Intrinsic Explainable Artificial Intelligence Using Trainable Spatial Weights on Numerical Weather Predictions

Oliver Neumann
Karlsruhe Institute of Technology
Karlsruhe, BW, Germany
oliver.neumann@kit.edu

Maximilian Beichter
Karlsruhe Institute of Technology
Karlsruhe, BW, Germany
maximilian.beichter@kit.edu

Benedikt Heidrich
Karlsruhe Institute of Technology
Karlsruhe, BW, Germany
benedikt.heidrich@kit.edu

Nils Friederich
Karlsruhe Institute of Technology
Karlsruhe, BW, Germany
nils.friedrich@kit.edu

Veit Hagenmeyer
Karlsruhe Institute of Technology
Karlsruhe, BW, Germany
veit.hagenmeyer@kit.edu

Ralf Mikut
Karlsruhe Institute of Technology
Karlsruhe, BW, Germany
ralf.mikut@kit.edu

ABSTRACT

Addressing the volatility of renewable energies like solar and wind is crucial for the energy system's stability and optimal utilization of renewable energies. Accurate energy forecasts are important to improve scheduling. Electrical demand and renewable energies are weather-dependent and Numerical Weather Predictions have proven to be beneficial for energy forecasts due to their fine-grained spatial resolution. State-of-the-art Deep Learning approaches for energy forecasting are black-box models. However, decisions in energy systems depend on energy forecasts, and, thus, it is important that models are explainable and trustworthy. Explainable Artificial Intelligence techniques exist that add explainability to energy forecasting models, but all existing methods are only post-hoc or do not use weather data on large spatial areas. This paper introduces a novel approach to forecast energy that scales and adds intrinsic explainability by design. Therefore, we use trainable spatial weights to make accurate forecasts on large spatial areas. The trained weights can be interpreted spatially to enhance explainability and increase trust. Furthermore, the spatial weights enable a wide range of future work, including postprocessing, subregion forecasting, hierarchical learning, and spatial-temporal weights.

CCS CONCEPTS

• **Applied computing** → **Forecasting**; • **Computing methodologies** → **Knowledge representation and reasoning**; **Neural networks**.

KEYWORDS

explainable artificial intelligence, energy forecasting, numerical weather predictions, neural networks, deep learning, energy transition, electrical demand, solar power, wind power

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1 INTRODUCTION

The world is currently facing a major challenge of transitioning from fossil fuels to renewable energies [5]. However, the volatile nature of renewable energies makes it difficult to ensure stable energy systems and maximize renewable energy usage. Forecasts of electrical demand and renewable energies are necessary to address this issue because they allow optimal energy system schedules [9, 20]. It is known that incorporating weather data improve the accuracy of energy forecasts, as renewable energies and electrical demand are heavily influenced by weather conditions [6, 8, 11, 18].

Numerical Weather Predictions (NWPs) with their high spatial and temporal resolution are widely used to forecast energy [1, 4, 7, 13, 15, 17]. Most of these approaches only consider small forecast regions or reduce the spatial dimensions to avoid a large number of weather features.

Some studies already apply energy forecasting approaches to large areas. De Felice et al. [7], for example, use temperature of NWP models to forecast the electricity demand for Italy and its subregions using Auto-Regressive Integrated Moving Average (ARIMA). To reduce the size of the weather data, they average the weather data for each region. The research conducted by Pierro et al. [17] involves forecasting the photovoltaic power in South Tyrol, Italy, using Fully Connected Neural Networks (FCNNs). To simplify the weather data, they divide the region into subregions through a clustering approach. Neumann et al. [16] forecast energy for Baden-Württemberg, a state of Germany, using weather station and NWP data. They use FCNNs to forecast the energy time series. To reduce the spatial weather resolution, they encode the weather input in a subnetwork or preprocess them.

