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Review Article

On minimization of the group variability of intermittent renewable generators

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Abstract: We discuss an approach to minimizing the group variability of generation in a system of intermittent renewable sources using the portfolio theory. The total variability of a system that can be modeled using various parameters as goal-functions is minimized given any desired level of expected long-term generation. An extensive analysis was carried out on a set of time series of measured generation data obtained from twenty wind plants in Croatia over five years in one hour and fifteen minutes, time resolutions. The choice of the goal function most relevant for the operational (and economic) consequences of short-term variability is discussed.

Keywords: *Optimization, Renewable sources, Variability of electricity generation.*

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1. INTRODUCTION

One of the main tasks of transmission system operators is to keep the balance between total generation plus net imports (or minus net exports) on the one hand and the total consumption on the other. Technologically, the biggest challenge is maintaining it near-real-time, after the last market before physical delivery is closed. Thus, the last opportunity to adjust market positions by trading individual residual imbalances is gone. To achieve that, the transmission system operator must hire a sufficient amount of flexible generation reserve to engage it for non-stop compensation of the remaining system-wide misbalance. The latter occurs because most of the load is not coordinated nor planned and thus behaves partially as a random variable. In addition, the production in newly massively introduced variable facilities, such as wind or solar plants, can only be predicted with limited precision because it depends on current wind velocity or insolation on plants' sites. The following literature review benefited primarily from [1].

It is self-understood that the wind speeds are not the same across more extensive territories. It mainly pertains to momentary velocities and their changes. The dynamics in sub-minute ranges, resembling stochastic processes, can prove almost entirely independent between different locations where individual wind plants are situated. However, the statistical correlation coefficients between wind speeds may be more prominent on longer time horizons (minutes, hours, and longer). In some cases, they may even be strong.

Regarding the electricity grid operation, the changes that occur in minutes or tens of minutes are especially interesting because, not having sufficiently predictable dynamics, they necessarily engage flexible system regulation reserves, which are costly. There have been hopes that the dynamic changes across different plant locations would average out largely, but that generally proved not to be the case (as demonstrated later in this paper). However, in the forward-looking policy planning, there are some possibilities to utilize known (that is, pre-measured) statistical properties of wind speed time series at candidate locations. Obtaining minimum variability for any given expected level of average yearly production power is the leading research goal of this article. It was already studied by other authors, e.g. [2,3]. In such a way, mere policy measures (essentially costless) would reduce a part of the costs associated with variability. Such costs were systematically studied in [4].

On a practical side, there have been analyses of technical consequences of increased variability. In one such study [5], the connection with increased problems with system reliability, with low to the middle level of renewable sources (from now on: RES) connected to the grid, was not proved. However, increased challenges for system operation were identified. Other studies tried to establish how the increasing RES share influences the wholesale value of energy in general or that produced in RES. For example, [6] found that the value of RES-generated energy is already below the base-load. The paper [7] studied implementation costs of wind production technology with middle shares in the system, concluding that they are somewhere about five dollars per megawatt-hour. Another interesting result was published in [8], where it was concluded that the organization of power trade at intra-day time horizons stimulates improvements in forecasting the wind intensity. That leads to a decreased need for regulation reserves. Finally, in [9], it was found that the system costs of RES integration at one-fifth of penetration could amount to about one-tenth of the wholesale electricity price.

In [10], the impacts of temporal unpredictability and dynamic generation variability exert pressure on system operation. However, the unpredictability of the exact moment when a more significant change in wind intensity occurred seemed more challenging. The study [11] looked for the differences in the economic value of electricity produced in wind plants with tighter or looser dynamic co-variabilities. It concluded that they are mild, up to one-tenth of the average value. One of the conclusions found in [12] was that the sun-generated energy is valued more at lower shares in the total mix and that the wind-generated energy is higher than solar at larger shares. In [13], it was argued that the organization of electricity trade might influence the RES-generated energy value to a significant extent.

Suppose one had available coherent sets of time series wind speeds (in specific temporal resolution) at different candidate locations. Then, at least in principle, these speeds can be mapped to electricity production per megawatt of installed power. The mapping function would depend, basically, on the technical features of the system turbine-generator. Therefore, the momentary generation power at a location would be proportional to the total installed power. Suppose next that the spatial correlation coefficient across individual mast sites at every micro-location is very near to a perfect one (because the wind plants are made of some individual generators scattered across a particular piece of ground but close to each other). For example, there is micro-evidence from the Croatian power system [1]. Two different wind plant locations, relatively close to each other (in the order of kilometers), exhibited a long-term correlation coefficient of 0.9. It might imply an even tighter correlation if they were "right at the same hill". The optimization problem would then be as follows:

Suppose one wanted to install 1 MW of production capacity scattered over a set of locations. What relative weights should one assign to each of them to ensure minimum variability for any given level of average energy output in the long run?

To demonstrate practical possibilities to apply variability minimization strategies, we used coherent time series of actual measured production data from Croatian wind plant sites, normalized to the powers installed at each location. In that way, we used the existing power plants as "measuring devices" to obtain the time series of actual electricity production instead of the wind speeds from which one must first estimate the electricity production. For our goal, it is the most helpful type of data describing Nature. Moreover, that provided a detailed set of production data at all locations, synchronized in time, which enabled an analysis of the true potential for statistical cancellation of wind variability across a more expansive territory.

2. MINIMIZATION OF VARIABILITY IN THE GROUP OUTPUT

When thinking about possible optimization strategies aimed at minimization of temporal variability of production from a set of wind plant locations (but not limited to that technology), the concepts of so-called Modern Portfolio Theory (MPT) [14], used since a long time ago in the financial sector, come to mind. MPT in its earliest forms was criticized for the lack of generality [15] because it relied on the assumption that the time series in question were stationary in time and normally distributed. Those limitations resulted from computational complexities that were too hard to handle when Markowitz conceived the theory in the early fifties. However, nowadays, they are not an obstacle anymore. Therefore, at least regarding the nature of statistical distributions of data, optimization can be quickly done regardless of them. When it comes to stationarity, it is more connected with the very nature of the processes that govern the modeled processes. For instance, the stationarity requirement may be problematic in the financial sector. However, in the realm of meteorological phenomena such as wind intensity, it may not be that problematic, at least not in more extended periods, such as decades. Nevertheless, the longer the period in which the time series data are gathered, the better the picture of the Nature one obtains.

