ANALYSIS OF THE USE OF SUPPORT VECTOR REGRESSION AND NEURAL NETWORKS TO FORECAST INSOLATION FOR 25 LOCATIONS IN JAPAN

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1. Introduction

Photovoltaic systems power output are highly sensitive to variations of insolation. A sudden change in the weather or a displacement of clouds in the sky can cause a meaningful decrease in the power output of such systems. If photovoltaic systems are installed in large scale, such power output oscillations can result in control and operation issues. With a proper forecast of insolation, however, variations in the power output of photovoltaic system can be known before hand allowing for power companies to keep the supply of power stable, balancing the use of photovoltaics with the use of other energy systems for example.

To forecast insolation, artificial neural networks have been widely used in a variety of configurations (Mellit & Pavan 2010, S. Cao & J. Cao 2005, Dorvlo et al. 2002, Mohandes et al. 1998). The advantages of using artificial neural networks are related with their ability to recognize patterns, easiness of implementation and generalization capacity. Nevertheless, a method able to forecast accurately insolation in places with unstable weather, or with a high number of partially cloudy days, is still not available. In this regard, the use of support vector regression may bring some benefits, as it is an artificial intelligence technique based on the latest advances in statistical learning (Cristianini & Shawe-Taylor 2000). To verify if there is any merit in the use of support vector regression to forecast insolation, a comparison using the results obtained with an artificial neural network as reference would be interesting.

Considering that, the objective of this study is to determine if the use of support vector regression can effectively provide gains in the accuracy of insolation forecasts when compared with the forecasts done with an artificial neural network. The ν support vector regression and a multilayer perceptron artificial neural network with the backpropagation algorithm were used separately to forecast insolation. Both forecast techniques were applied with the same input data. The input data comprised numerically predicted and calculated weather related variables. The numerically predicted weather variables were provided by the GPV-MSM system developed by the Japan Meteorological Agency. The GPV-MSM system provides data for locations in a mesh with points equally spaced (5 km) covering Japan and surrounding areas.

In this study one-day-ahead forecasts were done using input data predicted at 18h of every day before the day of the insolation forecasts. Furthermore, 60 days previous to each forecast day were used in the training of each method. Forecasts of insolation were done from January 1st to December 31st of 2008. A day of forecasts was regarded as hourly forecasts from 5h to 19h. Both forecast techniques were configured after extensive training procedures to find the configuration that yield the best possible forecasts. In total, one-day-ahead forecasts for 25 locations in Japan, covering places as far from each other as Hokkaido and Okinawa, were done. The accuracies of both forecast techniques were compared using two kinds of errors as evaluation parameters; the hourly mean absolute error and the hourly root mean square error.

2. Forecast Techniques

2.1. Artificial Neural Networks

An artificial neural network, ANN, is a model that attempts to simulate some of the information process of the brain (Samarasinghe 2007). There are several kinds of ANN that can be used to address the insolation forecast problem. In the present study, the ANN used was of the feed-forward multilayer type with back-propagation learning with a recurrence mechanism. The recurrence mechanism consists of the use of the previous outputs of the ANN on its input layer.

The structure and information flow of the ANN are illustrated in Fig. 1. The ANN has 3 layers and the information flows from the input layer to the output layer through connections between neurons of the different layers. In each neuron connection there is a weight, which linearly modifies the data flowing between the neurons it connects. Inside every neuron that does not belong to the input layer there is an activation function, eq. 1. Such activation function is based on the hyperbolic tangent, and it operates over the sum of all the linearly modified inputs arriving on a neuron in a given time step *t*. The result of this operation is the output of each neuron outside the input layer. Such output is then sent to the neurons of the next layer where the process is then repeated. The process stops with the calculation of the outputs of the neurons located in the output layer (in this study the ANN had only one output neuron). These outputs are regarded as the result provided by the ANN in a given time step *t*. Each time step was regarded as one hour, thus the ANN provided hourly insolation forecasts. The recurrence mechanism woks directing the output neuron of the ANN, O_t, to a context layer. The information in the context layer was then used as input of the ANN with the other *n* inputs *x*, to calculate the insolation forecast in the next time step. For the forecasts of insolation of a given time step *t*, the insolation forecast of the previous 3 time steps, $x_{r(t-1)}$, $x_{r(t-2)}$, $x_{r(t-3)}$, were used.