Besides forecasting accuracy, explainability and trust are also important in energy forecasting. Forecasts utilized in vital infrastructures such as energy systems require a high level of reliability, as operational decisions depend on them. While researchers have

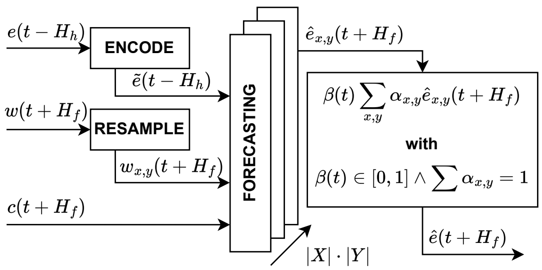


Figure 1: Illustration of the proposed neural network architecture that use spatial weights $\alpha_{x,y}$ and temporal dependent weight $\beta(t)$ to forecast energy.

explored Explainable Artificial Intelligence (XAI) methods on energy forecasting [14, 22], most proposed methods are post-hoc methods. Only one intrinsic XAI method has been suggested for energy forecasting, but without using weather data [12]. Moreover, no XAI methods have been applied to large regions using weather data for energy forecasting.

Based on that, we identify two research contributions related to energy forecasting. The first contribution is to add intrinsic explainability by design in energy forecasting models to avoid black-box models and enhance trust. The second contribution is to ensure model scalability on large regions without reducing weather dimensionality. To close these gaps, we propose a Spatial Weights Neural Network (SWNN) architecture based on learnable spatial weights. This architecture scales with the forecasting region while keeping the number of parameters low. This enables a wide range of future work, such as post-processing spatial or temporal weights, forecasting on subregions, hierarchical learning, and spatio-temporal weights.

2 METHOD

Our proposed method aims to achieve two goals: First, scale with an increasing number of weather features without reducing the available spatial resolution of the weather data. Second, design a forecast model that offers intrinsic explainability, allowing interpretable and adjustable model weights to incorporate expert knowledge without retraining.

To achieve the first goal, we use a single global model to forecast energy for each spatial cell separately. This results in a scalable method even for huge spatial regions. We then combine all forecasts using a weighted sum calculation. These weights are trainable and can be easily interpreted and adjusted to achieve our second goal. By interpreting the weights, we can determine which cell forecasts contribute the most to the global forecast and where energy is consumed (electrical demand) or generated (solar and wind power).

In detail, we use a FCNN to encode the historical energy time series $e(t-H_h)$ to $\tilde{e}(t-H_h)$ with historical horizon $H_h \subset \mathbb{N}$. Instead of encoding the spatial weather forecasts $w(t+H_f)$ with forecast horizon $H_f \subset \mathbb{N}+$, we only resample them such that $w_{x,y}(t+H_f)$ refers to the weather forecast on spatial cell (x,y). Next, we concatenate the encoded historical energy $\tilde{e}(t-H_h)$, the spatial weather forecast $w_{x,y}(t+H_f)$, and the calendar information $c(t+H_f)$. These feature sets are passed to a global FCNN to forecast energy for each cell (x,y). Based on the trainable weights $\alpha_{x,y}$, we combine all forecasts $\hat{y}_{x,y}(t)$ into one global forecast by using the calculation of a weighted sum. To ensure that the sum of the weights $\alpha_{x,y}$ is one, we apply the softmax function [2]. However, with the softmax function, the weights could not increase or decrease over time. Therefore, we multiply a temporal dependent weight $\beta(t)$ on the weighted sum. The temporal weight $\beta(t)$ is realized by using a small FCNN with one hidden layer which is capable of extrapolation. To ensure the temporal dependent weight $\beta(t)$ ranges between zero and one, we apply the sigmoid activation function [10] on $\beta(t)$.

In conclusion, the actual global forecast $\hat{e}(t+H_f)$ is described by

$$\hat{e}(t+H_f)=\beta(t)\sum_{x,y}\alpha_{x,y}\hat{e}_{x,y}(t+H_f),$$

where $\hat{e}(t+H_f)$ is the actual global forecast, $\beta(t)$ the temporal dependent weight, $\alpha_{x,y}$ the spatial weights and $\hat{e}_{x,y}(t+H_f)$ the forecast for each cell (x,y). The overall data processing of the proposed method is illustrated in Figure 1.

3 EVALUATION

We evaluate the proposed SWNN approach on datasets from four different countries, i. e., Norway, Germany, Italy, and Spain. We forecast electrical demand, solar, and wind power 72 hours ahead except for Norway, where historical solar power data is not available. To assess our approach's effectiveness, we compare it to a similar Baseline Neuronal Network (BNN) that encodes the weather data instead of resampling it using Mean Absolute Error (MAE), a common evaluation metric for energy forecasting. Further details on the experimental setup can be found in the Appendix A.1.