We shall here briefly explain the MPT in its canonical form [14]. Define a set of N coherent time series, X_i, with expectations E_i and standard deviations σ_i. Here, the index i denotes individual data series: $i \in [1,N]$. Let ρ_{ij} denote the correlation coefficient between the series i and j. Let us define a "*portfolio*" as a weighted sum of the series as $\Sigma_i \, r_i \, X_i$, where Σ_i denotes the sum over all indexes i, and r_i denotes the weight factor for the series i. The statement of the problem of the portfolio optimization is:

$$\text{Minimize} \quad \sigma^2 = \sum_i \sum_j r_i r_j \sigma_i \sigma_j \rho_{ij} \qquad i,j \in [1,N]$$

$$\text{Subject to constraints:}$$
$$\sum_i r_i = 1$$
$$r_i \geq 0 \tag{1}$$
$$E = \sum_i r_i E_i$$

The decision variables are the *r*'s. As we will demonstrate later, the goal function does not have to be the variance of the portfolio. It can be any parameter that the designer deems purposeful.

The numerous optimization procedures were done numerically, using the non-linear optimization solver software, over a set of the real-life measured time-series data in the time resolutions of 1 hour and ¼ hour. For the sake of brevity, only a part of the information obtained will be presented in this paper. Using the numerical algorithms enables the modeler to optimize for other group parameters than the plain variance, which was used primarily because of a need to obtain problem formulations simple enough for analytical computation. The structure of the data is explained in more detail as follows:

- *Timespan*: 2014-2018 (time series of data measured at each plant in two different temporal resolutions: 1 hour and 15 minutes).
- *The number of wind plants*: from 9 at the beginning of 2014 to 20 at the end of 2018.
- *The number of data samples per year*:
    - 1-hour resolution: 8760 (normal year); 8784 (leap year);
    - 15-min. resolution: 35040 (normal year); 35136 (leap year).
- *Type of data*:
    - Original recordings: average production power in megawatts (MW) during the sample interval (1 hour or 15 minutes).
    - Normalized data: each sample is divided by the production capacity (MW) installed at the corresponding plant site.

All data were measured by the Croatian Transmission System Operator coherently in time, with high accuracy. Without the temporal coherence, any calculation of statistical correlation coefficients between the series would not be possible.

A notion of "*load factor*" will be used from now on in the text. It can be specified on all levels, from an individual site to any group of sites, to the entire portfolio under analysis. It is defined as the ratio between the total energy produced in an individual plant or a group of plants in a long period (e.g., a year) and the product of the total installed power and that same period of time. It equals the statistical average of the normalized data samples taken in the same period.

To illustrate the concept of variability minimization, we shall construct a few simplified imaginary examples. Take four wind plant locations out of twenty operating in Croatia at the completion date of this article. The primary descriptive statistics of those locations are given in Table 1. A random 24-hour period was taken from the 2015-2018 time series of 15-minute measured generation powers. The four locations were observed in the same 24-hour period. The momentary generation powers were normalized to the installed power at each location. This restriction to 24 hours (96 individual samples per site) made the time series visible to the reader because drawings containing the whole 4-year set of samples would not be readable. We will now observe how these restricted data can be combined to achieve different goals in the best possible way, keeping in mind that it pertains to that 24 hours only. Given the small data set size in the example, simple optimization routines were performed in Excel according to different criteria.

Table 1. Some descriptive statistics of the four wind-plant locations utilized in the example presented in this Section.

	Loc. 1	Loc. 2	Loc. 3	Loc. 4
Average	0,452	0,303	0,562	0,506
Standard deviation	0,310	0,191	0,310	0,231
Average/Variance	4,714	8,314	5,848	9,514

Fig. 1 illustrates the main idea. Four individual time series are in the left part of the picture. The abscissa values are the ordinal numbers of the samples in the restricted time series, whereby these samples are spaced by 15 minutes. The dynamics of the four graphs are different, although there are some overall similarities. On the right side, there is a graph of their combination, with weight factors given above it, optimized for maximum Average-to-Variance ratio. As one can see, the resulting curve appears to be more "tamed" than any individual one. The resulting Average curve lies somewhere between the individual ones, which is the only possible outcome since it is a linear combination. The standard deviation is, however, smaller than any of the individual ones. As a result, the optimal Average-to-Variance ratio from the four series is much larger than any individual one. Note that the weight factor for the first location turned out to be zero. It means that this location would get a negative weight factor without the non-negativity constraint from (1). Thus, for example, if a policymaker intended to install 1.000 MW of new wind generation capacity with the highest possible Average-to-Variance ratio, the distribution among the four locations would be zero MW to the Loc. 1; 525 MW to the Loc. 2; 153 MW to the Loc. 3; and 322 MW to the Loc. 4. Fig. 2 exhibits a direct comparison, on the same graph, between the individual curves and the resulting one, all from Fig. 1.

Fig. 3 gives a comparison of the curves resulting from different optimization criteria:

- S1 - equal weights (blind averaging, no optimization),
- S2 - average-to-variance ratio,
- S3 - average-to-standard deviation ratio,
- S4 - average absolute hourly change,
- S5 - average squared hourly change,
- S6 - average 15-minute change,
- S7 - average squared 15-minute change.

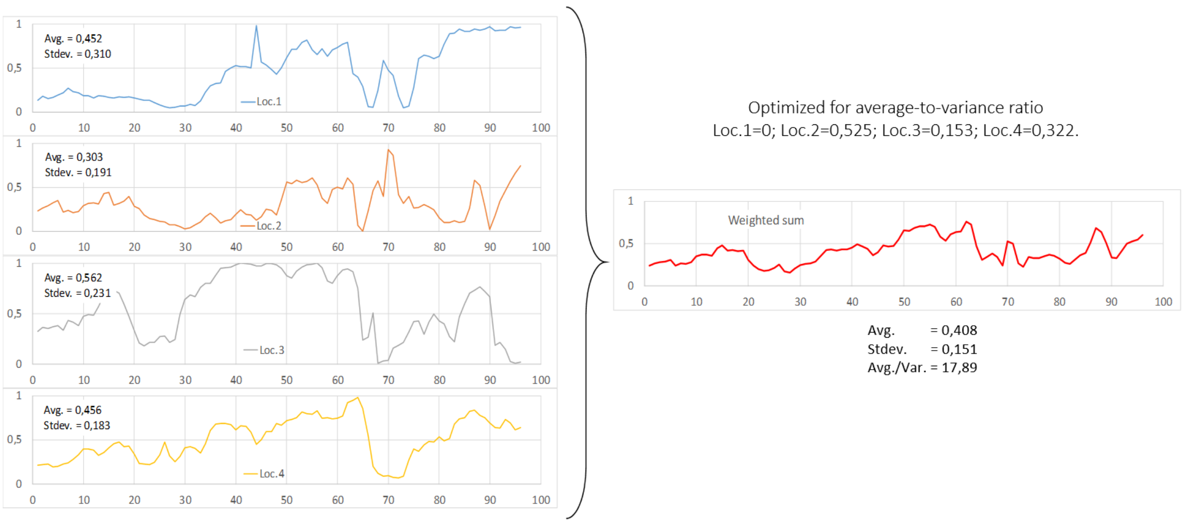

Figure 1. The measured normalized wind generation time series at four locations in 24 hours combined for maximized Average-to-Variance ratio. Source: Authors

