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ANALYSIS OF EXTREME RAMP EVENTS IN OPTIMAL VARIABLE RENEWABLE ELECTRICITY PORTFOLIOS USING EXTREME VALUE THEORY

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ABSTRACT

Geographically diversified VRE portfolios can be used to smooth out the volatility of VRE output ramps. This study, using Taiwan as case study, developed efficient frontiers of optimal VRE portfolios to minimize the volatility for each possible level of total installed VRE capacity that can meet 10%, 20% and 30% of electricity demand. Our analysis shows that optimal portfolios are also beneficial to reduce the magnitude of extreme downward ramp events, which are sudden losses in VRE power outputs. We specifically investigated hourly extreme ramps that are expected to occur on average once-every-three-year. They are 13-30 % of each unit of installed VRE capacity for optimal VRE portfolios, which are significantly smaller than that (20-64%) for most individual VRE assets. This result helps to manage risks associated with extreme ramp events in power system operation. To capture the benefits associated with optimal portfolios, it is recommended for policy-makers to coordinate the investment and development of VRE assets across multiple locations.

Keywords: variable renewable electricity, mean-variance portfolio, extreme value analysis, generalized extreme value distribution, extreme ramp

NOMENCLATURE

Abbreviations

EVA	extreme value analysis
GEV	generalized extreme value
MVP	mean-variance portfolio
VRE	variable renewable electricity

Symbols

x_p	total installed VRE capacity needed in the portfolio (MW)
x_i	installed capacity variable of each VRE asset (MW)
$\sigma_{p,ramp}$	portfolio ramp volatility
X	vector of installed capacity variable per VRE asset
$\mathbf{cov_{Nramp}}$	covariance matrix of normalized ramp between different assets
$x_{max,i}$	geographical potentials per VRE asset (MW)
$\mu_{i,N}$	normalized mean output per VRE asset
D	Taiwan's electricity demand in 2030 (290.6 TWh)
L	required VRE penetration in electricity demand
$\sigma_{p,Nramp}$	normalized portfolio ramp volatility
$O_{p,N(t)}$	normalized portfolio output at time step t
$O_{i,N(t)}$	normalized output per VRE asset at time step t
$R_{p,N(t)}$	normalized portfolio ramp at time step t
z	random extreme event z
$G(z)$	cumulative probability density function of a random extreme event z
μ	location parameter
σ	scale parameter
ξ	shape parameter
T (z)	return period of a random extreme event z
B	block period (month)

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1. INTRODUCTION

To achieve the Paris Agreement target of limiting the global mean temperature increase to 1.5-2 °C, decarbonization of the electric power sector, including large-scale development of variable renewable electricity (VRE) technologies such as wind and solar is key. Due to their variable and uncertain nature VRE technologies pose challenges in power system operation. The sudden ramp-up and ramp-down of VRE outputs (which are increases or decreases in power outputs) necessitate additional back-up capacity, operating reserves and other flexibility resources to ensure generation adequacy and system reliability, resulting in so-called "integration costs" [7].

One effective way to reduce the impact of VRE ramps is to develop geographically diversified VRE portfolios, which smooth out output ramps from individual VRE assets. Previous studies [4, 6] have applied mean-variance portfolio (MVP) analysis to obtain the efficient frontier of optimal VRE portfolios, where the portfolio volatility (i.e. standard deviation) of output ramps is minimized for each attainable (expected) output level. Although optimal VRE portfolios are helpful to reduce the frequency and magnitude of the majority of ramps, their effect on extreme ramps is yet unclear. Due to the non-Gaussian fat-tailed distribution of VRE ramps, low-order statistics (e.g. mean and variance) are insufficient to capture extreme ramps in terms of the distribution's tail behavior [1, 5]. As rare but high-magnitude events, extreme ramps can cause large disruptions in power supply and threaten generation adequacy, when availability of back-up capacity and operating reserves in the system is low and when VRE's share in the electricity generation mix is high. This is particularly an issue for isolated or islanding power systems which have limited access to flexibility resources (e.g. storage, dispatchable power plants, demand-side response) in absence of interconnection [3]. Analysis of extreme ramp events in VRE portfolios is thus of importance to support the planning and operation of power systems, especially when optimal portfolios are considered as a promising solution to facilitate the integration of VRE.