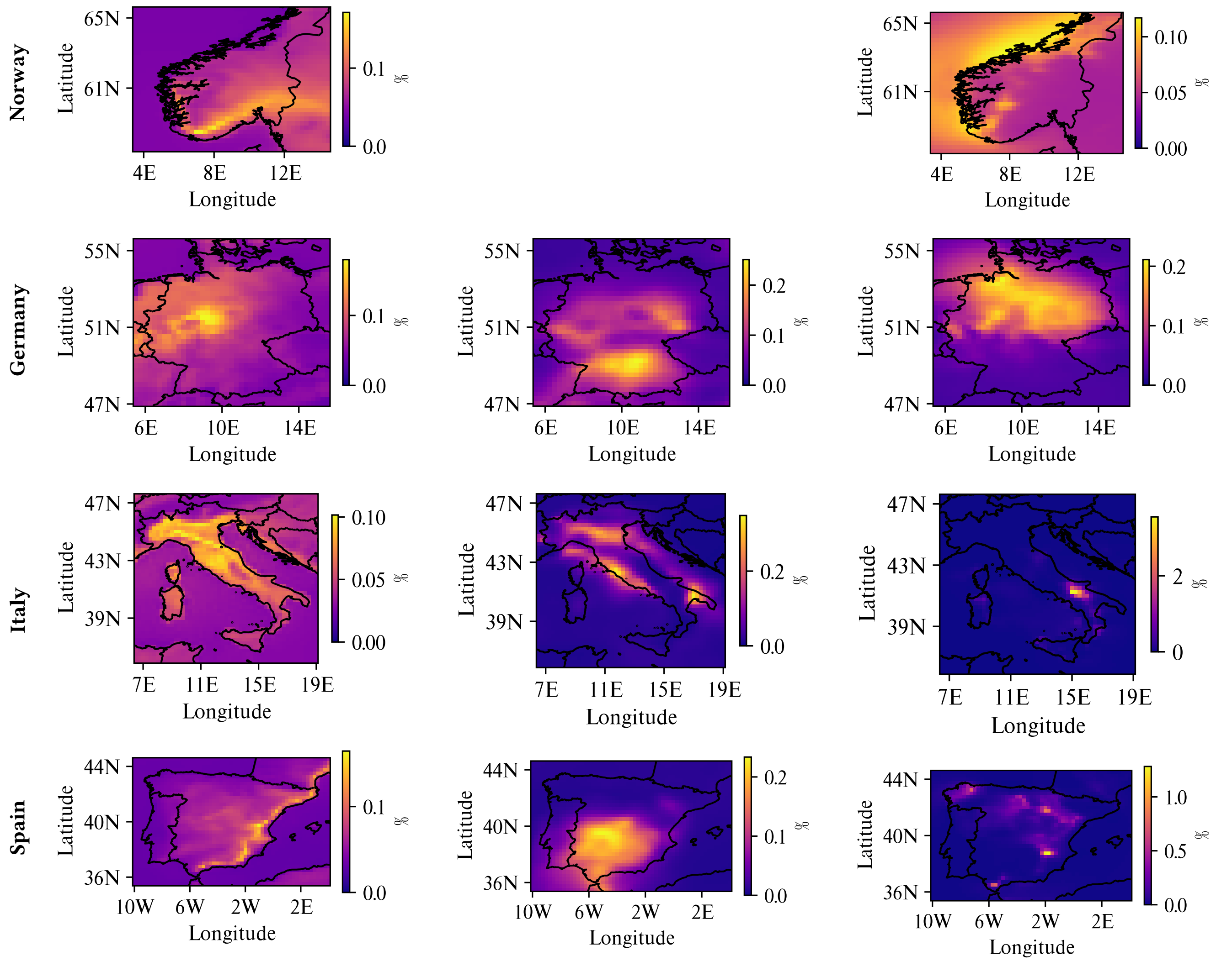
Our approach scales with the number of weather features without raising the number of parameters. The actual numbers are listed in Table 1. The number of parameters remains similar even for large regions. Only additional spatial weights $\alpha_{x,y}$ are needed if the region is getting larger.

Regarding the forecasting accuracy for electrical demand, the proposed approach improves the MAE for all countries except Norway. While forecasting solar power, our approach performs better for Germany and Italy and similar for Spain. For wind forecasting, our approach performs again better for Germany but worse for Norway, Italy, and Spain. Overall, the forecasting performance is comparable to the BNN. All results are also listed in Table 1.