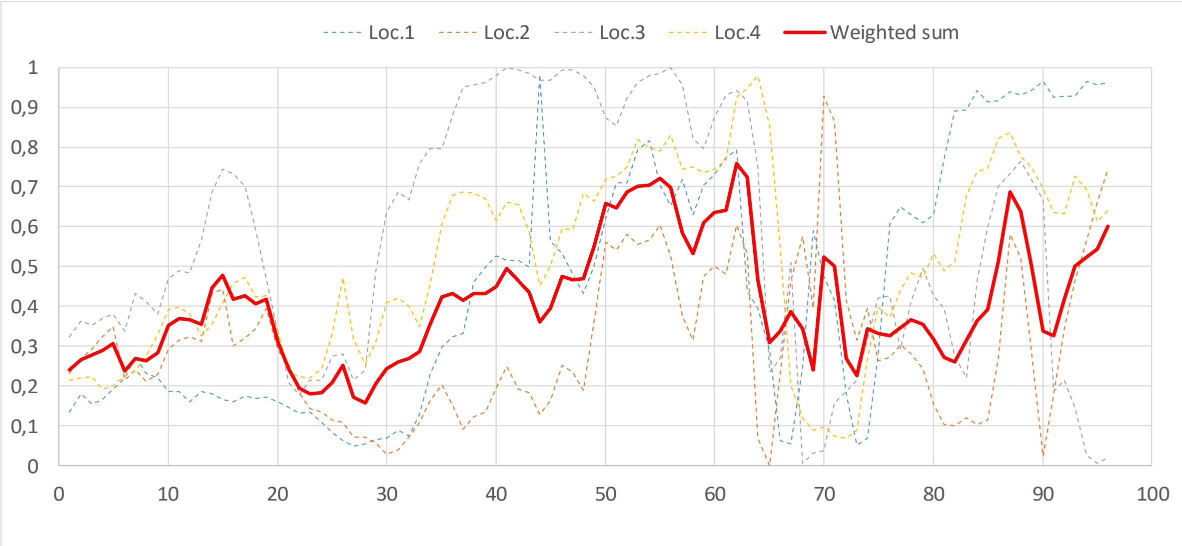

Figure 2. Comparison between the individual locations' time series curves and the resulting curve, all from Fig. 1, optimized for the Average-to-Variance ratio. The reduction of costly variability is significant. Source: Authors.

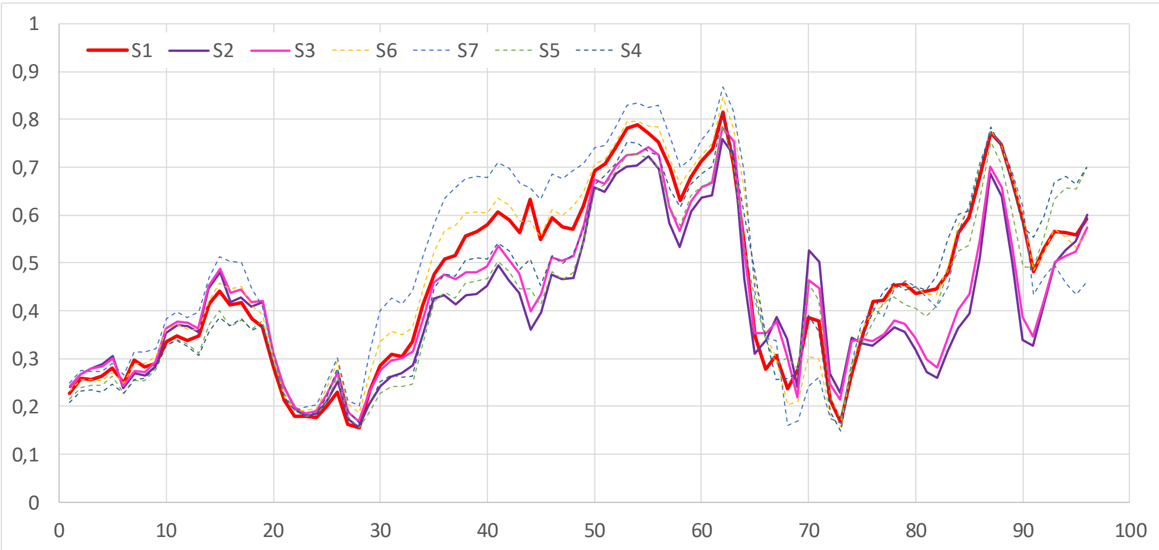

Figure 3. The curves resulting from different optimization criteria. Source: Authors.

All those curves appear to be "better" than the original ones regarding the general variability properties. Even the blind averaging seems to be taming the dynamics. However, given that we used just four minimal time series, we cannot make any firm conclusions of a general kind from these illustrative examples.

2.1. Optimization Procedures

Let us first examine the realistic space of portfolios in the E - σ plane. Fig. 4 and Fig. 5 were taken from [1]. Fig. 4 depicts a subset of 20 thousand stochastically generated portfolios out of one million calculated. The larger white dots stand for the individual sites, whereas the smaller blue ones belong to the randomly generated portfolios computed simply by a random assignment[1] of the *r*-values to the nine individual plants whose 2014 hourly data were used to create this example, ensuring that all *r*'s are non-negative and sum up to 1.