This study aims to investigate extreme hourly ramp events in optimal VRE portfolios[1] through extreme value analysis (EVA). EVA is a statistical branch specialized in assessing the tail behavior of the distribution. In the context of extreme wind ramps, we focus on downward ramps rather than upward ramps. This is because unlike upward ramps that can be solved by curtailment, downward ramps are more relevant for generation adequacy. Although previous EVA-based analyses have analyzed extreme ramps for individual wind farms [1, 3], this study represents the first attempt of applying EVA to VRE portfolios. The Taiwan region of China is selected as the case study area due to its high relevance. Taiwan is the 21st largest economy and 14th largest electricity-consuming region in the world. It has a large islanding power system isolated from mainland China, relying heavily on energy imports. As Taiwan has set ambitious 2030 renewable targets to phase out nuclear power, boost energy security and reduce CO_2 emissions, this year is chosen as target year for the analysis.

2. THEORY

2.1 Mean-variance portfolio analysis

The MVP analysis originates from financial theory. It is used to select individual financial assets to formulate a series of optimal portfolios subject to the trade-off between (expected) return and risk. The optimal portfolios are positioned on an "efficient frontier", where risk is minimized at a given return, or return is maximized at a given risk. In the context of energy planning, MVP often focuses on minimizing the ramp volatility of VRE portfolios for each attainable (expected) portfolio output, when the total installed VRE capacity is given [6]. This results in the efficient frontier of optimal VRE portfolios that captures the geographical smoothing effect. [4] have formulated an alternative but equivalent framework. It minimizes the portfolio's ramp volatility for a possible range of total installed VRE capacity levels, when VRE's penetration in electricity demand is given. This study follows [4]'s framework with some modifications.

2.2 Extreme value analysis

EVA determines a stable asymptotical distribution of the tail behavior through sampling many extreme values of a random variable [2]. It requires stationarity of the sampled data. Extreme ramps sampled from a time series of portfolio ramps (being the first difference of a time series of portfolio outputs) are assumed to meet this requirement, since differencing increases stationarity [3]. The sampling of extreme values can be

[1] It is important to stress that this study does not aim to minimize extreme ramp events in VRE portfolios, which can be achieved through building up portfolios based on high-order statistics (e.g. skewness and kurtosis). These portfolios are not necessarily optimal in terms of the trade-off between portfolio volatility and expected portfolio output.

either based on the block maxima (or minima) method or the peaks over threshold method [3]. Due to the practical difficulty in selecting a proper threshold for each optimal portfolio, this study opts to use the former method. The block (B) is a predefined time period, which can be a year, a month or a day. The sampled extreme values (being the maximum value per block) are fit by the generalized extreme value (GEV) distribution. The cumulative probability density function of the GEV distribution for a random extreme event z is

$$G(z) = \exp\left[-\left\{1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right\}\right]_{+}^{-1/\xi}$$

, where G(z) is cumulative probability density function of random variable z; $\mu\,(> -\infty), \sigma\,(> 0)$, $\xi(< \infty)$ are respectively the location, scale and shape parameter; $y_+ = \max\{y, 0\}$ [2].

The quantile z of the GEV distribution can be interpreted as a return level associated with a return period T (z) [3]:

$$T(z) = \frac{B}{1-G(z)}$$

In other words, an extreme value with a magnitude no less than z is expected to occur on average once every return period T (z). Based on the inverse function of G (z), the expected extreme event associated with any return period can be estimated.

3. METHOD

The method of the present analysis consists of two main steps, and they were performed through ArcGIS and RStudio. In the first step, we developed the efficient frontiers of optimal VRE portfolios for Taiwan, which consist of three VRE technologies (onshore wind, offshore wind and solar PV). In the second step, we fit extreme downward ramps sampled from the time series of hourly portfolio ramp to the GEV distribution. The fitted GEV distribution enabled us to estimate the expected extreme ramp event that occurs on average once every three years. The method is briefly elaborated below:

