q_i is the net injected reactive power at bus i, V_i is the voltage at bus i, θ_{ik} is the difference in voltage angle between bus i and k, G_{ik} is the real part of the admittance Y_{ik} of the line between bus i and k and B_{ik} is the imaginary part of the admittance Y_{ik} of the line between bus i and k.

For the sake of abbreviation, in this paper we denote the set of $2B$ load flow equations (1),(2) as:

$$\phi(V, \theta, L_n) = 0 \quad (3)$$

where V and θ are the B-dimensional vectors of voltage and angles respectively and L_n is a $2B$-dimensional vector of net-load values P (active power) and Q (reactive power):

$$L_n := [P_1, .., P_B, Q_1, ..., Q_B] \quad (4)$$

In that model, the loadability limit or critical points are the points where the demand values reaches an extremum value after which there is no solution of the load flow equations. As demonstrated in (12), in the B-dimensional parameter space, the points satisfying those conditions belong to a manifold of dimension $B - 1$ which is called the bifurcation surface or *critical surface*, or:

$$L^*_{n,crit} = \{L_n \mid g(L_n) = 0\} \quad (5)$$

where $g(L_n)$ is the critical surface.

Let's define the *stable region* (hyper-volume) inside the critical surface in the $2B$-dimensional parameter space:

$$S_{stable} = \{(V, \theta, L_n) \mid |L_n < L^*_{n,crit}, \phi(V, \theta, L_n) = 0\} \quad (6)$$

Similarly, inside the stable region we can define the under-voltage-limits and over-voltage-limits as the points where the demand values reach the extremums causing the voltage state variable V_i at bus i to reach the respective extremum statutory limit respectively due to excessive local generation ($L_n < 0$) or load ($L_n > 0$), or:

$$L^*_{n,i,under} = \{L_n \mid \phi(V, \theta, L_n) = 0, V_i = U_v\} \quad (7)$$

$$L^*_{n,i,over} = \{L_n \mid \phi(V, \theta, L_n) = 0, V_i = O_v\} \quad (8)$$

where O_v is the over-voltage threshold and U_v the under-voltage threshold.

Therefore, inside the stable region (hyper-volume), we can define a smaller *Acceptable Region* (hyper-volume) which is upper bounded by the over-voltage multi-dimensional surface and lower-bounded by the under-voltage multi-dimensional surface that can be represented by the set:

$$\begin{aligned} S_{acc.} = \quad & \{(V, \theta, L_n)| \quad | L_n < L^*_{n,i,under}, \\ & \qquad \phi(V, \theta, L_n) = 0, \\ & \qquad V_i \geq U_v\} \\ \cup \quad & \{(V, \theta, L_n)| \quad | L_n > L^*_{n,i,over}, \\ & \qquad \phi(V, \theta, L_n) = 0, \\ & \qquad V_i \leq O_v\} \end{aligned} \quad (9)$$

Thus there exist multi-dimensional surface boundaries that respectively separates:

- The set of acceptable loads versus the set of unacceptable loads that cause over-voltage at one given bus i
- The set of acceptable loads versus the set of unacceptable loads that cause under-voltage at one given bus i

There exists no analytical solutions to calculate those boundaries and it is therefore appropriate to utilise numerical solution to this problem.

2.2 Model a risk event predictor using machine learning technique

We are proposing to use Machine Learning (ML) technique to quickly assess the voltage risks (over-voltage risk and under-voltage risk) at selected buses in response to any given net-load set of values. The advantage of this approach is the scalability and ease of use once the classifiers have been appropriately trained. Support Vector Machine (SVM) is a well accepted numerical method adapted to solve classification problems where the model parameters are defined to maximise the *margin*, which is the smallest distance between the decision boundary and any of the training samples. In our case, the decision boundaries coincide with the above defined surfaces (7)(8) and we train 2 distinct two-class linear models per bus:

(1) Over-voltage model that discriminate between acceptable region and over-voltage region for that bus
(2) Under-voltage model that discriminate between acceptable region and under-voltage region for that bus