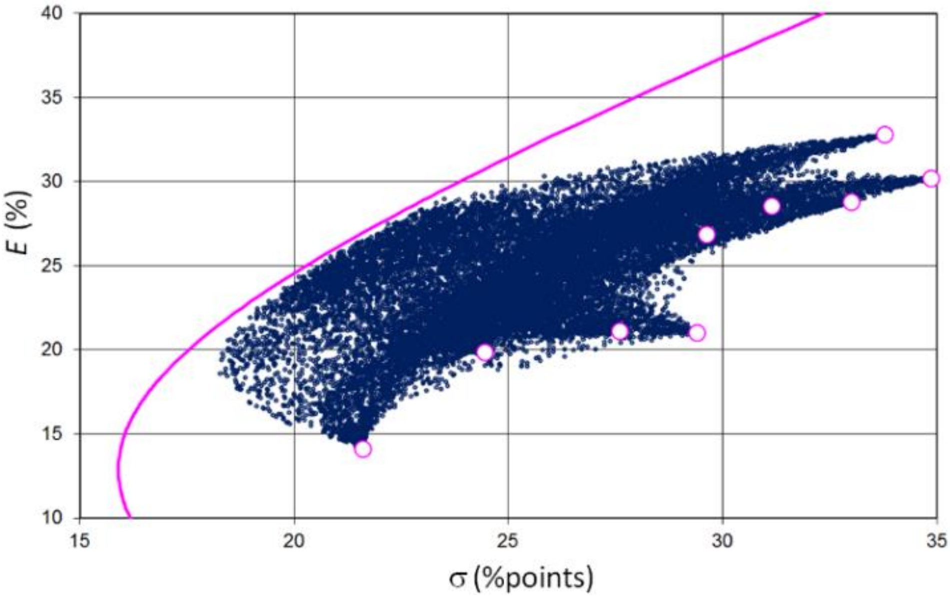

Figure. 4. Small dots: 20 thousand random portfolios made with nine then active wind plants, based on 2014 15-minute data. Source: [1].

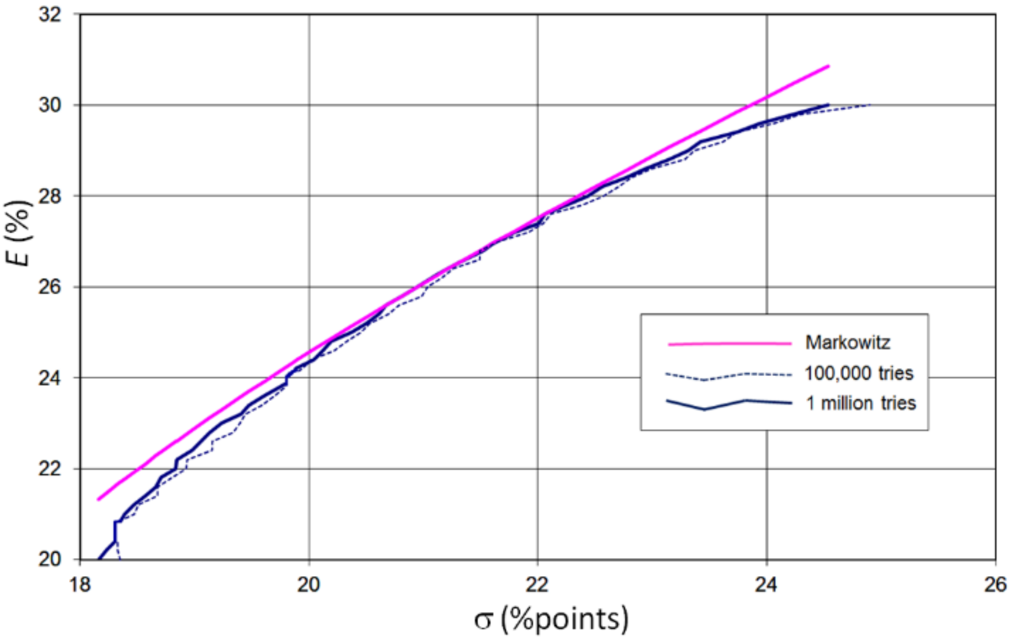

Figure 5. Comparison of experimentally obtained efficient frontiers and the unconstrained ("Markowitz") one for 2014, obtained from 15-minute data. Source: [1].

[1] A technical note: assigning *r*'s using the simplest uniform distributions proved not to be a good strategy because the portfolios tended to gather close to the individual plants massively. Thus, obtaining good approximations of actual borders of the feasibility region would require at least hundreds of times more random computations. Therefore, the *r*-value drawing procedure that created much more diversity in the final results was created, the description of which is not of interest here. However, it can be found in [1].

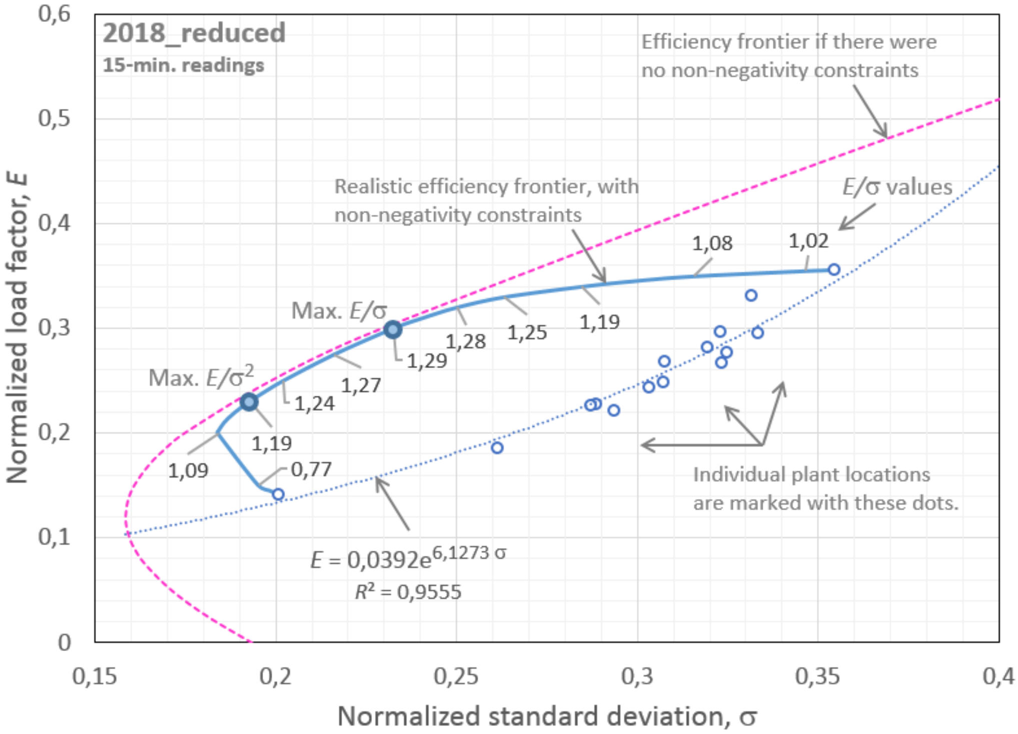

Figure. 6. Efficient frontiers derived from the data for 15 Croatian wind plant sites, using the 15-minute readings from the entire 2018. Source: authors' calculation.

