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Forecasting the probability of commercial wind power development in lagging countries

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A R T I C L E I N F O

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A B S T R A C T

There is significant under-utilization of wind energy resources, particularly in countries that have high wind potential. From the 67 highest wind potential countries, 39 have installed less than 500 MW of wind power capacity, while the remaining countries have an average installed capacity of 20,596 MW. In the lagging countries, there is significant potential for sustainable value creation, however large investment gaps need to be closed. Entering a new market for wind power Original Equipment Manufacturers is complex and requires a prediction of the future market size. Quantitative research to promote wind power internationalization is scarce. The objective of this paper is therefore to estimate the market size by predicting the probability of commercial wind development in the lagging countries. The purpose is to help the Original Equipment Manufacturers in their market entry decisions. The second purpose is to provide an example how to reduce risk required to close the Sustainable Development Goals financing gap. Using a binary logistic regression model based on technological path creation theory, the probability for the 39 lagging countries to enter the wind power commercialization stage was predicted. Results show that 12 of the lagging countries have a high probability to commercialize wind energy. A new simulation-based approach was presented to stimulate wind power market entry. The prediction of adoption probability proves useful to reduce risk required to close the financing gap to achieve the Sustainable Development Goals.

1. Introduction

Renewable energy resources are more equally distributed globally compared to fossil and nuclear resources (UNDP, 2000). There are many countries with significant wind resources, however large shares of this capacity remain unexploited. From the 67 highest wind potential countries defined by Zwarteveen et al. (Zwarteveen et al., 2021a, 2021b), 39 have less than 500 MW wind power installed and, the remaining 28 countries have an average installed wind energy of 20,596 MW (International Renewable Energy Agency, 2020a). The technical potential in these high wind countries is $\geq$ 1 PWh/yr (Lu et al., 2009), which represents a generating capacity of on average $\geq$ 114,000 MW, or $\geq$ 380,000 MW of installed wind power with an assumed capacity factor of 0.3. It shows that specifically the 39 lagging countries have significant unused potential compared to the 28 frontrunners and that it is not the technical capacity that is limiting them from installing more wind energy. Of the 39 lagging countries, 36 are developing and emerging markets (as defined by the International Monetary Fund (2018)). In the net zero carbon strategy of the International Energy Agency (2021) wind energy is expected to grow 11 fold until 2050 with the majority of growth in emerging markets. This illustrates the importance and potential of sustainable development in the emerging world.

Successful triple bottom line post-pandemic recovery requires evidence-based economic analysis and initiatives to strengthen the local economy (Ranjbari et al., 2021). Increasing wind energy could support the targeted recovery: the job creation per 1 million USD spend under a stimulus program was 2.6 times higher for wind energy compared to oil and gas (Bacon and Kojima, 2011). Local job creation is one of the socioeconomic benefits wind energy brought to Europe (Ortega-Izquierdo and Río, 2020) and it is essential for sustainable development in emerging markets (Arnold, 2018). Increasing the wind power generation capacity in the lagging countries also contributes to achieving Sustainable Development Goal (SDG) 7, which is to ensure global access to affordable, reliable, sustainable, and modern energy (United Nations, 2018). Attracting significant financial resources is essential to achieve the SDGs (Barua and Chiesa, 2019). The private sector has an important role to achieve the power-related SDGs, yet a large investment gap exists (UNCTAD, 2014). Barua (2020) highlights a less engaged private sector

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as a high priority and critical challenge to close the investment gap and proposes to create attractive risk-return business models as a solution to promote private investment. The wind power Original Equipment Manufacturers (OEMs) that are the most successful in internationalization, measured in total abroad sales and number of countries covered (Yusta and Lacal-Arántegui, 2020), also suffer from high pressure on their margins resulting in recent profit warnings (Binnie et al., 2021; Thomas and Sanderson, 2021). Even though domestic environmental regulations in leading countries resulted for the local wind industry in global competitive advantages (Kuik et al., 2019), still, prudent market entry strategies are required to capture the global benefits. A reliable estimation of a future risk-return is needed before expansion decisions can be taken. However, unavailability of reliable data is another challenge regarding the gap in financing the SDGs (Barua, 2020). Generating data that can be used by wind power OEMs to estimate future risk-return of their market entry is essential.

