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Forecast of renewable wind power generation in Scottish farms for optimal renewable energy management

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ABSTRACT

Climate change and depletion of fossil fuel are two of the major global challenges calling for urgent actions. Localised generation of renewable energy such as wind power has been adopted by farms as an effort for decarbonisation. It is important to develop the capability to accurately predict wind power generation featured by intermittence and fluctuation so that optimal renewable development plans can be formulated. In this work, the Autoregressive Distributed Lag modelling approach was employed to study the influences of economic and environmental factors (pressure, wind speed, temperature, and electricity price) on wind power generation on a Scottish farm. The proposed Autoregressive Distributed Lag model well explain the wind power generation with an accuracy of 91.8%. The results showed that when wind speed increases by 1%, the wind power output increases by 0.256% in the long run. We forecasted a total wind generation capacity of 1894.9 MWh from September 2020 to September 2021 based empirical environmental and economic data. In this case, the annual carbon emission of on-farm wind power usage was estimated to be 5.3664 tonnes. The on-farm wind power generation would reduce the electricity-related carbon emission by 278.87 tons over the 13 months.

Keywords: Sustainable development; Renewable energy; Wind power; ARDL model.

1. INTRODUCTION

The depletion of fossil fuels and climate change are two of the most significant global challenges. Renewable energy plays a critical role to meeting the growing energy demand and serves as an essential means to mitigate the climate change challenge. The farming sector in the UK has put significant effort in decarbonisation, and on-farm renewable generation is one of the measures commonly adopted. Currently, farming contributes over 10% of the UK's emissions from three major sources, i.e. nitrous oxide from fertilizer use, methane from livestock, and carbon dioxide from electricity or fuel for tractors and vehicles (Wray, 2017).Same as the post CUE conferences, the CUE2020, powered by the international journal, Applied Energy, seeks to showcase what is new and exciting in energy research and development that offer opportunities for translation into sustainable solutions.

The world's total wind power generation capacity is about 130 million MW (Wei et al., 2019). As an abundant renewable energy source, wind power plays a critical role in reducing the carbon footprint of electricity generation. Moreover, developing small- or medium-scale wind power facilities on farms often maximises the use of the farm's topographical features that are associated with steady wind speeds and high land availability. Towards optimal renewable energy planning and utilization, it is important to predict the potential of wind power generation accurately. Although a number of models have been developed to forecast the solar power generation (Csereklyei et al., 2019; Demirhan, 2020; Wang et al., 2019), relevant models are still rare for on-farm wind power production featured by significant fluctuation and intermittence. This work will fill the knowledge gap by applying the Autoregressive Distributed Lag (ARDL) modelling approach to study the correlation between wind power generation and economic and environmental factors based on the data from a Scottish farm (Auchmore Farm). The ARDL model developed by Charemza and Deadman has been commonly used to test the statistical significance between economic growth, energy consumption, CO_2 emissions and renewable energy (Nkoro & Uko, 2016).

In the following section (Fig. 1), the compilation of raw data will be firstly described followed by the selection and explanation of the empirical model and relevant test methods. The stationarity of variables will then be verified to justify the use of the ARDL approach, and the long-term and short-term coefficients and relationships will be determined. The stability of the estimated coefficients will be evaluated. The accuracy of the developed ARDL model will be validated followed by the application of the model to predict the carbon saving associated with the on-farm wind power generation.