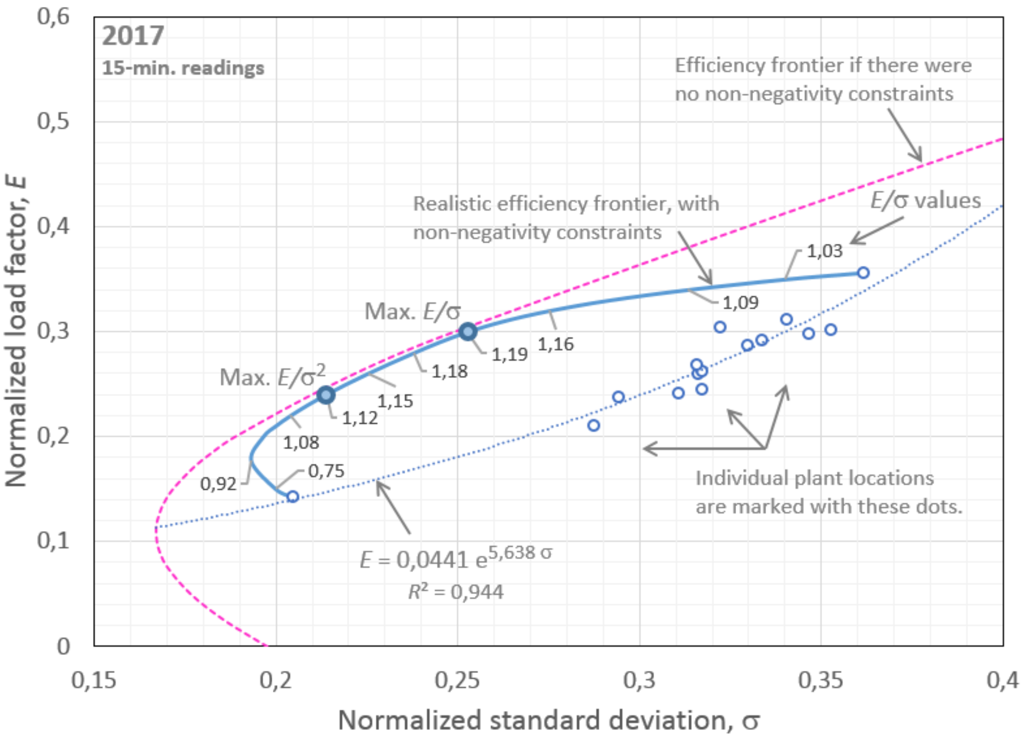

Figure 7. Efficient frontiers derived from the data for 15 Croatian wind plant sites, using the 15-minute readings from the entire 2017. Source: authors' calculation.

Note that the simple two-dimensional graph does not allow the correlation coefficients between the individual plant time series to be displayed, although, in reality, they do exist. The magenta-colored lines in Figs. 4 to 6 are so-called "Markowitz efficient borders," resulting from the "classical" MPT without enforced non-negativity constraint. Whereas in the financial world (the "normal" area where MPT is usually utilized), it could make sense in the form of "short-sales", see e.g. [14,15], in the realm of electricity generators, it would be physically impossible. However, the unconstrained efficiency border is good to compute for the "sanity check" because every portfolio constructed from the given individual sites must lie to the right of that quadratic hyperbola. Fig 5 compares the efficient borders computed from the complete set of one million random portfolios and the subset of one-tenth of them. The two experimental efficiency borders were obtained by searching for the portfolio with the lowest variance σ^2 among all with the expectation in some close pre-determined neighborhood of the observed value E and repeating this across the whole range of attainable E's.

Fig. 6 and 7 give the efficient frontiers (unconstrained and realistic) obtained from 15-minutes data during one whole year each (2018 and 2017, respectively). They also display the individual plant loci in the E-σ plane, which is not precisely the same because the wind parameters were not precisely identical in the two years. However, one can note one particular characteristic of Nature, at least in the Croatian coastal region, where the plants are situated: the larger the wind energy output at a location, the more significant its volatility. It is because it closely follows an exponential law.

While the efficient frontiers are a good graphical illustration of what one can achieve with the minimization of variance, the solutions of practical interest are the weight factors assigned to individual sites at the point of optimum achieved concerning a particular goal function used. Figs. 8 and 9 present the solutions for 15 locations (marked by capital letters) from Figs. 6 and 7 for 2018 and 2017. The capital letters in these pictures are the anonymized codes of the concrete 15 wind plants, which data were used in the calculations.

Note that at first glance, the two graphs look similar. However, paying attention to the details, notable differences are revealed, especially in the region between maximized E/σ^2 and E/σ. The solutions seem most stable when only a few of the sites with the highest load factors E_i are used for the installation of the wind farms. However, as already commented, they also exhibit the highest volatility. Our results suggest that it would be good to use dominantly the sites more abundant with the wind (for the best stability in time). That would lead to portfolios with still relatively high production variability, yet considerably lesser than without the optimization. In our present research, it surfaced out as *an essential* point when it comes to the optimization of variable energy production.

Now that optimization for total variability in terms of variance is explained, attention should be put on what poses a problem in the power system operation. The most critical limited resource relevant for that is the capacity of flexible units to which the transmission system operator pays to stay available for system regulation, to counterweight the swift changes in the intermittent renewable sources output. It is a well-known problem.

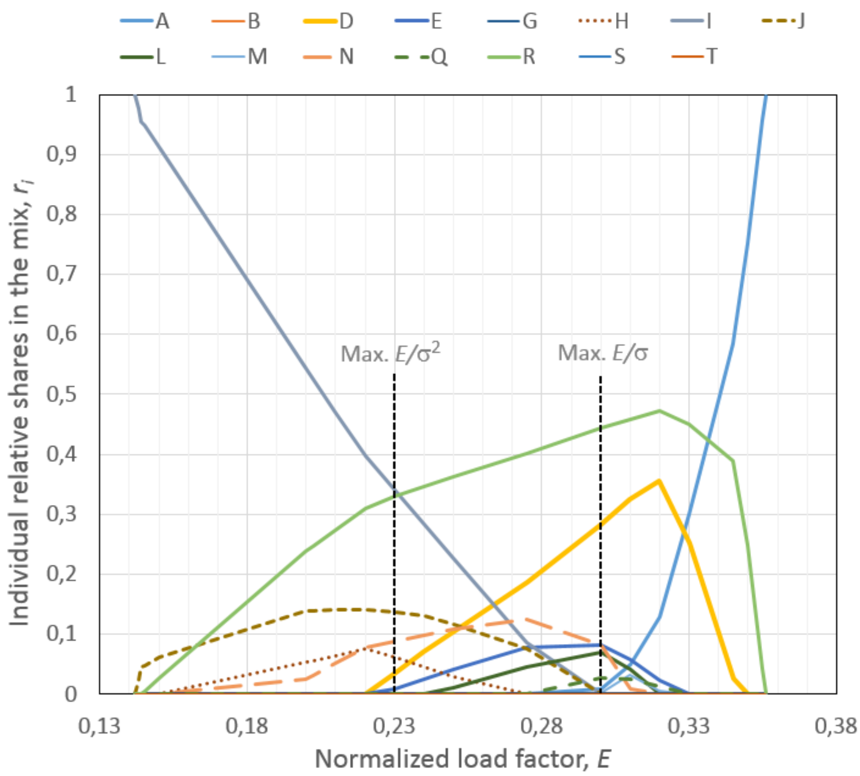

Figure 8. Solutions of the optimization problem for 15 Croatian wind plant sites, using the 15-minute readings during the entire 2018. Source: authors' calculation.