Looking at the spatial weights $\alpha_{x,y}$, we can observe that the proposed models learn sensible regions (see Figure 2). For electrical demand, the weights correlate with highly populated areas. For solar and wind power, it correlates with locations of solar and wind power farms. Regarding the temporal weights $\beta(t)$, they show mostly an increasing trend over time (see Figure 3).

4 DISCUSSION

Overall, our experiments indicate that the performance of the SWNN is comparable to the FCNN approach. So, our approach scales along spatial dimensions while still being competitive. Only the number of $\alpha_{x,y}$ weights increases for larger regions. This could be interesting, especially for areas with a small amount of historical data, e. g., developing countries. Other architectures, like ones



(a) Electrical Demand

(b) Solar Power

(c) Wind Power

Figure 2: Images of spatial weights trained on ground truth weather data of the best-performing model for Norway, Germany, Italy, and Spain and all three forecasting targets, i. e., electrical demand, solar, and wind power. The spatial weights show how much a region contributes to the global forecast. So, higher values refer to more important areas.

based on convolutions, may have a smaller number of parameters but lose spatial complexity.

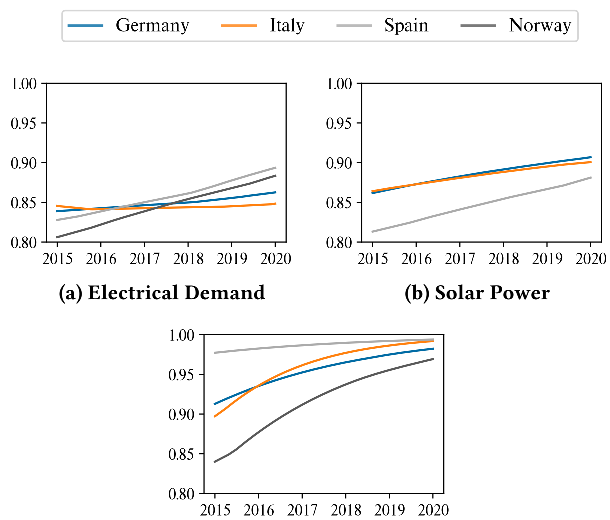
The temporal weight $\beta(t)$ shows a positive trend in most cases, which makes sense because the share of solar and wind power should increase over time. However, further investigations are needed to validate the temporal weights learned by the model.

Regarding the spatial weights, we show that they converge to a meaningful map that correlates with regions where electricity is consumed or solar and wind power is generated. However, we see that there is a difference between the spatial weights that are trained on ground truth and forecast weather data (compare Figure 2 and Figure 7). The spatial weights trained on ground truth weather data are much smoother than those trained on the forecast weather data. However, in practice, only forecast weather data is available. Thus, further investigations are needed to improve the spatial weights trained on forecast weather data.

Regarding explainability and trust, visualizing the spatial weights of the model gives us more in-depth insights into what the model is learning. The concept of spatial weights is comparable to the attention mechanism [19]. The attention mechanism is an approach permitting intrinsic explainability. However, the spatial weights of the proposed SWNN are independent of the model input, the spatial weights of an attention mechanism depend on the matrix product of the query and key input embeddings. Thus, the weights of weather cells in attention depend on the actual sample input.

Table 1: Number of parameters (Params) and forecasting MAE including standard deviation for seven runs of the BNN and proposed SWNN approach for all four countries, i. e., Norway (NOR), Germany (GER), Italy (ITA), and Spain (SPA).

Region	Model	Params	Demand	Solar	Wind
NOR	BNN	15M	**0.25±0.01**	-	**0.17±0.01**
	SWNN	0.13M	0.27±0.01	-	0.20±0.01
GER	BNN	15M	1.28±0.04	0.53±0.01	1.76±0.05
	SWNN	0.13M	**1.24±0.09**	**0.46±0.02**	**1.60±0.06**
ITA	BNN	24M	0.93±0.04	0.20±0.01	**0.45±0.01**
	SWNN	0.13M	**0.90±0.03**	**0.19±0.01**	0.50±0.01
SPA	BNN	22M	0.52±0.03	**0.23±0.01**	**0.63±0.01**
	SWNN	0.13M	**0.49±0.01**	0.23±0.01	0.83±0.02



(a) Electrical Demand **(b) Solar Power**

(c) Wind Power

Figure 3: Visualization of the temporal weight $\beta(t)$ trained on ground truth weather data of the best-performing proposed model to allow the global forecast to increase or decrease over time. The weights are shown for Germany, Italy, Spain, and Norway and all three energy forecasting targets.