In general terms, the SVM models formulates as:

$$Y(L_n) = w^t \times \alpha(L_n) + b \quad (10)$$

where w are coefficients, $\alpha()$ denotes a fixed feature-space transformation and b is the bias. Training the models, or identifying the model parameters (w, $\alpha()$, b) correspond to a quadratic convex optimization problem as described in (4) and (13). For each model type (over-voltage and under-voltage) and bus i, we will require a set of training data that will comprise M input net-loads vectors $L_{n1}, .., L_{nM}$ with corresponding target value $Y_1, .., Y_M$ where $Y \in \{-1, 1\}$ corresponding to the voltage of bus i being respectively within threshold ($Y = -1$) or not ($Y = 1$), meaning being under-voltage or over-voltage respectively depending on the model type .

In order to generate those training sets, a network configuration and related network parameters are identified, and a Monte-Carlo simulation on the system is executed extracting net-load values for every bus from a stochastic distribution, solving the load-flow and comparing the voltage at each bus with the thresholds to capture the target values for each model type as described in Fig.2.

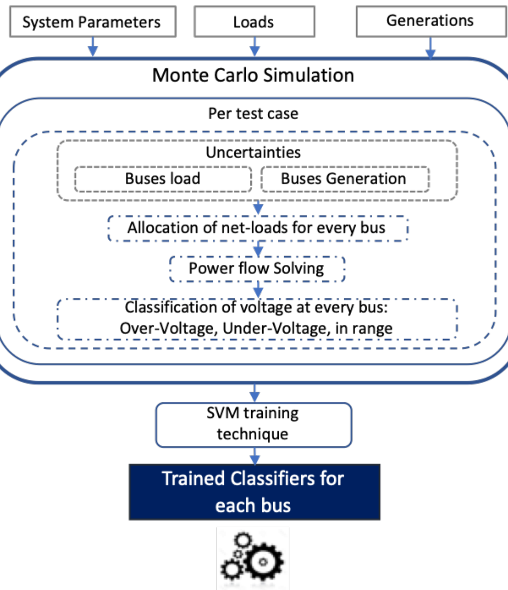

Fig. 2. Training Dataset generation framework

Each training set is used to train the respective classifier, meaning identifying the model parameters as described in (4), i.e the $w, \alpha(L_n)$ and b in (10). It should be noted that the values of the net-loads used in the Monte Carlo simulation at each bus are extracted from a uniform distribution within their maximum operating range. Using uniformly distributed net-loads within their maximum range of operation enables us to uniformly sample the surface boundaries when building the training set for the SVM classifiers. The number of samples is empirically chosen so that the SVM classifiers are sufficiently accurate in their prediction. The accuracy will be defined as the proportion of true results (true positives and true negatives) among the total number of cases examined and arbitrarily set to be close to 95%.

Once the classifiers are trained they can be used to assess any given set of new intermittent net-load vector for the same configuration of the power system and predict potential voltage risk events. The creation of the training set data for the classifiers is computational intense, but is a one-off exercise. Once trained and tested, the classifiers which are simple linear functions can be used to assess the voltage risk for any given set of net-loads.

2.3 Scenario Analysis - Voltage Risk Probabilities

The strength of the method is that the SVM classifiers are decoupled from the stochastic distributions of the net-load and can repetitively be utilised to quickly assess the occurrence of a risk event in response to load and generation profile within the system.

Leveraging the law of big numbers, the proposed risk framework will use large Monte Carlo simulations to determine the marginal voltage risk event probability for every given node in response to any scenario of intermittent DER within the system as illustrated in Figure 3.

