Error reduction of solar forecasts by zero-mean adjusted composition

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Abstract— **Renewable energy production, especially wind and solar, suffers from high intermittency. Accurate forecasts are therefore necessary to respond to these fluctuations appropriately, ensuring grid stability. Literature on the topic of renewable energy forecasts tends to view systems and evaluate the performance of their respective forecasts in isolation. But renewable energy production systems, like solar, often exists as a farm spanning multiple panel and inverters which all feed into the same grid. This paper demonstrates, why instead of this isolated view it is beneficial to evaluate performance on multiple systems in conjunction and that this effectively reduces the overall error of the forecasts.**

I. Introduction

Due to the rising global temperatures and the potential severity of problems connected with it, worldwide there is an effort to reduce emission of greenhouse gases. As production of electricity with fossil fuels is one of the main contributors to CO_2-emission [1], production from renewable energy sources have come into focus. But this transition from non-renewable to renewable energy sources, does not come without its own issues. One of these issues is the fact that their production is highly volatile, commonly referred to as intermittency [2]. In comparison fuel-based power can be produced whenever needed and the amount can also be adjusted to a certain extent. This intermittency does lead to new challenges in ensuring power grid stability and consumers on-demand access to power, as all power demand must be met with the equal amount of supply. Beyond that also the opposite is true, meaning all supply must be met with demand, or in other words produced electricity must be consumed [3].

To still guarantee this balance even with large share of wind and solar power within the grid accurate forecasts are needed. As these forecasts give an idea of the produced power at a future point in time, appropriate measure can be undertaken to ensure that production and demand are matching. The literature about renewable energy forecasts is vast, but in general forecasts are created and evaluated for isolated systems [4] although multiple of these owned by the same operator feed power into the grid. This paper demonstrates, why instead of this isolated view it is beneficial to evaluate performance on multiple systems in conjunction and that this approach effectively reduces the overall error of the forecasts. A more accurate forecast in return should lead to reduced needs for spinning reserve and thereby also lower operational cost of the electrical grid [2].

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II. Research Methods And Design

A. Forecast Composition Hypothesis

Instead of looking at forecast for different systems in isolation, multiple systems as a whole will be viewed as a composition. Forecast are most often created for single system, for example one wind turbine only or in the case of solar one forecast per inverter. But a solar farm consists of many of those systems, all with the same operator and all feeding into the same grid. A composite view can utilize the effect that while forecast for some systems will produce errors of overestimation, others will produce errors of underestimation. If we combine those forecast these oppositely singed errors will naturally equal each other out to some extent. This should decrease all common relative error metrics, but especially the MAPE metric is influenced by that. Also, the MAPE error of multiple combined forecasts can never be greater than the maximum error of its individual components, as better performing forecasts will compensate for worse performing once. The mathematical notation are as follows

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (1)$$

$$MAPE_{comb} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\sum_{i=1}^{m} A_{ti} - \sum_{i=1}^{m} F_{ti}}{\sum_{i=1}^{m} A_{ti}}\right| \quad (2)$$

$$MAPE_{comb} \leq \max(\{MAPE_1, \ldots, MAPE_i\}) \quad (3)$$

Where A_t is the actual value and F_t is the forecasted value of period t, n is the number of total observations, and m is total number of individual forecasts. The Hypothesis therefore is that with increasing number of forecasts combined, the overall combined MAPE also continues to decrease.

B. Evaluation Approach

To validate this hypothesis, sets of combinations of forecasts are created and the respective percentage error of each of the combinations is calculated. Each set includes only combinations of a certain size, the first set would be all the individual forecasts, the second set would be combinations of two forecasts and so on, until the last set, which represents all forecasts combined. The number of sets is therefore equal to the number of individual forecasts. Optimally each set includes all possible combinations, but the number of possible combinations the largest set will have increases exponentially with the number of individual forecasts (*n*), as depending on set size (*r*) their number is equal to

$$\frac{n!}{r!\,(n-r)!} \tag{4}$$

In this paper 36 individual forecasts will be used for validation, the largest set where 18 forecasts are to be combined would thereby have 9,075,135,300 possible combinations. Creating all combinations therefore is not feasible. Instead forecasts are randomly chosen to be combined, so that per set the number of combinations is equal to number of individual forecasts (each set has 36 combinations), with the exception being the last set which includes the combination of all forecasts, where there is only one possibility. Successively the error of each combinations is calculated and the range of errors within each set is obtained. The progression of average, maximum and minimum error throughout these sets will be displayed and should deliver a robust basis to judge effectiveness of forecast composition. Particular attention is to be brought on whether the changes in error with each additional increment of set size is linearly or exponentially increasing or decreasing.

