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A southern, middle, and northern Norwegian offshore wind energy resources analysis by a transfer learning method for Energy Internet

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Abstract. As renewable energy sources offshore wind energy develop quickly, countries like Norway with long coastlines are exploring their potential. However, the diverse wind resources across different regions of Norway present challenges for study for effective utilization of offshore wind energy. This study proposes a novel method that utilizes transfer learning techniques to analyse the resource differences between these areas for optimum energy generation. The suggested approach is tested using real-world wind data from Norway's southern, middle, and northern regions. The results show that transfer learning successfully bridges resource discrimination, boosting wind resource prediction precision in the target domains. The work can contribute to optimizing offshore wind energy utilization in Norway by addressing the resource disparities and forecasting between the different regions.

1. Introduction

Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report offered a renewed global assessment of climate change mitigation progress and pledges [1]. The Energy Internet (EI) holds significant promise for climate change mitigation by enabling the integration of renewable energy, promoting energy efficiency, enhancing grid flexibility, and supporting transportation electrification [2]. Specifically, the emerging data-driven EI can utilize vast amounts of generated data on energy consumption, production, and grid operations to optimize energy management, identify energy-saving opportunities, and further enhance climate change mitigation efforts through advanced analytics and artificial intelligence [3].

Wind energy is a clean and renewable source, emitting no greenhouse gases during operation. With its abundance and scalability, wind energy plays a crucial role in the transformative Energy Internet [4]. Wind energy costs have declined dramatically over the years, making it increasingly cost-competitive with traditional fossil fuel-based power. Wind energy harnessing projects are quickly developing due to advancements in turbine technology and the construction of offshore wind parks.

The wind is an intermittent resource that is highly dependent on weather patterns. This variability challenges grid operators and requires proper management with integration with other energy sources, energy storage systems, and demand response mechanisms. Advanced forecasting and related control systems are necessary to ensure a reliable and stable wind energy supply [5].

Offshore wind power is Norway's promising renewable energy source [6]. However, the harsh environmental conditions in Scandinavia, such as low temperatures and high winds, may damage turbines while rendering maintenance difficult. The country has a nearly 83,000 km coastline and complex mountainous terrain facing the North Sea and the Norwegian Sea. Norway presents significant potential for offshore wind energy development. To harness this potential, accurate wind resource analysis is crucial for effective project planning and optimization. Transfer learning, a machine learning technique that transfers knowledge from one domain to another, offers a promising approach to overcoming data limitations and improving the accuracy of wind resource analysis across these regions.

The present article proposes a novel transfer learning approach for investigating the relationships between southern, middle, and northern Norwegian offshore wind resources and their win speeds forecasting.

2. Norwegian Offshore Winds and Transfer learning

2.1. Offshore Wind Energy in Different Parts of Norway

Norway's offshore wind energy potential varies across its northern, middle, and southern regions due to their distinct geographical characteristics and weather conditions. Such as northern Norway faces challenges related to harsh Arctic conditions, the middle region must navigate fjord-based landscapes, and the southern region must balance various maritime activities.

Northern Norway has immense potential for offshore wind energy generation. The region is characterized by its cold climate (high density) and strong winds, making it an ideal location for wind farms. The abundance of offshore wind resources and proximity to major electricity demand centers create a favorable environment for wind energy development [7]. Additionally, the region's relatively shallow waters make it more cost-effective to install offshore wind turbines [8]. However, the challenging climatic conditions in the Arctic pose significant obstacles to offshore wind energy projects in Northern Norway. Harsh winters, freezing temperatures, and ice formation require specialized technologies and engineering solutions to ensure the efficient operation of wind turbines [9]. Moreover, the region's remote location necessitates the development of a robust transmission infrastructure to transport electricity to mainland grids.

With its diverse topography (mountains and fjords), Middle Norway presents opportunities and challenges for offshore wind energy. The fjords act as natural wind corridors, amplifying wind speeds and creating favorable conditions for wind power generation [10]. However, the complex and rugged terrain poses engineering challenges regarding turbine installation and maintenance. Careful consideration must be given to the visual impact on scenic landscapes and the potential effects on wildlife habitats.