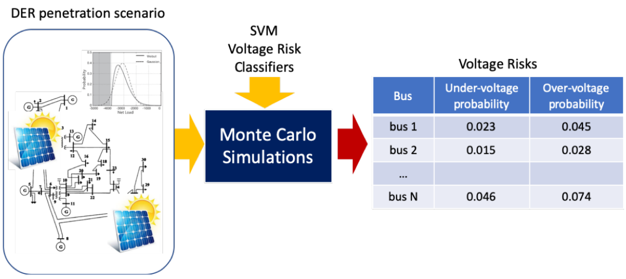

Fig. 3. DER scenario voltage risk assessment framework

The voltage risk framework enables to quickly assess the impact of different net-load distributions or scenarios in terms of voltage risk event probability of occurrence, our simulations have shown that the assessment is 800 times faster with our method compared to traditional load flow equation solving (1.9 second versus 26 minutes for 110,000 simulations).

3. VOLTAGE RISK SEVERITY - FINANCIAL IMPACT

The previous section has described a framework usable to assess the voltage risk events probabilities in response to given stochastic net-loads where the risk events are *Over voltage* and *Under voltage*. As described in (3), (14), in probabilistic risk assessment the risk value associated to a scenario S_i over a period of time is the product of its probability P_i and consequence X_i integrated over the period of time T or

$$Risk_{S_i} = \int_T P_i \times X_i \, dt$$

In our case, we have identified two different types of events or scenarios and developed a methodology to estimate their probabilities of occurrence P_i but need to identify metrics to assess their consequence X_i in monetary value.

For the scenario identified (under-voltage and over-voltage), the consequence is mainly felt by the consumers and the excursion of voltage can disrupt or damage the connected appliances or machineries. In Australia, regulations are in place to enforce the DNSPs to maintain the voltage within statutory limits and a non-respect, even temporary, entitles the consumers to lodge claims that must be managed and cleared by the DNSPs. The cost of those complaints can be used as a metric to assess the consequence of over-voltage and under-voltage scenarios as follows :

$$Risk_{over} = \int_T P_{over} \times \sum_k (P_{compl} \times C_{compl} \times C_k) \, dt \quad (11)$$

$$Risk_{under} = \int_T P_{under} \times \sum_k (P_{compl} \times C_{compl} \times C_k) \, dt \quad (12)$$

where P_{compl} is the respective probability of receiving consumer complaint following over/under voltage event, C_{compl} is the average cost of complaint and C_k the number of customer of each type impacted by the event. The proposed voltage risk framework estimates the point in time P_{over} and P_{under} and identifies the bus where it occurs, and therefore helps to assess the number of customers impacted. C_{compl} can be extrapolated by DNSPs from past events and similarly, the P_{compl} can be extrapolated by DNSPs from historical data depending on the severity, duration, and location of the event.

4. SIMULATION RESULTS

In this section we illustrate on a test case (IEEE 118 buses test network (15)) end-to-end and step-by-step the methodology required to build the risk framework. A set of

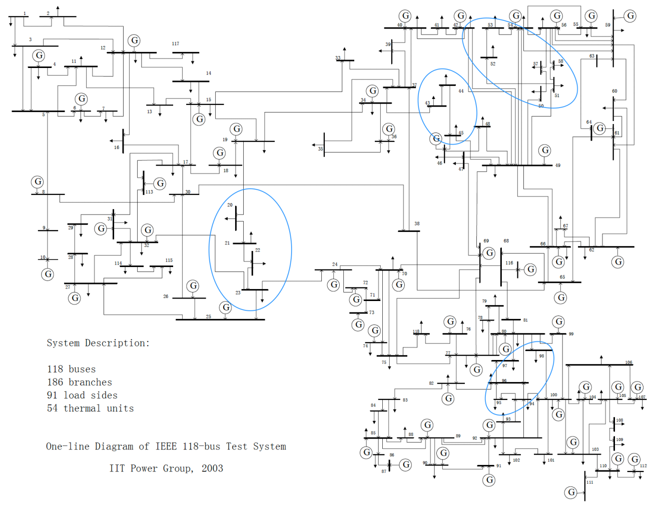

Fig. 4. IEEE 118 Test system

buses has been identified to accommodate solar PV generation and arbitrarily selected in pockets to simulate high concentrations of intermittent loads in some geographic area (circled in figure 4). The Risk events considered in this simulation are the over-voltage and under-voltage.