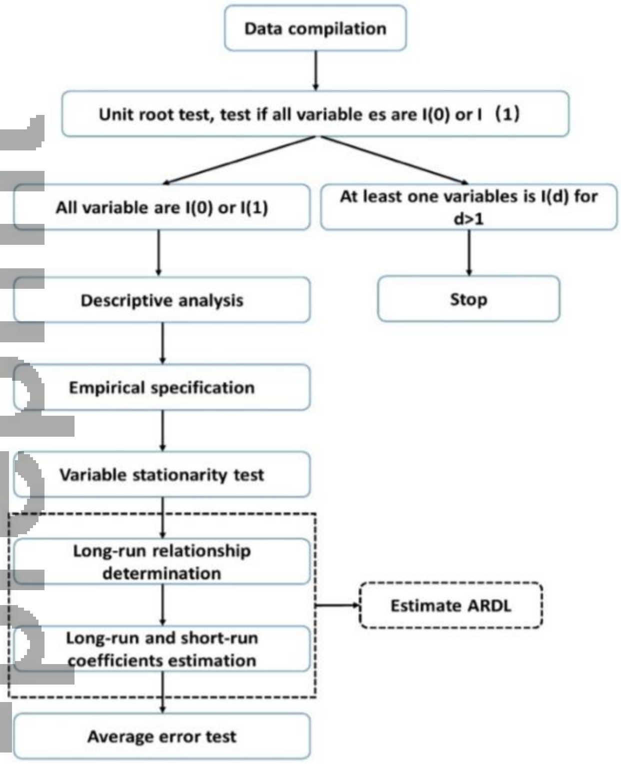


Fig 1. A schematic of the methodology.

2. METHDOLOGY

2.1 Raw data

Monthly wind power generation data from July 2015 to Feb 2020 was collected from the Auchmore Farm, with a total of 56 observations. We used 52 observations the ARDL modelling and 4 observations for validation.

2.2 Empirical specification

The wind power output per hour (*OP*) is specified as a function of temperature (*T*), pressure (*P*), wind speed (*WS*), and the electricity price (*EP*).

$$\ln OP_t = \alpha_0 + \alpha_1 \ln P_t + \alpha_2 \ln T_t + \alpha_3 \ln WS_t + \alpha_4 \ln EP_t + \varepsilon_t \qquad (1)$$

where ln[*x*] denotes the natural log of variables *x*; *t* denotes the time trend; ε denotes a random error.

2.3 Econometric analysis

2.3.1 Unit root test

For the unit root test, Augmented Dickey-Fuller (ADF) test is employed. Since we have 52 observations as experiment data , it is more appropriate to use the ADF test because it requires a smaller sample size and lower power properties than other unit root test methods (e.g., PP, KPSS, ERS, NP) (Leybourne et al., 2005). The F-statistic is used to test the co-integration relationship between the variables in the ARDL model. The results of the unit test are shown in Table 1.

2.3.2 Stationarity of variable series

In the ARDL model, the Augmented Dickey-Fuller (ADF) unit root test was first used to analyse the stationarity of all variables. The maximum lag lengths applied in the tests were determined to be 4 based on the rule proposed by William (Schwert, 2002). The Akaike Information Criterion (AIC) is a method that measures the goodness of fit of a statistical model for a given set of data by selecting the optimal lag length (You et al., 2017). Table 1 shows the results of the ADF tests. At the 5% significance level, the time series of $\ln OP$, $\ln T$, $\ln WS$, and $\ln EP$ are stationary at the level I(0). The results also show that the nonstationary variable ln P is stationary at the first-order difference (I(1)).

Table 1. Summary of ADF tests on the stationarity of variables.

	Variable	t-Statistics	First Difference	t-Statistics	Order of integration
52 samples	$\ln OP$	-4.6239332***	$\Delta \ln OP$	-8.836539***	I(0)
	$\ln P$	-4.929392***	$\Delta \ln P$	-7.266615***	I(1)
	$\ln T$	-5.436832***	$\Delta \ln T$	-4.699812***	I(0)
	$\ln WS$	-4.82886***	$\Delta \ln WS$	-9.333521***	I(0)
	$\ln EP$	-1.478894**	$\Delta \ln EP$	-7.319298***	I(0)

**: statistical significance at 5% level

***: statistical significance at 10% level

2.3.3 ARDL bounds testing approach

For the ARDL bounds testing approach, there are two major steps that need to be done: (1) determining the long-run relationships among the variables, and (2) estimating the corresponding coefficients.