Southern Norway, characterized by its milder climate and varied coastal conditions, offers a distinct setting for offshore wind. The region benefits from a relatively stable wind regime and moderate water depths, facilitating efficient turbine installation and maintenance [11].Furthermore, the proximity to densely populated areas and existing energy infrastructure makes it an attractive location for offshore wind projects. One of the critical challenges in southern Norway lies in the competition for maritime space. Since the region is home to fishing, shipping, and oil and gas industries, careful planning and cooperation are required to prevent possible problems. Despite these obstacles, Norway's dedication to clean energy and technological capabilities place it at the forefront of offshore wind energy development[12].

2.2. Transfer learning

Machine learning techniques have advanced dramatically in recent years, allowing the construction of sophisticated models capable of handling complicated problems. However, the performance of machine learning algorithms is frequently dependent on the availability of large-scale, high-quality training datasets [13]. Acquiring such information may be difficult in many fields, including offshore wind energy, where data collection is costly, time-consuming, and logistically challenging. To address these issues, researchers have turned to transfer learning, a technique that leverages knowledge learned from one domain to improve performance in another. It provides a viable solution by lowering the need for extensive data gathering and computing resources.

3. Methodologies and Experiments

This study draws on the fundamental idea of transfer learning to construct analytical forecasting models and constructs a modeling framework based on actual Norwegian regional offshore wind datasets.

The transfer learning analytical procedure is shown in Eq. 1, 2, and Fig. 1. Firstly, the wind data from the south and the middle of Norway are used as training model data, i.e., source domain, to perform prediction analysis on the wind data from the north, i.e., target domain (blue lines). Then, use south and north for the middle (orange lines). Finally, using middle and north for the south analysis (green lines) (SM-N, SN-M, and MN-S).

$$Z_t = f\left(X_t, X_{t-1}, X_{t-2}, \cdots, X_{t-p}; Y_t, Y_{t-1}, Y_{t-2}, \cdots, Y_{t-p}\right) + \varepsilon \tag{1}$$

$$Z_{t+n} = g\left(Z_t, Z_{t-1}, Z_{t-2}, \cdots, Z_{t-p}; X_t, X_{t-1}, X_{t-2}, \cdots, X_{t-p}; Y_t, Y_{t-1}, Y_{t-2}, \cdots, Y_{t-p}\right) + \varepsilon \tag{2}$$

where Z is the target domain, X and Y represent source domains, f (.) and g(.) are the nonlinear relationships needed for learning by the proposed model, and ε is the model error.

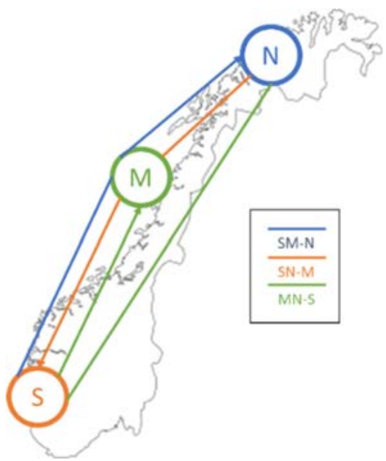

Figure 1. Transfer learning analytical procedure for Norwegian offshore winds.

From the perspective of the detailed structure of the analytical model, Fig. 2 shows the proposed layer-to-layer structure of the analytical model based on Long Short-Term Memory (LSTM) networks. Firstly, source domain datasets are loaded into a Bidirectional LSTM (Bi-LSTM) module (Fully connected layer for internal outputs and the regressor, Two-layer seven LSTM units with reverse directions.). The module can learn the sequence's backward and forward information at every time step to fully explore temporal dependence in the sequence. It effectively increases the information to the deep learning network and the context available to the LSTM blocks [14]. Then, the Bi-LSTM module outputs are sent to standard neural networks with three hidden dense layers with random 10% dropout (connections and nodes) to avoid overfitting. Finally, the target domain data are analyzed with the above well-trained networks. The process above is repeated three times to reach the SM-N, SN-M, and MN-S transfer learning for offshore winds and enable accurate and robust analysis across all three regions.