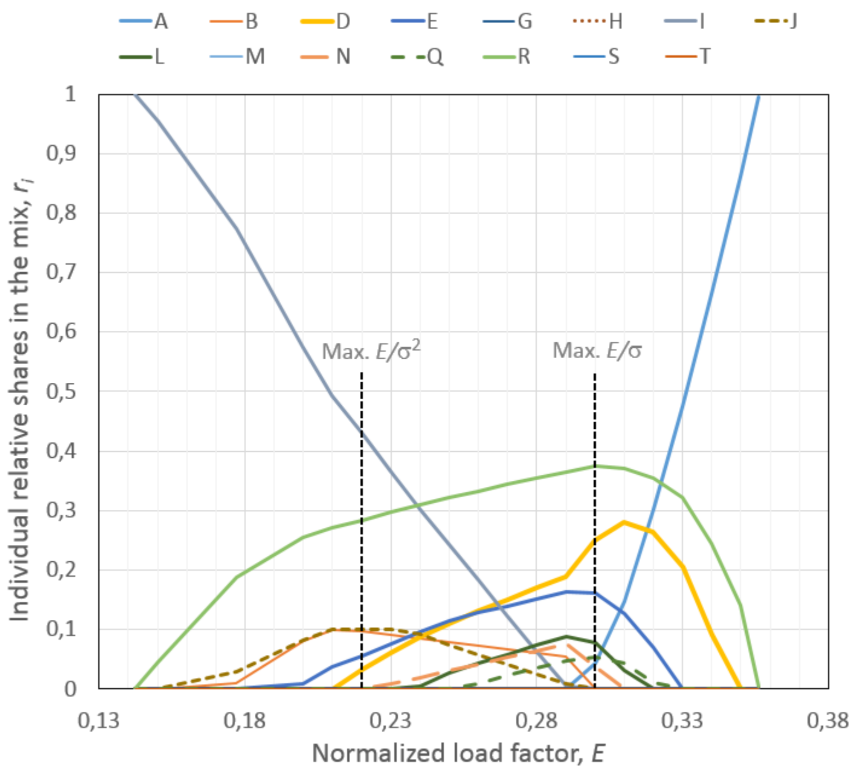

Figure 9. Solutions of the optimization problem for 15 Croatian wind plant sites, using the 15-minute readings during the entire 2017. Source: authors' calculation.

For example, after studying the seven-year stream of 5-minute readings of the energy output from an extensive system of wind plants in the north-western USA, the authors of [16] found out that the demand for fast regulation can be expressed as:

$$M_{\text{Reg}} = \frac{\alpha}{\beta} p^{\beta} + \gamma p, \tag{2}$$

where the Greek letters denote positive real constants. M_{Reg} is a quantity that shows how many times the total installed power of wind plants can exceed the currently available 15-minute flexible regulation reserve if the system operator deems the risk of default of p percent still acceptable, nothing else being variable in the power system. Fig. 10, taken from [16], gives the results of the experimentally derived M_{Reg} for the above-mentioned American wind plant system in the whole of the year 2013, together with the curve (2) fitted to the data using the least squares. For example, according to Fig. 10, if the operator of the system studied in [16] were willing to accept no more than 2% probability of getting short in the temporarily available flexible regulation reserve, the total flexible capacity held in reserve for the regulation purposes would not have to be less than about one-twentieth of the total installed power of the wind plants. To sum up, when contemplating minimization of the short-term variability, it is better to use some parameter that reflects the short-term changes in the total output of a system of wind plants rather than simple variance or standard deviation.

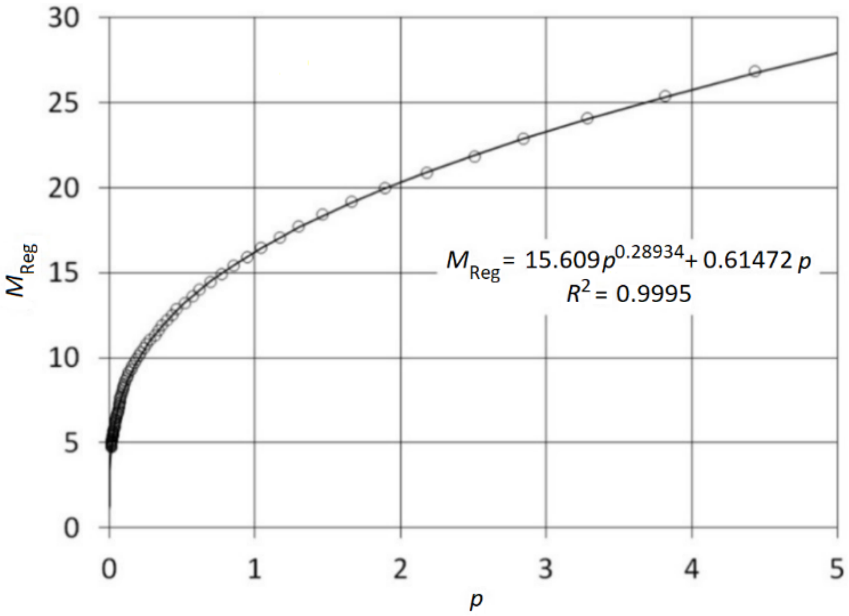

Figure 10. Experimentally obtained demand for fast regulation and the best-fit function (2). Source: [16].

Perhaps it is worth mentioning that there were ideas that the variability of RES and the total system load could partially compensate for each other. However, a case study [17] demonstrated that it is not valid. Naturally, optimizing the spatial allocation of installed capacity discussed here is not the only option one can use to combat intermittency's technical and economic consequences. For example, [18] provides a robust assessment of short-term wind power forecasting models. They are relevant because the grid operators' main problems with intermittency come from the fact that the changes in momentary generation power from the variable RES are not predictable in the temporal dimension. Developing models that would enable better predictions would significantly reduce operational risks associated with intermittency, hence the economic costs. Further, [19] and [20] discuss various aspects of storage solutions related to the grid operation and enhancing flexibility in the conditions with an increased share of variable RES.