The attention mechanism neglects the usability within transferring and modifying the weighting through varying inputs, which our approach delivers. This enables more advanced opportunities, which we want to describe briefly below.

Postprocessing. The spatial weights can be postprocessed after training by applying simple image processing methods such as increasing contrast or blurring. Additionally, experts can adapt the weights by removing irrelevant regions or adding useful ones. This method could enable tackling concept drifts known by experts, like adding farms that have been put into operation.

Neighbor Cells. The SWNN forecasts energy for each spatial cell using the corresponding weather data of that specific cell. However, incorporating neighboring cells may be worthwhile because it allows the model to interpolate weather data spatially and can provide more accurate forecasts.

Subregion Forecasting. During inference, we can use spatial subregions on a globally trained model to get energy forecasts on subregions. That enables us to forecast energy on subregions even without training data. This is particularly useful for maintaining energy system stability, especially when a lot of renewable energy is produced in one region that is needed in another region. However, we need to conduct further evaluations to assess the forecast quality of subregions.

Hierarchical Learning. With our approach, it is possible to train one global model with data from subregions, e. g., train a global model with data from Germany and its Transmission System Operators (TSOs). The training step for Germany is the same. For the TSOs subregion, we can use the same model but select only the relevant spatial weights pertinent to the TSO's region. This method increases the amount of training data, enhances the accuracy of spatial weights, and improves the forecasting accuracy in subregions.

Spatial-Temporal Weights. Currently, we use two different sets of weights. Spatial weights $\alpha_{x,y}$ for the weighted sum and the temporal weight $\beta(t)$ to allow weight changes over time. These weights only allow linear adjustments. However, this is not likely because, for example, solar farms are built or dismantled over time. Therefore, we suggest combining the spatial and temporal weights into one spatial-temporal weight $\alpha_{x,y}(t)$ to enable the non-linear changes over time.

5 CONCLUSION

This paper introduces a novel approach to forecast energy on large spatial scales using trainable spatial and temporal weights to enhance explainability and add trust to the forecast models. Additionally, the number of parameters stays small even for large spatial areas while still utilizing all the weather information and offering competitive forecast accuracy.

We show that the trained weights improve the explainability and converge against sensible values that add trust to the model. Explainability and trust are critical for energy system stakeholders because they allow reasoned decision-making and strategic planning.

We evaluate our approach on the four countries, Norway, Germany, Italy, and Spain, by forecasting electrical demand, solar, and wind power. We show that the presented approach is competitive regarding forecast accuracy compared to a similar neural network that does not utilize spatial weights. Especially for Germany, the spatial weights approach improves the forecast accuracy in all three cases.

Visualizations of the spatial weights show what regions are important when forecasting energy and give more profound insights into what the model is learning. Moreover, we discuss promising, more advanced approaches based on the spatial weights, i. e., postprocessing weights, using neighbor cells, subregion forecasting, hierarchical training, and nonlinear spatial-temporal weights.