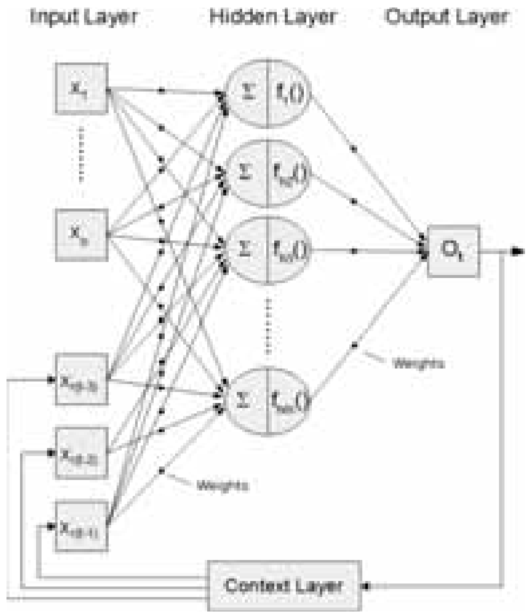


Fig. 1: Structure of the ANN used to make the insolation forecasts.

$$f_n(x) = 0.52 \times \tanh(x) - 0.51 \qquad \text{(eq. 1)}$$

The ANN was trained using a set of known input-output data. For each input set an output value and its error was calculated. The error was determined using the expected output value as reference. The expected output value was the measured insolation at the same time in the same location of the forecast value. Once the error was known, it was propagated back to the weights of the ANN. The weights were updated with partial batch learning after a day of training patterns. The application of this procedure for all the sets of input-output data selected for the training was regarded as an epoch. The training of the ANN was stopped after repeating it for a predefined number of epochs. After the training stage finished, the ANN was then used to forecast insolation using data not included in the training set. The values for the main configuration parameters of the ANN are in Table 1.

Tab. 1: Values of the configuration parameters of the ANN.

Learning Rate	Momentum Term	Layers	Training Duration	Training Period
0.004	0.4	3	1000 epochs	60 days

2.2. Support Vector Regression

Support vector regression, SVR, is a kind of support vector machine, a learning algorithm developed by (Vapnik 1999) to deal with classification and regression problems. The SVR works using mapping functions to express the input parameters in a hyper dimensional space, where the original problem is expressed in terms of a lagrangian function and then learning is done using an optimization procedure. The SVR used in this study is known as ν support vector regression and it was developed by (Schölkopf et al. 1998). In the ν support vector regression the ε-insensitive loss function used in the optimal robust estimation procedure is automatically minimized yielding estimates as accurate as possible. In Fig. 2 the architecture of a support vector machine is presented.

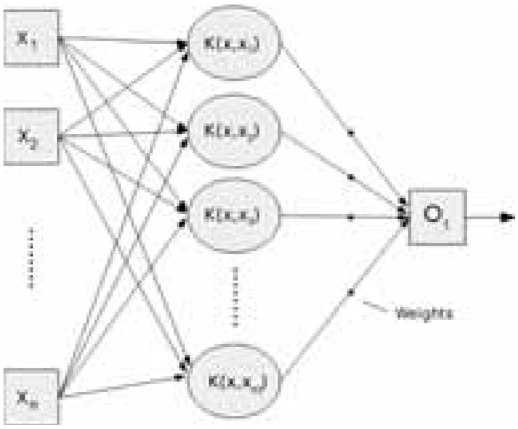


Fig. 2: Structure of a support vector machine.

As showed in Fig.2 the mapping of the input to the higher dimension space is done using a kernel function. The kernel function used in this study is the radial basis function showed in eq. 2.

$k(x_i, x_j)e^{-\gamma|x_i - x_j{}^2|}$ (eq. 2)

In order to use the ν support vector regression to forecast insolation, several configuration parameters, such as the parameter γ in eq. 2 for instance, have to be chosen beforehand. To find suitable values for the configuration parameters a validation data set, different of the data set used in the forecasts, was used. Several values for the configuration parameters were tested and the ones that yielded the best results for the validation data were chosen. All the forecasts of insolation with SVR were done using the Matlab port of the LibSVM library (Chang & Lin 2001).