$$\ln OP_t = a_0 + \sum_{i=1}^{p} a_{1i} \ln OP_{t-i} + \sum_{j=0}^{p} a_{2j} \ln P_{t-j} + \sum_{j=0}^{p} a_{3j} \ln T_{t-j} + \sum_{j=0}^{p} a_{4j} \Delta \ln WS_{t-j} + \sum_{j=0}^{p} a_{5j} \Delta \ln EP_{t-j} + \varepsilon_t \qquad (2)$$

where Δ denotes the first difference operator and p denotes the number of lags. The other variables are as previously defined. The maximum lag lengths in the ARDL model are specified to be 4.

2.4 Results and discussion

2.4.1 Descriptive analysis

The temporal variation of wind power output (*OP*), pressure (*P*), temperature (*T*), wind speed (*WS*), and electricity price (*EP*) for the wind-power plant are shown in Fig 2(a-e) and Table 2. It can be seen from Fig 2(a) that the high *OP* is mainly from November to January, and the low output is from May to July. The peak *OP* reached 261 MWh in January 2020, and the lowest was 46 MWh in July. From Fig 2(b), the annual *P* remained stable with an average of 1010.26 Pa. The maximum value of *P* was 1022.4 Pa in October 2016, and the minimum one was 994 Pa in February 2020. From Fig 2(c), the *T* remained stable month-on-month. The average was 7.9°C, the maximum value of T was 16°C in July 2019, and the minimum one was 1°C in January-February 2018. The WS value was higher from October to January, and slightly lower from May to September. The highest WS was 20.5km/h in November 2015, and the lowest one was 7.8km/h in July 2019. The highest *EP* was 67.69£/MWh and the lowest one was 33.85£/MWh.