C. Conditions

To utilize this effect to its fullest the condition must be that forecast are balanced in regards to over- and underestimation, meaning neither can the population of forecast have predominantly positive or negative errors. The mean of all real integer errors must be zero or at least close to zero.

To ensure this following method can be employed, to correct such skewness if present. Using the forecast of the training data, the real integer errors (signed errors, not absolute) of the forecast is calculated. Then the average error per time group (for e.g. hour of the day) is calculated. This information is then transferred to the forecast on test data, by adjusting the forecast value by the mean error of is respective time group established on the training data. As a result, the average error is closer zero than before, as now its inherent tendency of over- and underestimation is accounted for. Note that this just one simple option to correct the forecast towards a zero means. These factors could also be seasonal and differ from case to case. In an even more advanced system, this time grouped average errors could be constantly updated, as they might change with time.

D. Forecasts

Since the forecasts themselves are not the center of this paper, followingly only a short description of their conception is given. There is a total of 36 datasets (one dataset per inverter) consisting of 10 minutely observations of power generation, irradiance and inverter temperature. The datasets stem from three different stations out of which two are located in Kaohsiung, Taiwan while the other is located in Toufen, Taiwan. All datasets span the time from 13th December 2019 to the 30th June 2020, a total of 201 days. For the training set the first 139 days were chosen, the rest of the days make up the test set, which will be data used for the composition. One forecast model for each dataset is created which predict power generation for one step (10 min) ahead using a simple one-layer LSTM model. The parameters (batch size=144, nodes=16, epochs=50) are intentionally identical for all datasets to show the effectiveness of the composition even with unoptimized forecasts.

The reason why there is not only singular forecast for all these systems together is that each system has their own unique characteristics that influence their power production (efficiency coefficients, installation angles etc.). Producing only one forecast would not be able to cover all these. Therefore, influential unique information is lost and likely a worse performance would be achieved.

III. Results

Out of the initial 36 forecasts, the min. MAPE is 3.066%, while the max. MAPE is 10.818% and the overall average is 5.035%. As seen in “Fig. 1”, all three statistics tend to generally decrease with increasing number of combined forecasts. While the mean and minimum decrease relatively smoothly, the maximum fluctuates until experiencing a