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A APPENDIX

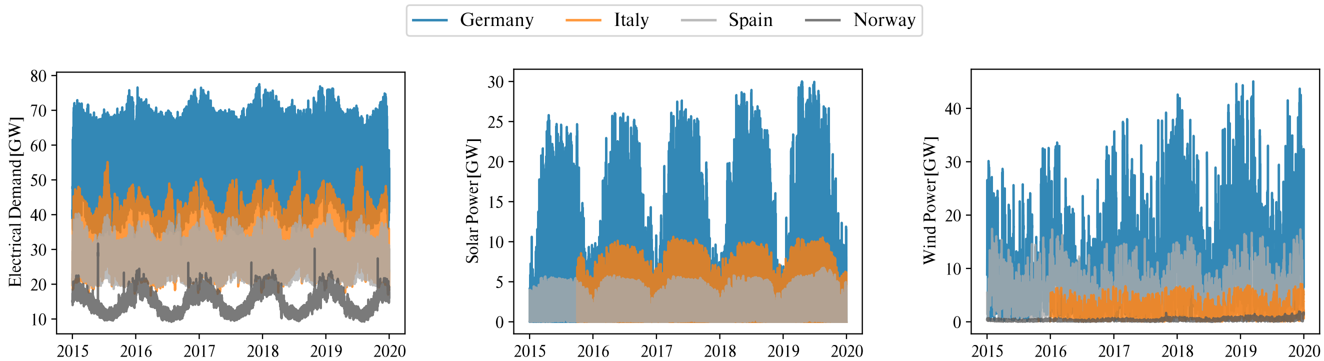
A.1 Experimental Setup

To evaluate the proposed model, we require access to historical energy and weather data. For energy data, we rely on the Open Power System Data (OPSD) dataset that provides hourly historical energy for several countries and regions of Europe [21]. The energy data are visualized in Figure 4. To obtain historical weather data, we use the ECMWF Reanalysis v5 (ERA5) and High Resolution (HRES) datasets from the European Centre for Medium-Range Weather Forecasts (ECMWF) [3]. An exemplary weather input is shown in Figure 5. Our chosen regions include Norway, Germany, Italy, and Spain, ensuring diverse countries based on location and size.

To compare our approach against a State-of-the-Art (SOTA) baseline, we choose the architecture proposed by Neumann et al. [16] which is similar to our proposed architecture. Instead of resampling the weather data, they encode the data using a fully connected BNN and create a global forecast in one step. All code is available at GitHub[1].

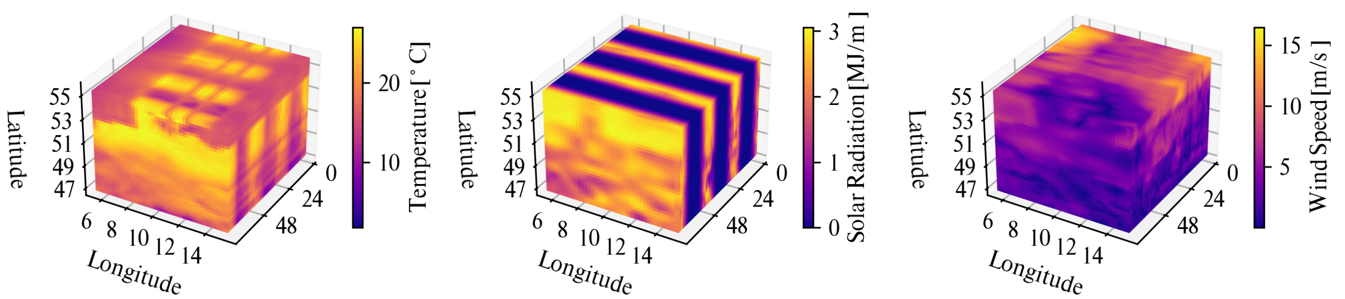
Both Neuronal Networks (NNs) are trained on data from 2015 to the end of 2017. However, the energy data from the beginning of 2015 is unavailable when forecasting solar and wind power for Italy. So, training for Italy starts at the beginning of 2016 when forecasting solar or wind power. Also, solar power data is not available for Norway. That is why Norway is not evaluated on solar

[1] https://github.com/KIT-IAI/Intrinsic-Explainable-AI-Using-Trainable-Spatial-Weights



(a) Electrical Demand (b) Solar Power (c) Wind Power

Figure 4: Illustration of the energy data set showing electrical demand, solar, and wind power for Norway, Germany, Italy, and Spain from 2015 up to 2020.



(a) Temperature (b) Solar Radiation (c) Wind Speed

Figure 5: Visualization of exemplary weather input data for Germany on 2016-06-01 12:00 for a 72 hour forecast horizon. The weather input for all three energy targets is shown, i. e., electrical demand (temperature), solar (solar radiation), and wind power (wind speed).

power forecasting. Regarding validation and testing, we use 2018 validation and 2019 for testing. To train the NNs and for evaluation, we choose the MAE.

Regarding the forecasting objective, a forecast horizon H_f of 72 hours is selected. Forecasts are produced twice a day at midnight and midday because weather forecasts of the HRES dataset are only available at these times. We chose a historical energy horizon H_h of 168 hours and passed the weather prediction of the next 72 hours in an hourly resolution to the model. In addition to the energy and weather information, we also provide calendar information to the models.