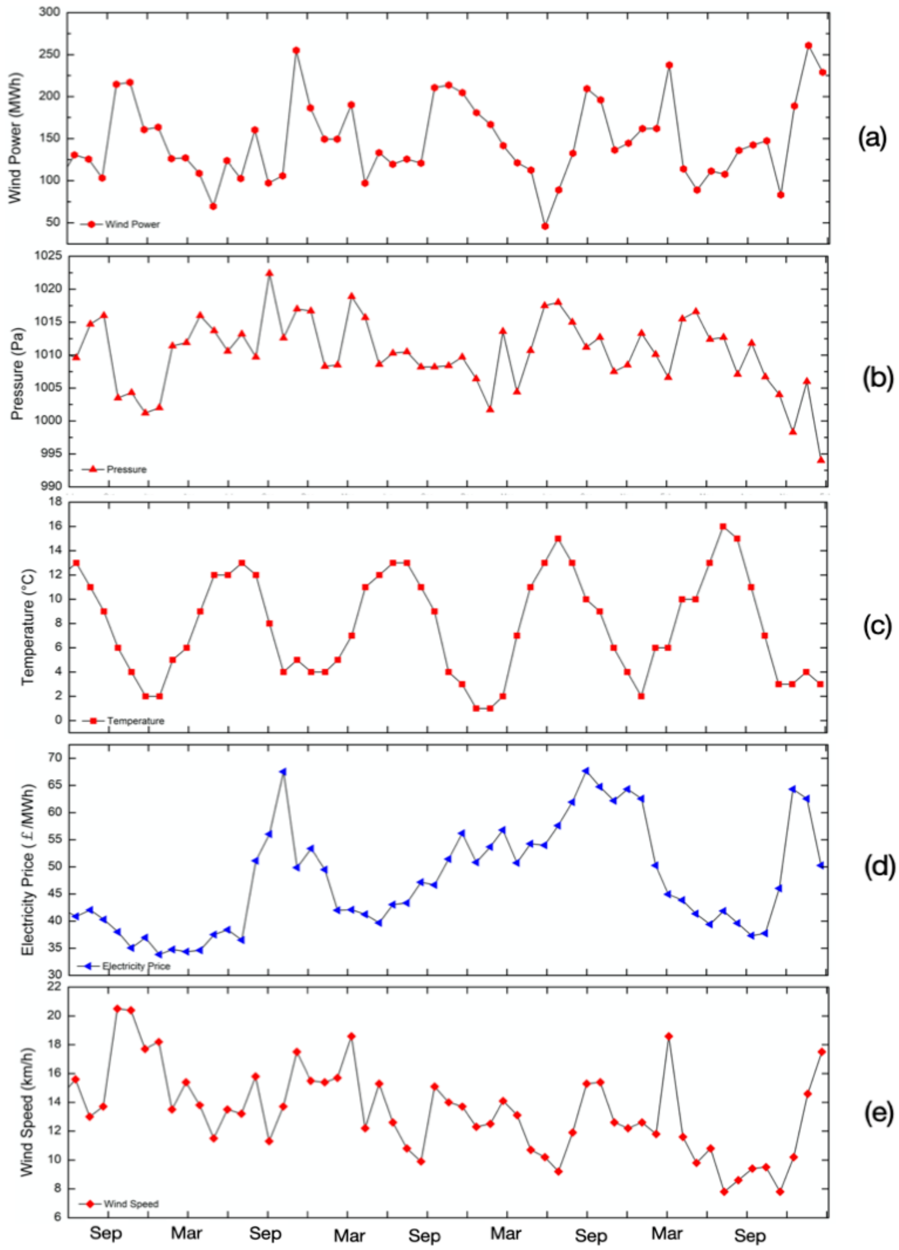


Fig 2. The temporal variations of (a) wind power generation, (b) pressure, (c) temperature, (d) wind speed, and (e) electricity price.

Table 2. Descriptive statistic of monthly variables

Variable	Mean	Standard deviation	Minimum	Maximum
Wind power (MWh)	147.1625	47.995	46	261
Pressure (Pa)	1010.259	5.3689	994	1022.4
Temperature (℃)	7.892858	4.2241	1	16
Wind speed (km/h)	13.42321	3.0129	7.8	20.5
Electricity price (£/MWh)	47.61911	9.7598	33.85	67.69

2.4.2 ARDL cointegration analysis

The results of F-statistics for the cointegration analysis are listed in Table 2 together with the critical value bounds.

Table 3. Summary of F-tests.

	F-statistics				
52 samples (k=4)	$F_{OP}(OP\mid P,T,WS,EP)$ =10.78498	$F_{P}(P\mid P,T,WS,EP)$ =5.563729	$F_{T}(T\mid P,T,WS,EP)$ =8.549596	$F_{WS}(WS\mid P,T,WS,EP)$ =12.65199	$F_{EP}(EP\mid P,T,WS,EP)$ =14.38380
	Critical values				
Significance level 1%		Significance level 5%		Significance level 10%	
Lower bound (I(0))	Upper bound (I(1))	Lower bound (I(0))	Upper bound (I(1))	Lower bound (I(0))	Upper bound (I(1))
3.29	4.37	2.56	3.49	2.2	3.09

#: k is the number of regressors.

2.4.3 ARDL long-run coefficients model

As shown in Table 4, the long-run and short-run elasticities for wind speed 0.0568 and 0.844, respectively. Only the short-run elasticity is significant at the level of 5%. This suggest that the wind power output increases by 0.844% when wind speed increases by 1%. The long-run and short-run elasticities for temperature is 0.257 and -0.0289 respectively. Only the long-run elasticity is significant at the level of 10%. The wind power output increases by 0.256% when the temperature increases by 1%. For electricity price, only the short-run elasticity is significant at the level of 10%.