3.1 Develop optimal VRE portfolios

Firstly, we divided the entire Taiwan region (including exclusive economic zone adjacent to the territorial sea) into 45 equal-sized (0.5° *0.675°) grid cells. As such, each VRE technology type at a specific grid cell becomes an individual VRE asset. Secondly, based on NASA MERRA meteorological reanalysis data of historical hourly wind speed and solar irradiance between 2000 and 2015, we obtained the 16-year time series data of hourly outputs and output ramps for each VRE asset through a power conversion model [9]. The hourly outputs and output ramps were normalized to the scale of 0-1 (on the basis of each unit of installed capacity) to enable comparison. We further characterized the mean and standard deviation of normalized hourly outputs and output ramps for each VRE asset, and the covariance matrix between different assets. Thirdly, taking into account various geographical constraints and different land cover types, we determined the geographical potentials (maximum capacity that can be installed) for each VRE asset. Fourthly, we performed MVP analysis to obtain the efficient frontier curves of optimal portfolios, based on a copperplate assumption. The objective is to minimize the portfolio volatility for each possible level of total installed VRE capacity, to meet 10%, 20% and 30% penetration levels of VRE in Taiwan's electricity demand in 2030 (290.6 TWh). The mathematical formulation of the optimization is as follows:

The total installed VRE capacity needed in the portfolio (x_p) is the sum of installed capacity variable of each VRE asset (x_i):

$$x_p = \sum x_i$$

The portfolio ramp volatility ($\sigma_{p,ramp}$) is the product of the vector of installed capacity variable per VRE asset (**X**), its transpose vector ($\mathbf{X^T}$), and the covariance matrix of normalized ramp between different assets ($\mathbf{cov_{Nramp}}$):

$$\sigma^2_{p,ramp} = \mathbf{X}\mathbf{cov_{Nramp}}\mathbf{X^T}$$

$\mathbf{X}$ is solved by the minimization of $\sigma^2_{p,ramp}$, which is subject to two constraints.

Firstly, installed capacity per VRE asset must be capped by its geographical potentials:

$$x_i \le x_{max,i}$$

Secondly, the portfolio output must reach the required VRE penetration level (10%, 20% and 30%) in electricity demand:

$$8760 \sum \mu_{i,N}\; x_i \ge DL$$

,where $\mu_{i,N}$ is the normalized mean output per VRE asset; D is Taiwan's electricity demand in 2030, which is officially forecasted at

290.6 TWh; L is the required VRE penetration level (which is set at 10%, 20% and 30% in this study).

To enable comparison on the basis of per unit installed capacity, the normalized portfolio ramp volatility ($\sigma_{p,Nramp}$) was calculated via:

$$\sigma_{p,Nramp} = \frac{\sqrt{\sigma^2_{p,ramp}}}{x_p}$$

The efficient frontier curves were obtained by plotting the normalized portfolio ramp volatility against the total installed VRE capacity for all optimal portfolios.

3.2 Fit generalized extreme value distribution

Firstly, based on the share of each VRE asset in the portfolio, the 16-year time series of normalized hourly portfolio outputs and output ramps were determined for optimal portfolios:

$$O_{p,N(t)} = \frac{1}{x_p} \sum x_i \, O_{i,N(t)}$$

$$R_{p,N(t)} = O_{p,N(t)} - O_{p,N(t-1)}$$

, where $O_{p,N(t)}$ and $O_{i,N(t)}$ are respectively the normalized portfolio output and output of an individual VRE asset at time step t; $R_{p,N(t)}$ is the normalized portfolio ramp at time step t.

Secondly, we sampled extreme ramps from the time series of normalized hourly portfolio ramps based on the block maxima method using a monthly block size. The sample only includes the largest downward ramp event for each monthly block period. This results in 192 sample points per optimal portfolio. Thirdly, we fit the sampled data to the GEV distribution for each optimal portfolio, using L-moment estimation method. Being the linear combination of order statistics, the L-moment method performs better in parameter estimation for fat-tailed distributions than other conventional methods such as the maximum likelihood estimation method [8]. The fitness of the GEV distribution was assessed descriptively for selected portfolios. Lastly, taking a three-year return period as example[2], we estimated the expected extreme ramp event that occurs on average once every three year (referred to as "once-in-three-year extreme ramp") for each optimal VRE portfolio positioned on the efficient frontiers. Based on the same procedure, we estimated the once-in-three-year extreme ramp for each individual VRE asset to enable comparison.