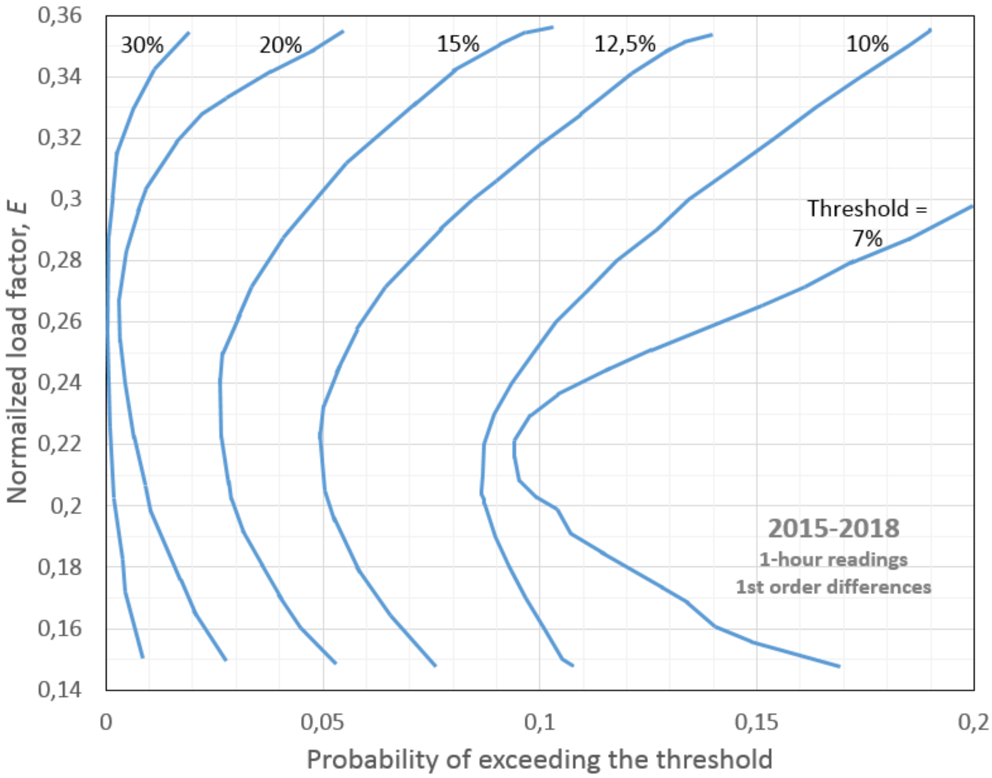

Figure 11. Efficient frontiers where the probability of a one-hour change (1st order difference) in total normalized production exceeding the Threshold is minimized for any given E. Derived from the 4-year time series of 1-hour readings, 2015-2018. Source: authors' calculation.

For example, we optimized a probability for a temporal change of total production to exceed a certain pre-defined threshold within one unit of time. For demonstrational purposes, in Fig. 11, we present the efficient frontier curves in terms of the group load factor E vs. the above-described probability. Fig. 12 shows the problem solutions (the sites' weight factors) for a curve of the Threshold of 20%. Note that the curves from Fig. 11 are limited to the range of $0.148 < E < 0.355$, where the portfolio solutions do not contain negative r-values. Note also that minimization by that criterion emphasizes the roles of two individual locations (A and I) with the most extreme characteristics (Fig. 12), suggesting (in this particular example) that the system can be optimally arranged by blending merely the two of them.

It is self-understood that optimal solutions for one criterion are not the same as for the other. Accordingly, the efficiency borders are not the same. Therefore, it is not possible to define which kind of optimization is "better". They are all "the best" concerning the concrete goal function that was applied. The real question for the policy planner is what goal function is the best for the intended policy goals. We can only compare the different solutions so to establish how far they are from each other. It would not be very good if the optimal solutions for concurrent goal functions would differ significantly. That kind of "sensitivity" to the "political goal function" would imply that inadequate policies themselves can be very costly or at least very risky (if there were no clear criteria for assessments of the policy outcomes themselves).

To illustrate that, we can observe Fig. 13. The values at the right-hand ordinate scale are probabilities that the absolute value of hourly change in generation power exceeds 20% of the installed capacity. The corresponding curve gives the minimized values against the expected average normalized production E of a portfolio. The values at the left-hand scale correspond to the quotient of the actual standard deviation of a portfolio with the average E and the minimum possible standard deviation for that same portfolio. In other words, we are trying to compare the portfolios obtained by (a) optimization for the minimized probability of significant hourly changes in generation power and (b) optimization for minimized portfolio variance. As displayed, the global optimum for minimized hourly change is somewhere around E = 0,27. At that point, the standard deviation is slightly above 10% larger than the lowest possible one at that very E. In the whole range of displayed *E* values, the standard deviations do not differ from their lowest possible values by more than 12,5% in the worst case.

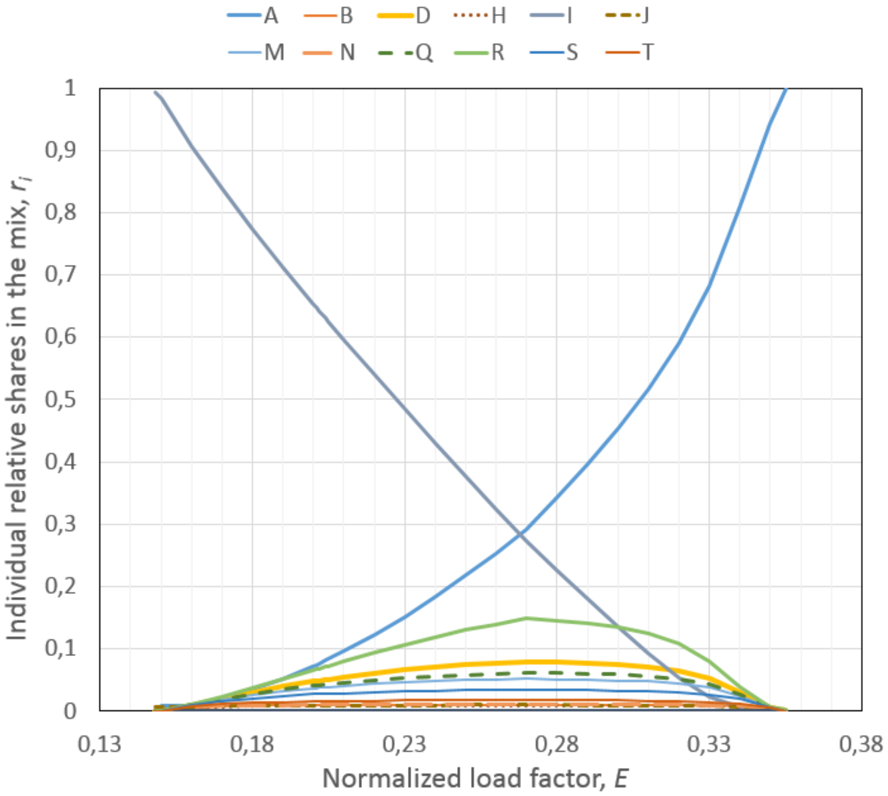

Figure 12. Solutions of the optimization problem along the curve for the Threshold = 20% from Fig. 11. Source: authors' calculation.