3. Problem Description

3.1. Input Data

To forecast insolation the extraterrestrial insolation, predicted temperature normalized, predicted humidity, and predicted cloudiness in 3 levels of altitude were used as input of the ANN and the SVR. The use of numerically predicted cloudiness is justified by the effect it has improving the quality of the forecasts of insolation (Kataoka et al. 2009, Fonseca Jr. et al. 2010). The values of the variables used as input data corresponds to the values for the hour which insolation is being forecast and for 1 hour before that. The extraterrestrial insolation was calculated using the methodology available in (Iqbal 1984) and the simplified equation developed by (Watt Engineering Ltd 1978). The predicted input data was provided by the GPV-MSM system of the Japan Meteorology Agency. This system provides forecast for next 15 or 33 hours according to the forecast time.

To make one-day-ahead forecasts the data used as input was predicted at 18h of every day before the forecast day. The forecasts of insolation were done in an hourly fashion from 5h to 19h. As every day of insolation was forecast from 5h to 19h, the forecast horizon varied from 11 to 25 hours ahead. Furthermore all forecasts were done after a training procedure, for the SVR and for the artificial neural network, in which the 60 days of data preceding the day of forecast were used.

3.2. Forecast Locations

In total 1 year, 2008, of insolation forecast for 25 cities in Japan were done. The locations for which forecasts were done are in Table 2. The locations latitude is expressed in degrees and minutes in the north direction. The longitude is expressed in degrees and minutes in the east direction. The variety of locations studied ensured forecasts for a variety of weather patterns.

Tab. 2: Name of the cities for which insolation was forecast, and their latitudes and longitudes.

	Location	Latitude	Longitude		Location	Latitude	Longitude
1	Abashiri	44°01'N	144°17'E	14	Maizuru	35 °26'N	135°19'E
2	Nemuro	43°19'N	145°35'E	15	Nagoya	35°09'N	136°58'E
3	Sapporo	43°03'N	141°19'E	16	Shizuoka	34°58'N	138°24'E
4	Obihiro	42°55'N	143°12'E	17	Osaka	34°40'N	135°31'E
5	Hakodate	41°48'N	140°45'E	18	Hiroshima	34°23'N	132°27'E
6	Aomori	40°49'N	140°46'E	19	Matsuyama	33°50'N	132°46'E
7	Akita	39°42'N	140°06'E	20	Kochi	33°33'N	133°33'E
8	Sendai	38°15'N	140°54'E	21	Kumamoto	32°48'N	130°42'E
9	Yamagata	38°15'N	140°20'E	22	Nagasaki	32°43'N	129°52'E
10	Maebashi	36°24'N	139°03'E	23	Kagoshima	31°33'N	130°33'E
11	Tateno	36°03'N	140°78'E	24	Naze	28°22'N	129°29'E
12	Fukui	36°03'N	136°13'E	25	Naha	26°12'N	127°41'E
13	Tokyo	35°41'N	139°45'E				

The insolation forecasts for every day in any given city were done after training the forecasts algorithms with 60 days of data of that city. Nevertheless, to also assess the generalization ability of each algorithm, their configuration parameters were set only once using data of Tokyo.

3.2. Comparison Parameters

To compare the accuracy of the forecasts done with SVR and the ones done with ANN, two errors were calculated, the root mean square error, RMSE, and the mean absolute error, MAE. The RMSE is calculated according to eq. 3 and the MAE according to eq. 4.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{fcs,i} - I_{msd,i})^2} \qquad \text{(eq. 3)}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|I_{fcs,i} - I_{msd,i}| \qquad \text{(eq. 4)}$$

$I_{fcs,i}$ in eq. 3 eq. 4 is the insolation forecasted at hour i expressed in kWh/m^2. $I_{msd,i}$ is the insolation measured, in kWh/m^2, at hour i. The RMSE and MAE were calculated, in kWh/m^2, over all the N hours of insolation forecasts done.

4. Results

4.1. All Cities

The results in Fig. 3 and Fig. 4 show the hourly RMSE and the hourly MAE for 1 year of forecasts done with the ANN and with the SVR. All the cities studied are in Fig. 3 and Fig.4 ordered from the northernmost city to the southernmost city, according to the order showed in Table 2.