A.2 HRES Evaluation

Similar to the ERA5 weather data, we also evaluated the proposed method on the HRES weather forecast data set. The forecasting accuracy is similar and shown in Figure 6. The spatial weights are noisier and shown in Figure 7. The temporal weights are comparable to the ERA5 based temporal weights and presented in Figure 8.

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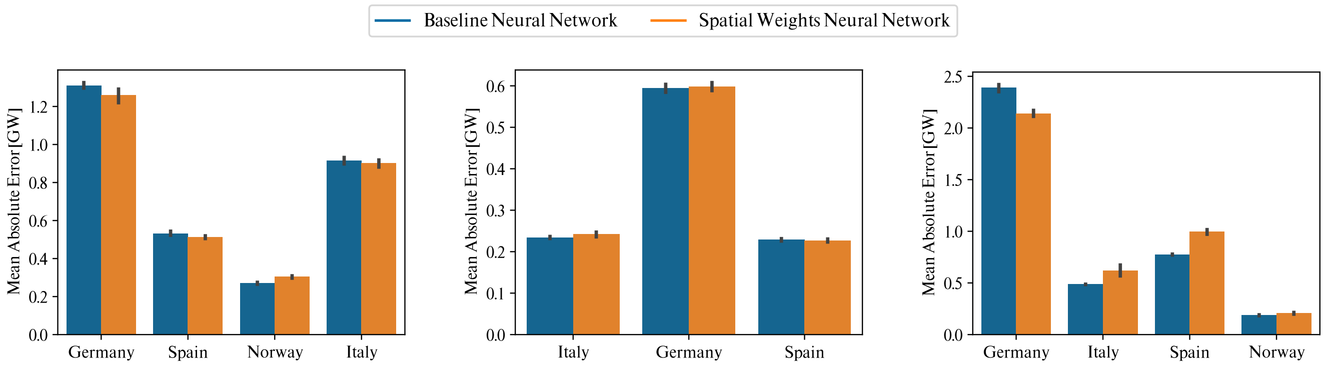


(a) Electrical Demand **(b) Solar Power** **(c) Wind Power**

Figure 6: Visualization of the mean MAE for the neural network and proposed spatial weights model among seven runs for Norway, Germany, Italy, and Spain on all three energy forecasting targets, i. e., electrical demand, solar, and wind power, trained on the HRES weather dataset.