4. RESULTS

4.1 Mean-variance analysis

We present the efficient frontier curves of optimal VRE portfolios that serve 10%, 20% and 30% of electricity demand in Figure 1. Each point positioned on the efficient frontiers represents an optimal portfolio. These portfolios are efficient in the sense that for a given total installed capacity (corresponding to meet 10%, 20% and 30% of electricity demand) the normalized ramp volatility is minimized and for a given normalized ramp volatility, the total installed capacity is minimized. A clear trade-off can be observed within the same efficient frontier, i.e. reducing the normalized portfolio ramp volatility must be at the cost of increased total installed capacity to meet the required VRE penetration in demand. To meet 10%, 20% and 30% of electricity demand, the required minimum total installed VRE capacity are 6888-8641, 14344-17316 and 22647-26552 MW, respectively. However, the selection of the installed capacity level depends on the policy preference to the normalized portfolio ramp volatility. For convenience, we refer to the portfolio positioned at the top-left point of the efficient frontier as the min-capacity portfolio and the bottom-right point as the min-volatility portfolio.

The trade-off between the normalized portfolio volatility and the total installed capacity is more obvious for the efficient frontier associated with a higher VRE penetration (30% versus 20% and 10%), reflected in the overall steepness of the curves. This can be explained by the necessary inclusion of more assets with lower mean normalized output in portfolios in order to meet a higher penetration of electricity demand.

[2] We consider a reliable power system should be able to manage once-in-three-year extreme events. However, the maximum level of extreme ramps that should be managed by the power system and its corresponding return period depend on the reliability standards, the demand profile and the value of lost load. They can only be determined through power system modelling.

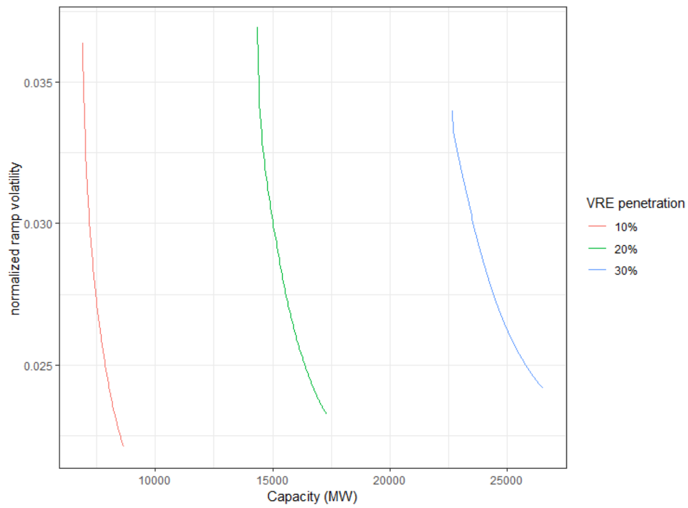

Figure 1. Efficient frontiers of optimal VRE portfolios that serve 10%, 20% and 30% of electricity demand

4.2 Extreme value analysis

For demonstrative purposes, the return plot for the min-capacity portfolio that serves 10% of electricity demand is presented in Figure 2. It is used to descriptively assess the fitness of the GEV distribution to extreme ramps. The return plot shows (both empirical and fitted) relationships between the return period and return level of extreme ramps. The dots, solid and dotted lines respectively represent the sampled extreme ramps, the GEV distribution-fitted extreme ramps and the 95% confidence interval. GEV distribution exhibits overall good fitness to the majority of sampled extreme ramps until the return level reaches ~35% of each unit of installed capacity (corresponding to a return period of 50 months). This suggests that GEV predicts better for the normal occurrence of extremes than "extreme extremes", due to the very limited sample size of the latter. Therefore, the use of EVA to estimate once-in-three-year extreme ramps (which belong to "normal extremes") in this study is justifiable.