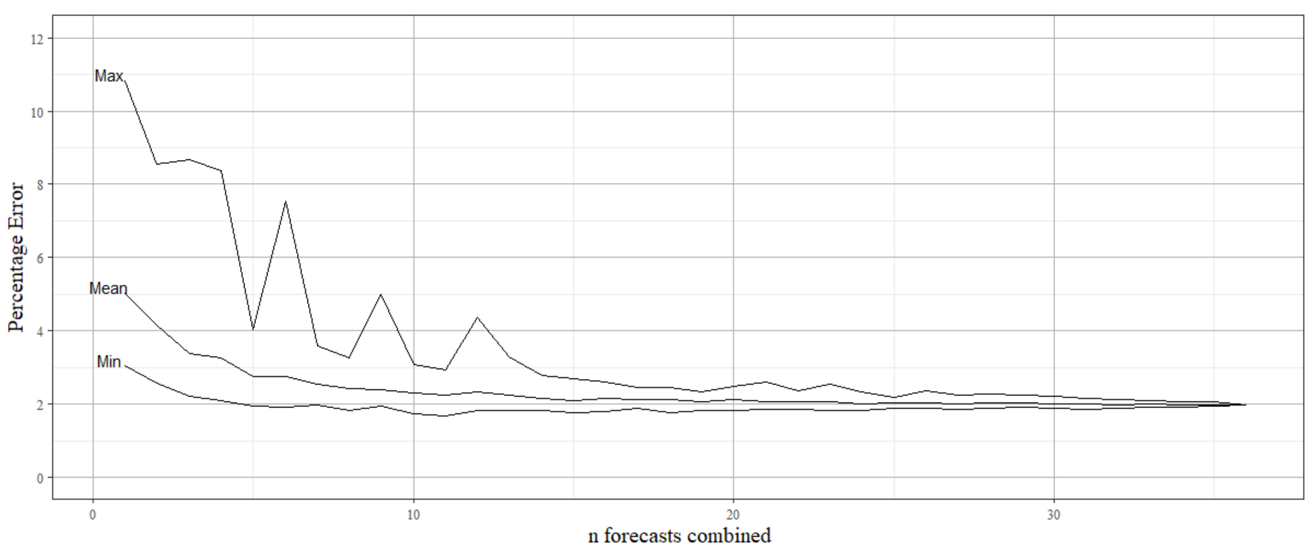

Figure 1. Progression of percentage error distribtuion over forecast group sizes

gradual curtailment from 14 combined forecasts onwards. Also, it is to be observed that magnitude of decreases for mean and minimum error is largest in the beginning, but is quickly converging at around 10-15 combined forecasts. In fact, the exact numbers shown in “Table I.” in the Appendix, reveal that after 11 combined forecasts the mean stop continuously decreasing but still reaching its overall minimum of 1.975% at 36 combined forecasts. The overall smallest minimum error of 1.673% is found at 11 combined forecasts, while afterwards the minimum error ranges from 1.765% to 1.975%, actually reaching its highest values after the minimum at the point where all datasets are combined. For all (36) combined forecasts, the MAPE for all statistics is 1.975%. The effective overall mean percentage error for the 36 forecasts has been reduced by roughly 60% simply by adjusting their true error to be centered around zero and consecutively combining them.

Another benefit is that extreme errors in individual forecast are cancelled out. While the overall highest single percentage error of the individual forecast lies at 17,720%, the highest single error of the combination that includes all forecasts lies only at 110%.

The fluctuation of the maximum error can be explained, through the chosen approach of randomly drawing datasets to create a limited number of combinations within each set. The number of samples obtained is extremely small compared to the number of possible combinations. Therefore, the samples within this set do not accurately reflect the distribution of all possible combinations of the respective set size. But this also highlights that the chance of experiencing a significant reduction of MAPE increases with an increasing number of individual forecasts, undermining the importance of this multi-system composition approach.

IV. CONCLUSION

As demonstrated the MAPE error of a composition of forecasts is always smaller than the largest error of its individuals. Beyond that if the forecasts are adjusted around a zero-mean error, a unifying composition of those forecasts can significantly reduce the error. Returns appear to be diminishing with each added forecast but more forecasts increase the chance that an effective cancelation of errors occurs.

The used forecasts have been generated all with the same pipeline, without optimization or any manual tinkering on individual datasets. In consideration of that the proposed method presents an approach that minimize effort on creation and is scalable for large number of systems while still producing accurate results. In practice this could lead to reduction of required means to balance out forecasting errors, like spinning reserve or batteries for solar energy and thereby reduce operational cost of the grid.

Further research could extend this approach to multi-step or long-term forecasts, where errors are usually higher than for one-step forecasts, to see if same effects can be observed. Also, more sophisticated techniques of zero-mean adjustment could potentially yield even better result as they should utilize the cancellation effect of composition to a greater extend.

APPENDIX

TABLE I. MAPE DISTRIBUTION

n forecasts combined	**MAPE Distribution**		
	Maximum (%)	***Mean (%)***	***Minimum (%)***
1	10.818	5.035	3.066
2	8.550	4.170	2.579
3	8.678	3.374	2.207
4	8.363	3.262	2.109
5	4.045	2.752	1.948
6	7.544	2.742	1.916
7	3.587	2.538	1.980
8	3.260	2.425	1.824
9	4.993	2.405	1.952
10	3.079	2.310	1.754
11	2.949	2.251	**1.673**
12	4.372	2.327	1.833
13	3.295	2.234	1.822
14	2.792	2.156	1.822
15	2.701	2.104	1.765
16	2.609	2.155	1.812
17	2.448	2.123	1.901
18	2.462	2.119	1.772
19	2.347	2.078	1.818
20	2.491	2.122	1.845
21	2.615	2.072	1.861
22	2.357	2.055	1.872
23	2.536	2.079	1.823
24	2.324	2.016	1.842
25	2.204	2.050	1.904
26	2.375	2.043	1.887
27	2.250	2.007	1.866
28	2.271	2.031	1.890
29	2.255	2.037	1.928
30	2.205	1.995	1.900
31	2.163	2.002	1.873
32	2.124	1.986	1.899
33	2.092	1.997	1.917
34	2.056	1.981	1.933
35	2.063	1.983	1.947
36	**1.975**	**1.975**	1.975

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