$$\ln OP_t = c_0 + \sum_{i=1}^{m1} c_{1i} \ln OP_{t-i} + \sum_{j=0}^{m2} c_{2j} \ln P_{t-j} + \sum_{j=0}^{m3} c_{3j} \ln T_{t-j} + \sum_{j=0}^{m4} c_{4j}\, \Delta \ln WS_{t-j} + \sum_{j=0}^{m5} c_{5j} \Delta \ln EP_{t-j} + \varepsilon_t \tag{3}$$

Table 4. ARDL long-run & short-run testing (52 samples)

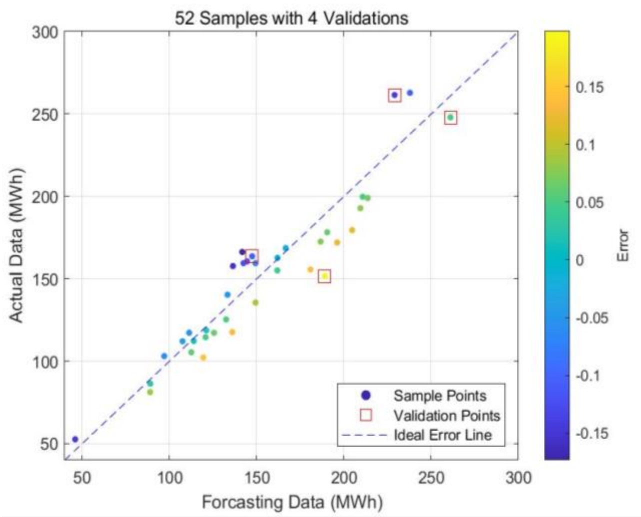
	Long run elasticity (DV: ln OP_t)				Short run elasticity (DV: ln OP_t)			
	ln P_t	ln T_t	ln WS_t	ln EP_t	Δln P_t	Δln T_t	Δln WS_t	Δln EP_t
Coefficient	-5.87238	0.25651*	0.056779	0.075070	-0.38214	-0.0289	0.844381**	-0.274245*
Standard error	11.12363	0.093984	0.162917	0.134589	5.97016	0.07179	0.146630	0.250817
t-statistics	-0.52792	2.729363	0.348513	0.557777	-0.0640	-0.4036	5.758567	-1.093406

DV denotes the dependent variable.
*: statistical significance at 10% level
**: statistical significance at 5% level.

2.4.4 ARDL model accuracy

The proposed ARDL model was used to predict the wind power generation which is compared with actual data. As shown in Fig.3, the blue dotted line denotes the ideal accuracy line (0% error). The color bar on the right shows the error range. The difference between the predictions and actual data range from -10% to 13% with an average difference of 8.2%.

Fig 3. Average error testing: 52 samples with 4 validations



2.4.5 *Carbon intensity*

The developed ARDL model is combined with the carbon intensity data of wind power in Scotland to evaluate the carbon saving potential of wind power generation on the farm. The carbon intensities of wind power and traditional grid electricity (coal, gas boiler, oil boiler, etc.) were obtained from the Scottish government and the national grid ESO website (2019b). Table 5 shows that the carbon intensities of wind power (including onshore wind, offshore wind, island wind) in year 2016, 2017, 2018, 2019, and 2020 were 0.05, 0.025, 0.0135, 0.007425, and 0.004158 ton CO_2/MWh, respectively. The carbon intensity of 2021 is predicted to be 0.002079 ton CO_2 /MWh (2019a). The environmental and economic factors for the next 13 months (from September 2020 to September 2021) were estimated based on their average values over the past four years (from 2016-2019) and substituted in the ARDL model to predict the monthly wind power output between September 2020 to September 2021. The predicted total wind power output for the 13 months is 1894.9 MWh. The carbon emission of on-farm wind power generation for the 13 months is 5.3664 tonnes (Eq. (4)), and the corresponding carbon emission of grid electricity usage is 284.24 tonnes, which suggests that the wind power usage over the 13 months will reduce the carbon emission by 278.87 tons.