Analyzing the results in Fig. 3, it is clear that from the point of view of the RMSE the difference between the forecasts done with the ANN and with the SVR was not meaningful. In 19 cities the support vector regression forecasts had slightly lower RMSE values, 1.7% lower in the best case, than the forecasts done with the ANN. In 7 cities the ANN forecasts had lower RMSE, 1.8% in the best case.

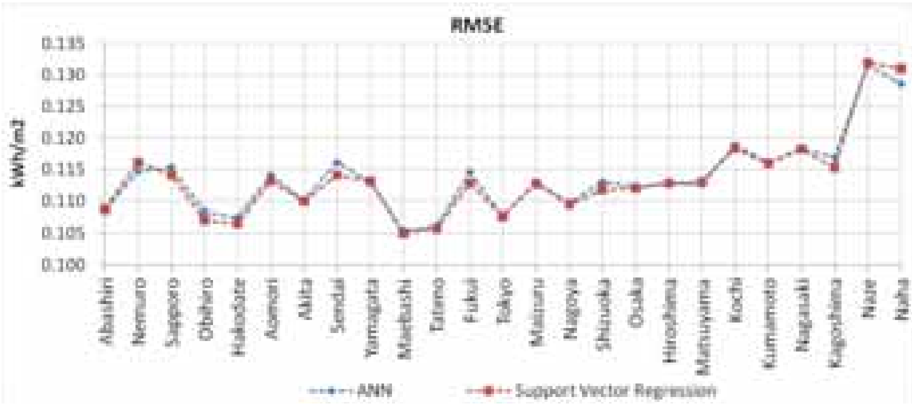


Fig. 3: Root mean square error of insolation forecasts for 25 cities.

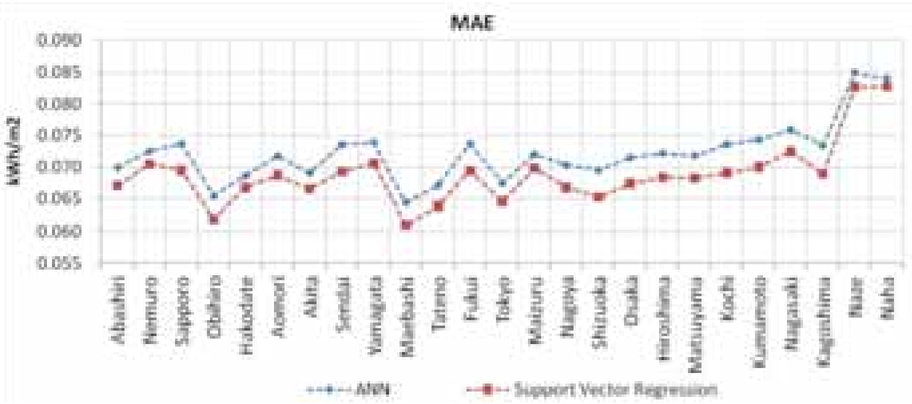


Fig. 4: Mean absolute error of insolation forecasts for 25 cities.

In terms of absolute errors, Fig. 4 shows that the forecasts done with SVR were better than the forecasts done with ANN in all cities studied. In average, considering the 25 cities studied, the forecasts done with SVR had a MAE 5% lower than the forecasts done with ANN.

Analyzing the error variation between cities, Fig. 3 and Fig. 4 show a clear trend between the errors and the latitude from Tokyo southwards. From cities as Sapporo, in Hokkaido, to Tokyo, in Honshu, the RMSE and MAE varied without definite trend. For the RMSE the values varied between 0.105 kWh/m^2 to 0.115 kWh/m^2. For the MAE the corresponding variation was between 0.06 kWh/m^2 and 0.075 kWh/m^2.

From Tokyo southwards, both errors increased gradually with the latitude until Kagoshima, located in Kyushu. From Kyushu to Naha in Okinawa, the difference increased substantially. As both errors calculated are absolute, such trend indicates a behavior coherent with the expected increase in the average insolation with the decrease of latitude. Nevertheless, it is interesting to note that such behavior happened only from latitudes lower than 35 degrees north.

4.2. Differences between Insolation Forecasts of 3 Cities

In order to verify where the forecast errors differ according to the city and with the forecast technique, 3 cities where selected, and their MAE and RMSE where calculated monthly. The cities selected were Sapporo, Maebashi and Naha. These cities were chosen by their location (north, east and south of Japan) and by their forecast errors.