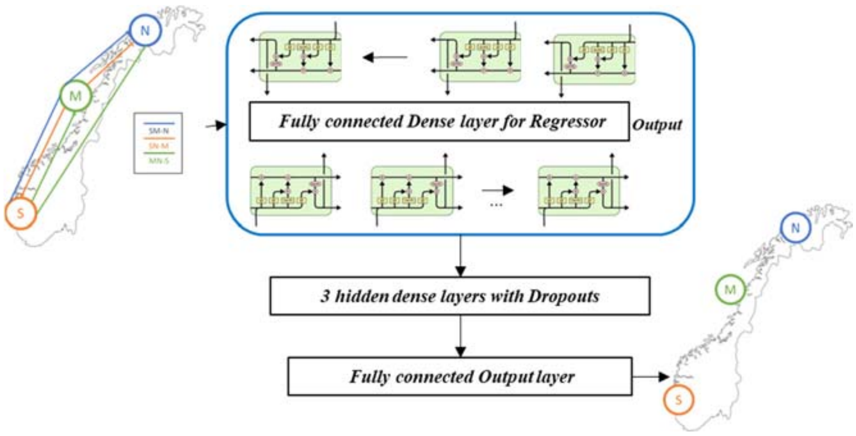

Figure 2. Learning networks process for Norwegian offshore winds.

4. Results

Three sites along the Norwegian coastline are selected for transfer learning analysis for offshore wind resources. Viz., Torsvåg Fyr (70.5882N, 19.2844E) in Northern Norway, Myken (66.7621N, 12.4809E) in Middle Norway, and Utsira Fyr (59.3102N, 4.8857E) in Southern Norway. The wind speed data are taken from Norsk klimaservicesenter and range from January 1, 2020, to December 31, 2022. The Root Mean Square Error (RMSE) ($RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (y(t) - \hat{y}(t))^2}$) and the correlation coefficient between modeled speed and the ground-truth speed values are used to evaluate the modeling performance.

The corresponding source domain datasets are loaded into the linear model and, according to Eq. 1, analyze the target domain (SM-N, SN-M, and MN-S). First, we establish linear mapping relationships between different areas of Norwegian offshore wind speed data as follows:

$$N_t = 0.225M_t + 0.018S_t + 4.028 + \varepsilon \tag{3}$$

where RMSE is 4.028, and the correlation coefficient is 0.268,

$$M_t = 0.246N_t + 0.205S_t + 5.128 + \varepsilon \tag{4}$$

where RMSE is 3.979, and the correlation coefficient is 0.327,

$$S_t = 0.023N_t + 0.241M_t + 6.251 + \varepsilon \tag{5}$$

Moreover, where RMSE is 4.401, and the correlation coefficient is 0.213. From Eqs. 3, 4, and 5, it can be seen that there is little correlation between the wind speeds of the three Norwegian regions. The wind speed correlation is tiny in the north and south (both linear slope coefficients are less than 0.03). The wind speed correlations are relatively significant in the middle and north and the middle and south (linear slope coefficients are larger than 0.2). Based on the three-modeling performance, the linear relationships could not be determined (large RMSE and small correlation coefficient). However, it can be generally said that the north and south can relatively well linearly represent the middle offshore wind speed.

Then, similarly, we model the datasets by Eq. 1 and the proposed transfer learning process in Fig. 2 from past 0 timesteps to 6 timesteps and summarize the performance in Table 1 (a) and (b). It can be obtained that, overall, the performance of the offshore wind power relationship analysis model improves slightly as more time (step 0 to step 6) steps data are integrated into the model. At step 0, the mapping modeling capability of the proposed model is significantly better than the linear models in Eqs. 3, 4, and

5, reflecting the nonlinear relationships of offshore Norwegian wind resources in different regions and the effectiveness of the proposed learning model. Similarly, the north and south wind speeds can more precisely express the wind speed in the middle. In contrast, the nonlinear relationship between the southern wind speed and the middle and northern counterparts is more complex to be modeled.