4.1 Train the SVM classifiers

The initial step of the method requires the creation of training data sets in order to train SVM classifiers as illustrated in Fig. 2. Following standard practice in Machine Learning, the models have been trained and validated using a 10-fold cross validation technique, (16). It is to be noted that the training procedure proposed requires solving the load flows for the entire system for each Monte-Carlo simulation. It is computationally intense, but this preliminary operation is required only once given a power network configuration. The performance of the classifiers is assessed using a *confusion matrix* which records correctly and incorrectly classified risk events. The classification performance will be assessed via commonly-accepted measures : the *F-1 score*, (17). To test the performance of the classifiers, an independent validation data set has been generated from a new Monte Carlo simulation on the same system configuration as the one used to create the training data set and the F-1 scores for the trained classifiers applied to this new validation data set are distinctively high (on average 99.2% and 98.8%). The elevated accuracy makes the classifiers trustworthy and useful to predict potential risk events.

4.2 Use the SVM classifiers to derive risk probabilities on planning scenarios

Appropriately trained classifiers are now used to predict risk events on respective bus in response to given net-load input. Illustratively, we are constructing multiple scenarios for our IEEE118 test buses system where we progressively introduce solar PV generation capacity on the selected pocket of weak buses (Fig.4). For each scenario, the maximum solar PV capacity is set to a value increasing from 75MW up to 150MW and in each case we analyse the effect of those potential new solar PV capacities on the over-voltage risk within the system over a full day. In order to generate the hourly net-load of the system, we randomly generate net-load values using the respective hourly value indicated in the profile illustrated in Fig.5 as a mean (and where the peak value is the scenario maximum capacity) and the standard deviation set arbitrarily to 0.2 to simulate intermittency. For each scenario, we executed

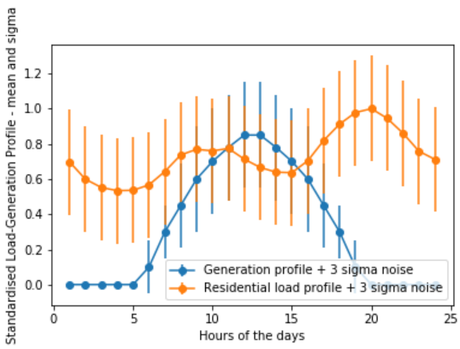

Fig. 5. Load and DER Generation profiles - mean values

$10k$ daily Monte-Carlo simulations to generate hourly net load series and the over-voltage risk events assessed using the respective trained classifiers. The hourly probability of risk event in each scenario has been inferred from the calculated frequency ($\frac{\#PositiveClass}{10{,}000}$). Fig. 6 illustrate the over-voltage probabilities per bus and scenario at 12PM.

The graph shows that some buses are more sensitive to intermittent generation than others and that is dictated by the network topology and internal parameters (line admittances, transformer tap ratios). Interestingly, the proposed method allows to identify and map the voltage

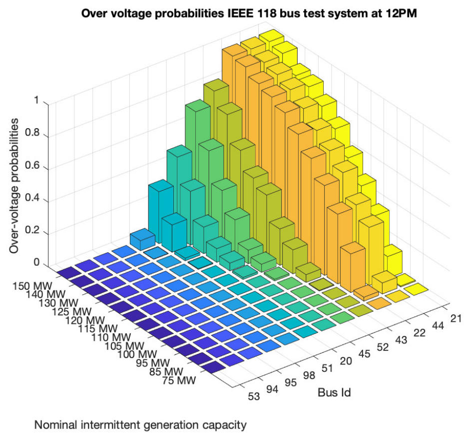

Fig. 6. Over-voltage risk probability for each weak buses at 12PM

risk's sensitivity of each bus under any set of given scenarios. Fig.7 illustrate for one bus the hourly over-voltage risk