In Fig.5a, 5b and 5c are the RMSE calculated for every month of 2008 for the 3 cities with RMSE percent variation of the forecasts found with SVR compared with ANN respective values. The pattern of the RMSE of the forecasts during the year clear change according to the location. For Sapporo, the effect of the seasons is important and in summer, where the insolation reached its highest values, is also where the RMSE reached its peak values. In Naha, insolation values are high are fairly uniform throughout the year. Therefore, for Naha, the RMSE of the corresponding forecasts were higher and without a clear monthly peak.

a b c

Fig. 5: RMSE variation from January to December of 2008 according to the forecast technique for 3 cities in Japan.

Comparing the results, in Fig. 5, of both forecast techniques, there was no clear trend for Sapporo or Maebashi. In the former location, the SVR provided better forecasts than the ANN in 7 months, out of 12. Nevertheless, the difference, for better or worse, was never higher than 4%. In Maebashi, a similar trend happened with the forecasts done with SVR being slightly better than the ones done with ANN in 6 months.

For Naha, a different behavior is observed. In 10 months of 2008 the forecasts done with ANN had better RMSE than the forecasts done with SVR. The difference between the forecasts RMSE was also higher than the difference observed in Sapporo and Maebashi, reaching, in its highest value, 13%, in November.

What happened in Naha is related with the insolation forecasts patterns provided by the 2 techniques and the measured insolation patterns. The insolation pattern in Naha has higher average insolation than other locations in Japan due to its latitude. Therefore, sudden changes in the weather will result in stronger drops of insolation. In those cases the technique that has lower values of insolation forecasts will have the lowest RMSE. As the insolation forecasts done with SVR, in average, presented higher values than the forecasts done with ANN, when unexpected drops of insolation happened, it presented higher RMSE than the forecasts done with the ANN. This behavior is illustrated in Fig. 6, by 4 of the 7 consecutive days of November, the month with the highest difference between the RMSE of both forecast techniques.

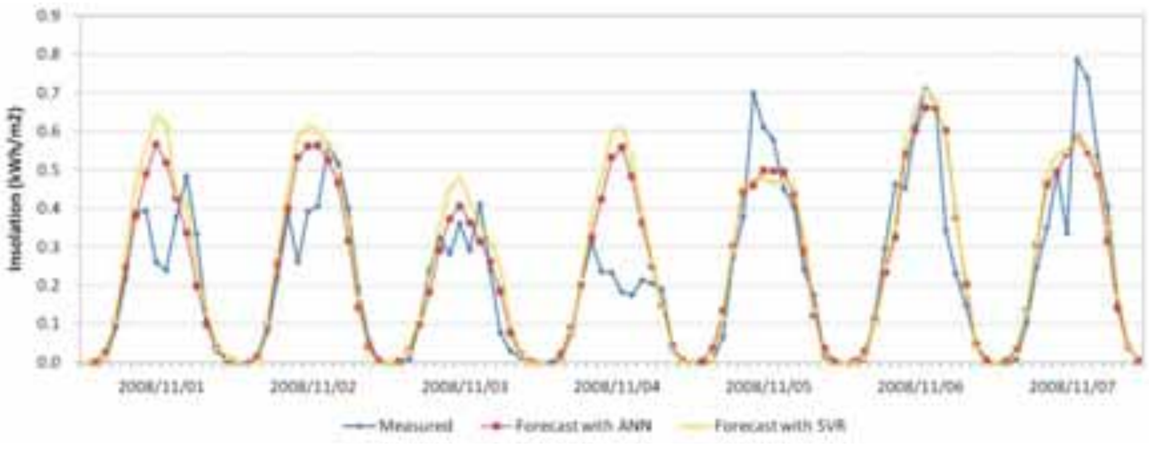
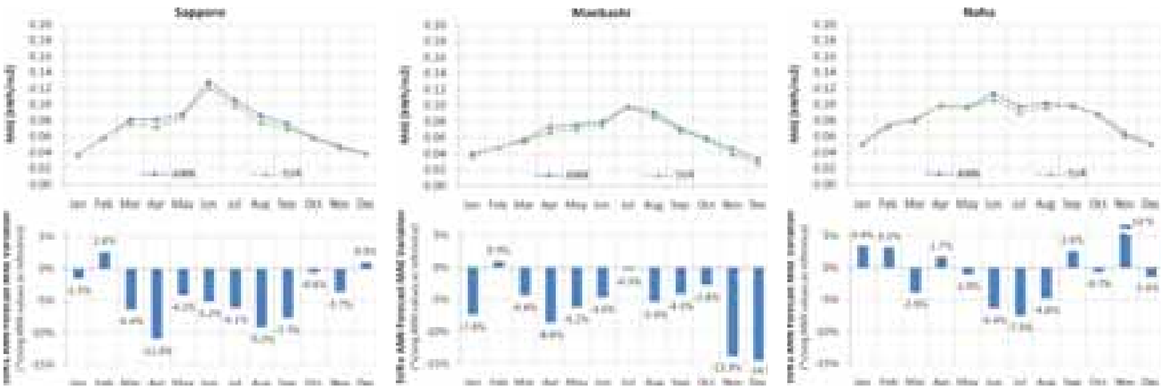