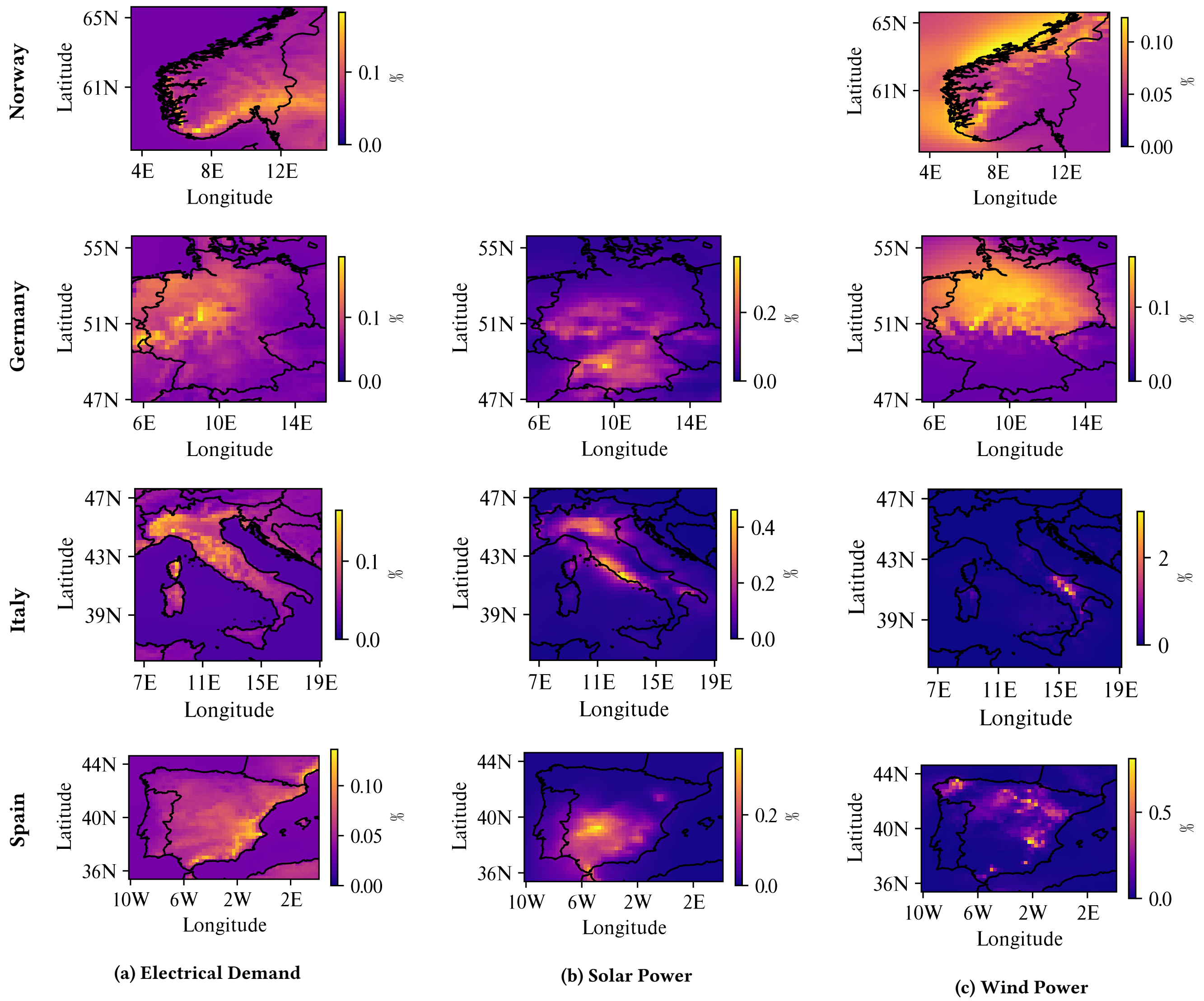
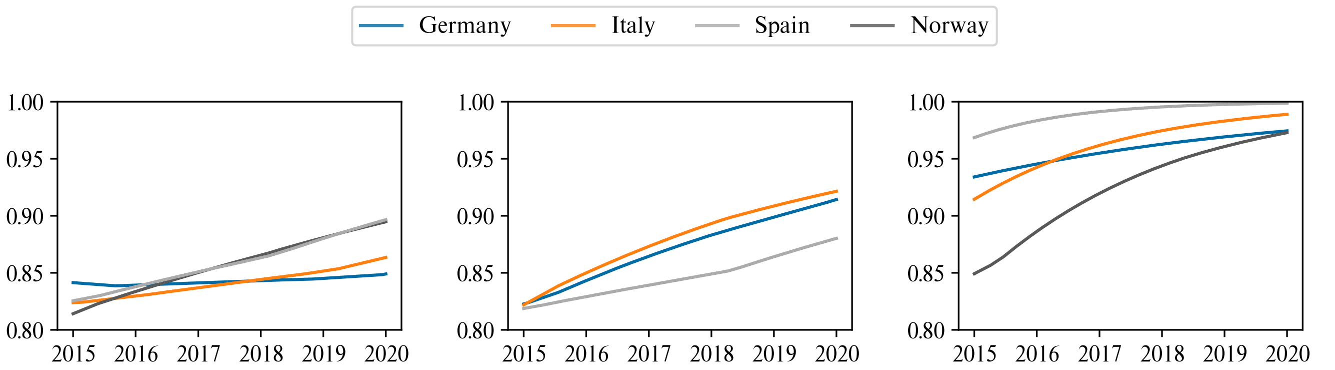


Figure 7: Images of spatial weights trained on forecast weather data of the best-performing model for Norway, Germany, Italy, and Spain and all three forecasting targets, i. e., electrical demand, solar, and wind power. The spatial weights show how much a region contributes to the global forecast. So, higher values refer to more important areas.



(a) Electrical Demand **(b) Solar Power** **(c) Wind Power**

Figure 8: Visualization of the temporal weight $\beta(t)$ trained on forecast weather data of the best-performing proposed model to allow the spatial weights to increase or decrease over time. The weights are shown for Germany, Italy, Spain, and Norway and all three energy forecasting targets, i. e., electrical demand, solar power, and wind power.