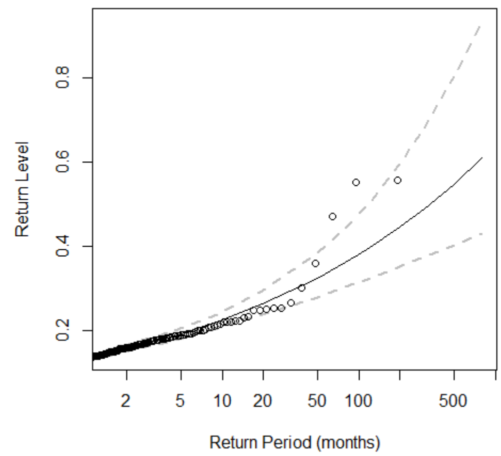

Figure 2. Return plot for the min-capacity portfolio that serves 10% of electricity demand

We present the estimated once-in-three-year extreme ramp events for optimal VRE portfolios positioned on the efficient frontiers in Figure 3. The magnitude of extreme ramps in terms of a division of each unit of installed VRE capacity decreases with increased total installed capacity along the efficient frontier. This also suggests a clear trade-off between the magnitude of extreme ramps and the total installed capacity for optimal portfolios.

To enable comparison, we also present the estimated extreme ramps and geographical potentials for each individual VRE asset in Figure 3. Although a few onshore and offshore wind assets exhibit smaller extreme ramps (based on historic data) than the min-capacity portfolios, they are still much larger than the min-volatility portfolio. The small geographical potentials of these assets also limit their participation in the optimal portfolios. The magnitudes of extreme ramps range between 13-30% of each unit of installed capacity, which are smaller than most VRE assets (20-64 %). This clearly shows additional benefits associated with diversification. Not only do optimal VRE portfolios reduce the volatility of VRE, they are also effective in reducing the magnitude of extreme ramp events.

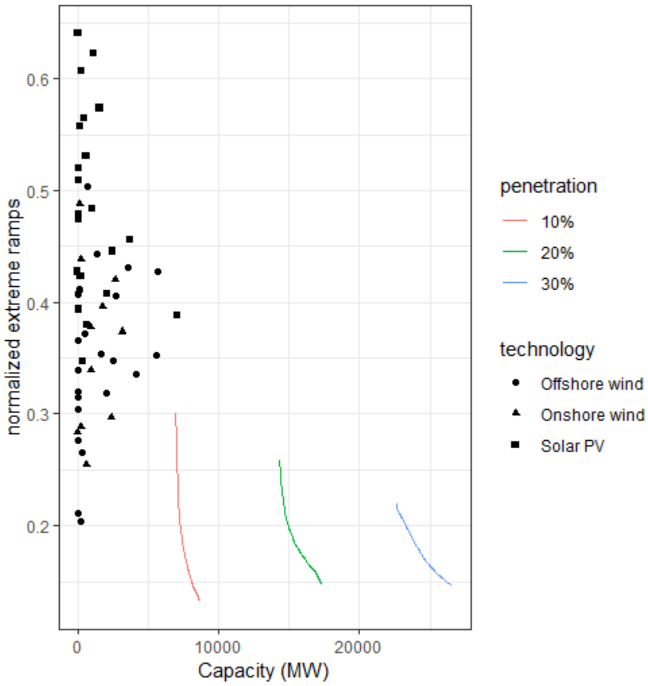

Figure 3. Once-in-three-year extreme ramps of optimal VRE portfolios (colored lines) and individual VRE assets (dots)

5. CONCLUSION AND DISCUSSION

Geographically diversified VRE portfolios can be used to smooth out the volatility of VRE output ramps. Using Taiwan as a case study area, this study developed the efficient frontiers of optimal VRE portfolios to minimize the (normalized) portfolio ramp volatility, for each possible level of total installed VRE capacity that can meet 10%, 20% and 30% of electricity demand. The analysis of extreme ramp events in optimal VRE portfolios using EVA shows that optimal portfolios are also beneficial to reduce the magnitude of extreme ramp events. The estimated once-in-three-year extreme ramps range between 13-30% (of each unit of installed capacity) for optimal VRE portfolios, which is significantly smaller than the estimated extreme ramps (20-64%) for most VRE assets in Taiwan. This result helps to manage risks associated with extreme ramp events in power system operation. To capture the benefits associated with optimal portfolios, it is recommended for policy-makers to coordinate the investment and development of VRE assets at different locations. Accordingly, the grid infrastructure in Taiwan should be reinforced and extended to enable the realization of optimal VRE portfolios. This is of particular importance, given the past outages in Taiwan due to unreliable grid infrastructure.

The present work of this study is based on two main assumptions, i.e. copperplate representation of transmission grid and stationarity of VRE output ramps. These two assumptions could be relaxed in future research.

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