Fig. 6: Seven consecutive days of measured and forecasted insolation in Naha during November of 2008.

This behavior can be related with the different functions used as activation function in the ANN, eq. 1, and as kernel function in the SVR, eq. 2. As Fig. 6 shows, the activation function in the ANN is generating in most of the cases lower forecast values than the kernel function in the SVR. In a location with strong drops in the insolation, as observed in Naha, the lowest forecast of insolation will have the lowest RMSE. A similar behavior was found by (Yona et al. 2008) when comparing radial basis function and backpropagation ANNs in Naha.

Finally, it should be noted that, from the 25 cities studied, such bias was only detected in Naha. From the point of view of the RMSE, the general behavior was forecasts done with SVR, were at least as good as or even slightly better than the forecasts done with ANN.

To show the difference between insolation forecasts for different cities and forecast techniques from the point of view of the MAE, a measure of error that given an equal weight to all error values, Fig. 7a, 7b and 7c are presented.



a **b** **c**

Fig. 7: MAE variation from January to December of 2008 according to the forecast technique for 3 cities in Japan.

From the point of view of the MAE the insolation forecasts done with SVR were significantly better than the forecasts done with the ANN. In Sapporo the difference reached 11% in April; in Maebashi the highest difference was 14.5% in December. Even for Naha, the insolation forecasts done with SVR had lower MAE in most of the months of 2008.

The fact the both techniques provided forecasts with the similar RMSE and different MAE indicates a trend regarding the magnitude of the error between insolation measured and forecasted. When there are large deviations between the insolation measured and forecasted, caused by a high level of noise in the input data for instance, the use of SVR did not offer meaningful improvement comparing with the use of ANN. Nevertheless, for conditions where large deviations are not expected and both techniques provide forecasts with a good level of agreement with measured values, the SVR was better than the ANN tested.

5. Conclusion

The objective of this study was to determine if the use of SVR can effectively provide gains in the accuracy of insolation forecasts when compared with the forecasts done with an ANN. To verify the difference between the accuracy of the results provided by both techniques, 25 cities in Japan had their insolation forecast. The results obtained indicate that for large errors insolation forecast done SVR were, in most of the times, at least as accurate as the forecasts done with the ANN tested. This conclusion is based on the RMSE variation, which was small for a whole year of forecasts and comparing with the values provide by both techniques.

In spite of the small difference found in the case of large deviation between insolation forecast and measured, for low to average deviations between insolation forecast and measured, the use of SVR was able to provide meaningful improvements in the accuracy of the results. This can be inferred from the MAE calculated. For all the cities studied, the MAE of the forecasts done with SVR where better than the MAE of the forecasts done with the ANN, when calculated over a year of results. From the point of view of the MAE, and comparing with the results provided by the ANN, the use of SVR caused improvements in the forecasts of insolation in the order of 5% for a year of results.

In this way, it can be concluded that the use of SVR to forecast insolation is an alternative at least as effective as a multilayer ANN with backpropagation learning, providing even improved results under certain conditions. Nonetheless, the results obtained indicate that further improvements are required in order to have a method able to provide forecasts with a high level of accuracy.

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