$$Y_{\text{carbon emission}} = OP_{\text{wind power generation}} \cdot I_{\text{carbon intensity}} \tag{4}$$

Table 5. Carbon footprint from 2016-2020

Date	2016	2017	2018	2019	2020	2021
Wind power carbon intensity (tCO_2 /MWh)	0.05	0.025	0.0135	0.007425	0.004158	0.002079
Grid carbon intensity (tCO_2 /MWh)	0.38	0.3	0.21	0.2	0.18	0.15

3. *Conclusions*

In this work, we used the ARDL approach to analyse the relationship between wind power generation in a Scottish farm and influential factors (wind speed, pressure, electricity price, and temperature). The accuracy of the developed ARDL model is 91.3%. For the short-run elasticity, the wind power output increases 0.844% as the wind speed increases 1%. Finally, it was shown that the Auchmore Farm's wind power generation will reduce electricity usage-related carbon emission by 278.87 tonnes in 13 months.

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REFERENCE

[1] A. Wray, Agricultural Statistics and Climate Change, 2017. <https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/666073/agriclimate-8edition-8dec17.pdf> [accessed at Feb/16/2020].

[2] X. Wei, Y. Duan, Y. Liu, S. Jin, C. Sun, Onshore-offshore wind energy resource evaluation based on synergetic use of multiple satellite data and meteorological stations in Jiangsu Province, China, Frontiers of Earth Science 13(1) (2019) 132-150.

[3] Z. Csereklyei, S. Qu, T. Ancev, The effect of wind and solar power generation on wholesale electricity prices in Australia, Energy Policy 131 (2019) 358-369.

[4] Y. Wang, W. Yan, S. Zhuang, Q. Zhang, Competition or complementarity? The hydropower and thermal power nexus in China, Renewable Energy 138 (2019) 531-541.

[5] H. Demirhan, dLagM: An R package for distributed lag models and ARDL bounds testing, Plos One 15(2) (2020) e0228812.

[6] E. Nkoro, A.K. Uko, Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation, Journal of Statistical and Econometric Methods 5(4) (2016) 63-91.

[7] P.P. da Silva, P.A. Cerqueira, W. Ogbe, Determinants of renewable energy growth in Sub-Saharan Africa: Evidence from panel ARDL, Energy 156 (2018) 45-54.
[8] A. Cherni, S.E. Jouini, An ARDL approach to the CO_2 emissions, renewable energy and economic growth nexus: Tunisian evidence, International Journal of Hydrogen Energy 42(48) (2017) 29056-29066.
[9] S. Toumi, H. Toumi, Asymmetric causality among renewable energy consumption, CO_2 emissions, and economic growth in KSA: evidence from a non-linear ARDL model, Environmental Science and Pollution Research 26(16) (2019) 16145-16156.
[10] S. Leybourne, T.H. Kim, P. Newbold, Examination of some more powerful modifications of the Dickey–Fuller test, Journal of Time Series Analysis 26(3) (2005) 355-369.
[11] G.W. Schwert, Tests for unit roots: A Monte Carlo investigation, Journal of Business & Economic Statistics 20(1) (2002) 5-17.
[12] S. You, K.G. Neoh, Y.W. Tong, Y. Dai, C.-H. Wang, Variation of household electricity consumption and potential impact of outdoor $PM_{2.5}$ concentration: A comparison between Singapore and Shanghai, Applied energy 188 (2017) 475-484.
[13] Carbon Intensity API. <https://carbonintensity.org.uk> [accessed at Feb/20/2020].
[14] Climate Change Plan: monitoring report 2019, 2019. < https://www.gov.scot/publications/climate-change-plan-monitoring-report-2019/pages/3/> [accessed at Jan/30/2020].
[15] Climate Change (Emissions Reduction Targets) (Scotland) Act 2019, (2019).