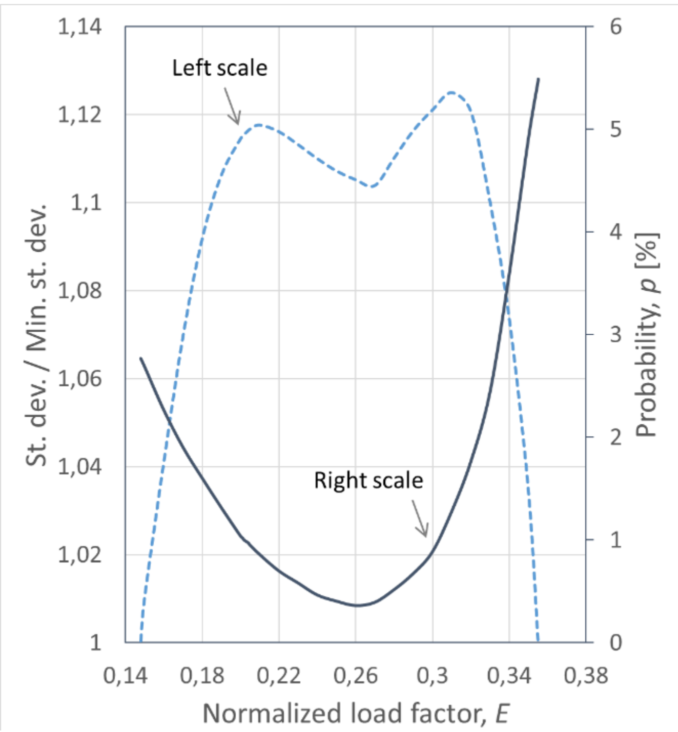

Figure 13. The probability that the hourly change in production will exceed 20% of total capacity and the ratio between the actual and minimum possible standard deviation. Source: Authors.

3. CONCLUSIONS

The volatility of the energy production from wind plants and/or other intermittent renewable sources is a significant (although perhaps not the most significant) problem in the current power system operation. Moreover, it can only grow as the share of such generators in the total mix increases. Therefore, it is essential to study the possibilities to minimize the short-term variability by organizational measures, such as the coordination of investments of the kind studied here and earlier literature by the other authors.

Our simulations, carried out on the measured production time-series data, suggest that the choice of more windy sites could be a good trade-off between the marginal loss of total load factor and decreased total variability expressed through the above described overshooting probability. Furthermore, the results suggest that this trade-off is harsher when the goal function is the probability of the hourly change in production exceeding a certain level than when it is the variance. It is essentially a combined consequence of the wind energy production non-normality, with fat-tailed distributions and temporal volatility. Thus, at least in the Croatian case, optimization for this particular parameter seems to lead to the choice of the most extreme locations (those with the highest and the lowest output and volatility).

Regarding the quantitative results, we can comment on those from the case study of Croatian wind plants.

First, we can observe the features of Nature and its variations over the years. By comparing Figs. 6 and 7, one can see that the loci of the individual wind farm locations in the E-σ diagram slightly vary. However, those variations are not very big. The following characteristic of the wind in the Croatian coastal region is the apparent exponential connection between expected electricity production and its standard deviation. The larger the expectation, the larger the standard deviation. This type of relationship was established experimentally with high Pearson coefficients, R^2. A "good" property is that the increase of E speeds up with the increase of σ, meaning that the tradeoff between the two is improving with increased volatility so that the most energy-abundant locations are not being ruled out from the optimal portfolios.

When carrying out optimization of variance σ^2 for any given expectance E, the resulting efficiency frontier almost equals the Markowitz frontier in the range between the portfolios with maximized E/σ and E/σ^2 (see Figs. 6 and 7). In a practical sense, it means that all the wind plant locations included in the optimization receive weight factors r_i greater than zero. Other efficient portfolios depart from the Markowitz border because the optimization process leads to $r_i = 0$. The E/σ ratio, which is a usual benchmark for portfolio efficiency in the framework of "classical" MPT, is optimized, in the Croatian case, at the expected load factor E of about 0.3 (which is a good result), and the expected normalized deviation σ of about 0.23 to 0.25, which exhibits the volatile nature of wind as an energy source in Croatia. Such a characteristic of Nature implies a need for (costly) fast regulation, which is discussed later in the article (see Fig. 10).

The solutions to the optimization problem (1) corresponding to the data written in Figs. 6 and 7 are given in Figs. 8 and 9. Clearly, the more a candidate location is close to any of the extreme ones in terms of the E/σ ratio, the more stable the solutions. It means that the portfolios comprised of the locations with either a high E and low σ, or a high σ and low E, tend to have the overall statistical parameters less dependent on seasonal (yearly) variations of the wind characteristics in Croatia's regions where the wind farms are usually installed. Another type of optimization (based on minimized dynamic variability instead of minimized variance, see Figs. 1 and 12) leads to a similar conclusion, that perhaps the best strategy could be to devise simple mixes of the two extreme types of locations, avoiding those with moderate E's and σ's. At least, based on the evidence presented in this paper, it can be asserted for the Croatian case study presented in this paper. However, due to the preliminary nature of our study, it would have to be corroborated with more research, based on more extended time series of observed data, which will, of course, become more available with time.

Regarding future work, it is interesting to explore the possibilities of minimization of variability in the areas with significantly different wind characteristics (e.g., with less short-term volatility of the wind speeds) in a similar manner, concentrating on minimization of dynamic overall portfolio variability instead of plain variance. Another critical area of research could be upgrading the current generation systems by minimizing the marginal (additional) variability, taking the already existing production units as an additional restraint in the optimization problem. Next, introducing substantially different generation technologies, such as solar, into the analyses could also prove to be of significant importance.

As the power system moves towards the goals of almost complete decarbonization with an ever-increasing speed, the importance of variability management's technical and economic challenges will increase.

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