Table 1 (a). RMSE for the transfer learning process in offshore winds relationships.

p	0	1	2	3	4	5	6
Torsvåg Fyr	3.5699	3.5637	3.5567	3.5351	3.5248	3.5196	3.5176
Myken	3.7554	3.7215	3.6933	3.6877	3.7274	3.7252	3.6496
Utsira Fyr	4.1768	4.1239	4.0858	4.0974	4.0918	4.1206	4.1151

Table 1 (b). Correlation coefficient for the transfer learning process in offshore winds relationships.

p	0	1	2	3	4	5	6
Torsvåg Fyr	0.2711	0.2729	0.2855	0.3032	0.3106	0.3161	0.3195
Myken	0.3375	0.3570	0.3744	0.3810	0.3585	0.3670	0.4081
Utsira Fyr	0.1845	0.2110	0.2482	0.2352	0.2394	0.2194	0.2260

Further, to explore whether offshore wind data from other regions can contribute to the target region's wind speed prediction, we develop prediction models based on Eq. 2 and Fig. 2 for time steps 1 to 6 ahead on northern, middle, and southern offshore wind data, respectively. The performance is shown in Fig. 3. Overall, the prediction model's performance decreases with increasing forecast steps, but the decreasing tendency flattens out. The best prediction is achieved for Torsvåg Fyr in the north and the worst for Utsira Fyr in the south. When comparing with the results obtained in the previously reported literature [15], it can be observed that the proposed model based on Bi-LSTM in this study significantly improves the prediction performance; in addition, it is also feasible to incorporate offshore wind data from other regions into the wind speed prediction of the target area.

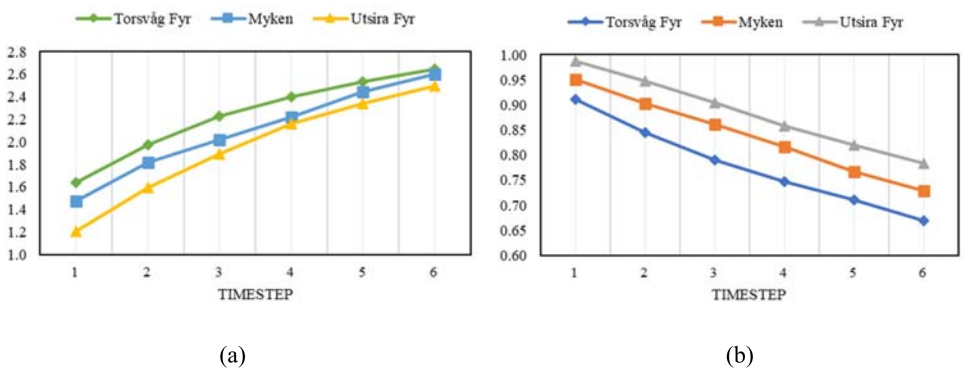

Figure 3. Speed forecasting performance with timesteps: (a) RMSE; (b) Correlation coefficient.

5. Conclusion

This paper investigates the relationships between southern, middle, and northern Norwegian offshore wind resources with a novel transfer learning mapping and multistep forecasting. First, the insignificant linear mapping for Norwegian offshore winds of three different areas is set up and proven. Then, the proposed transfer learning process is used to check the nonlinear mapping. Finally, we check the contributions of source areas for the target area wind speed forecasting. By leveraging transfer learning and deep learning models, the method enables understanding the wind resource variations, aiding in decision-making processes for efficient planning and deployment of offshore wind energy projects.

As per the study's results, the following conclusions can be drawn: 1. The relatively weak correlation between offshore wind speeds in northern, middle, and southern Norway reflects, in one way, the geographical variability of the wind resources. 2. The offshore wind data from different regions are also beneficial for wind speed analysis and prediction in other regions, despite the regional variability of wind resources. 3. The variability and nonlinear relationship of Norwegian offshore wind resources favour the large-scale exploitation of Norwegian offshore wind energy and its integration into the Nordic power grid and the developing Energy Internet.

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