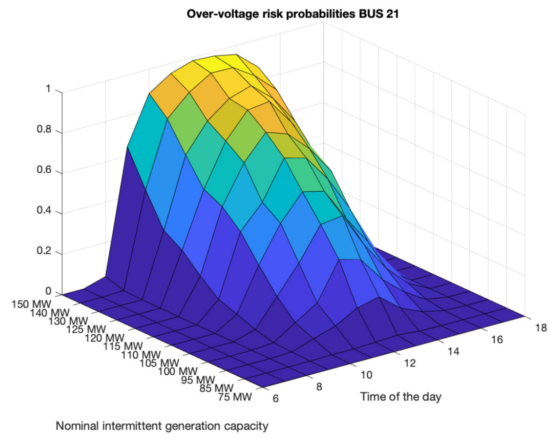

Fig. 7. Hourly over-voltage risk probabilities for BUS 21

probability per scenario which remarkably illustrate the good sensitivity of the classifiers that are used to generate the probabilities which unsurprisingly follows the shape of the generation profile as over-voltage is caused by an excess embedded generation within the system.

4.3 Risk Assessment - estimate the financial impact

To complete our risk assessment for this over-voltage simulation, we will calculate the daily impact of over-voltage risk for each scenario if no mitigation actions are undertaken. In E(11), P_{over} is the probability of over-voltage illustrated in Fig.7, $P_{compl.}$ is arbitrary set to 5%. To calculate the cost of complaint term we need to multiply an average cost of complaint with the number of customer impacted. The DNSP usually precisely know this information. For the sake of this simulation we will use an average cost of $\$1,500$ per complaint. For each scenario, we will estimate the number of customers dividing the nominal intermittent generation of the scenario by $5kW$, this equivalent to saying that the every customer connected to the bus is contributing to the intermittent embedded generation with $5kW$ solar PV and the scenarios are simulating an increase of penetration within the system. Tab.

1 summarises the daily risk monetary impact for 4 buses: bus 21, bus 22, bus 43 and bus 44. The risk values are to be

DER Capacity scenario	Bus Id 21	22	43	44
150 MW	\$15,58 M	\$16,19 M	\$10.68 M	\$16,17 M
140 MW	\$13,19 M	\$13,81 M	\$7,86 M	\$14,02 M
130 MW	\$10,56 M	\$11,36 M	\$5,34 M	\$11,57 M
125 MW	\$9,09 M	\$9,99 M	\$3.97 M	\$10,00 M
120 MW	\$7,62 M	\$8,55 M	\$2,77 M	\$8,70 M
115 MW	\$5,96 M	\$6,90 M	\$1,67 M	\$7,51 M
110 MW	\$4,39 M	\$5,30 M	\$0,88 M	\$5,93 M
105 MW	\$3,09 M	\$4,04 M	\$0,29 M	\$4,52 M
100 MW	\$1,71 M	\$2,45 M	\$48 k	\$3,18 M
95 MW	\$0,74 M	\$1,29 M	-	\$1,92 M
85 MW	\$31 k	\$89 k	-	\$0,33 M

Table 1. Simulated over-voltage risk values for 4 buses

used by the DNSP to assess the proper mitigation actions and investment on their network in order to appropriately manage those risks (accept, reduce, avoid or transfer)

5. CONCLUSION

This paper presents a novel end-to-end methodology to assess voltage risks and their financial impact within a power system. The benefits and contribution of the presented risk framework are presented below:

- **Versatility** to assess any scenario's type of nominal intermittent generation capacities and net-load profiles as developed in Section 2.3. In effect, the presented method decouples the problem of assessing the occurrence of a risk given one net-load profile and the capability of assessing vast amounts of scenarios.
- **End-to-end** relevant for network planning decisions supported by financially quantified risk values as developed in Section 3
- **Discrimination** to precisely identify weak buses within the system in response to scenarios, as the presented method in Section 2.2 trains individual classifiers by bus and risk event;
- **Scalability** to large scale distribution system due to intrinsic characteristics of SVM classifiers that are well suited and performing in high-dimension space, (4);

Future work will extend the Risk Framework to include the effects of reverse power flows and fault detection due to increased penetration of DER in the distribution networks.

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