Both advanced and emerging economies have reformed their electricity sector in the last decades (Jamasb, 2006). The main reason for privatization of the sector was to establish clear and stable price determination and incentives that restore financial viability (Newbery, 2004). In the process, the number and type of stakeholders involved with energy technology diffusion changed, providing a more important role for the private sector. Policies have an impact on private investment and vice versa (Cárdenas Rodríguez et al., 2015). Besides policy makers and private investors, wind power OEMs play an important role in wind energy diffusion: without their technology, wind energy can not be exploited. However, a market entry for a wind power OEM is an intricate strategic move. Internationalization into a new market can be done through export, licenses, joint ventures, and fully owned foreign investment (Buckley and Casson, 1998). Wind turbine technology is a complex export product. Localized production, transport, installation, commissioning, operation, and maintenance of wind turbines require the setup of a local company in each country where turbines are sold. Bidding on foreign wind power project supply tenders would be one market entry method, and Lacal-Arántegui (2019) defines five additional approaches to entering new markets specific to the wind power OEMs: joint ventures, licensing, acquisitions, developing wind projects or (partly) financing the wind projects. Based on the market entry of the automotive industry Sivakumaran et al. (2015) define two critical success factors: firstly market barrier-induced costs (country specific related entry costs, such as local content requirements) and secondly sales potential and synergies (estimation of future sales volume and potential cross-market synergies). Regarding wind energy, the barrier induced costs can be estimated up front before taking the market entry decision. However, predicting the sales potential is more difficult. Internationalization into a country without significant installed wind capacity means entering a market without noteworthy competition, which could result in first-mover advantages (Agarwal and Gort, 2001). Being a first-mover can also result in disadvantages, especially because of uncertainties in the market and complex green practices (Luan et al., 2013). If the market does not develop, the first-mover has unnecessarily invested in an expensive local setup. Therefore, market entry is only profitable in the long run if the sustainable returns of the sales exceed the barrier-induced costs. This highlights the critical importance of market forecasting for wind power OEMs.

The market size for wind energy can be described along four stages of path creation: pre-commercialization, early commercialization, commercialization, and widespread diffusion (Surana and Anadon, 2015). The objective of this paper is to estimate the market size by predicting the probability of entering commercial wind exploitation for the lagging countries in wind adoption. The purpose is to help OEMs in their market entry decisions. More broadly, the second purpose is to provide an example how to reduce risk required to close the financing gap to achieve the Sustainable Development Goals. This study uses a dataset created by Zwarteveen et al. (2021b) with the aim to predict the probability of the 39 lagging high wind capacity countries entering the commercialization stage. With todays and future's predicted probability, OEMs can have greater certainty when devising their market entry and market development strategy.

2. Method

Path creation theory explains how a nascent technology comes about, especially relevant in the early stages of diffusion. Paths and stages form the basis of the theory (Geels, 2002; Surana and Anadon, 2015). Alternatively, wind power diffusion can also be measured as 'wind power growth', often used to determine factors influencing the total installed wind capacity measured in MW (Popp et al., 2011). Because of the very low amount of wind energy installed in the 39 lagging countries, path creation can help to increase understanding how wind energy can evolve from the niches. Applying path creation theory to nascent wind power diffusion, Zwarteveen et al. (2021b) created binary logistic regression models to quantitatively model the transition between the stages. The first *(M1)* to model the transition from no wind to pre-commercialization (>1–50 MW installed wind power), the second *(M2)* to model the transition to early commercialization (>50 MW–500 MW installed wind power), and the third *(M3)* to model the transition to commercialization (>500 MW installed wind power). The accumulated wind power installation (International Renewable Energy Agency, 2020b) was transformed into binary the categories for each model. Based on a Systems Control inspired closed loop feedback mechanism, technology diffusion can be described along the 'desire for wind energy' (*why* is a country interested in wind energy), the 'mechanism of change' (*how* does wind diffusion take place) and 'disturbing factors' (such as war) (Zwarteveen et al., 2021a). Pioneering wind energy projects are frequently developed without supporting deployment policies (Steffen et al., 2018), hence the focus on the mechanism of change might not bring significant insight in early stages of wind diffusion. Therefore, the research variables of Zwarteveen et al. (2021b) were chosen to be related to the desire for wind energy (*why* is a country interested in wind energy) as this is particularly relevant in the first stages of path creation. The logic is that a mechanism of change will autonomously follow once the desire of change exists.

The purpose of this paper is to identify commercial opportunities in the lagging countries. Firstly, the binary logistic regression formula for the transition to the commercialization stage *(M3)* was simplified to predict the probability of commercialization. The model only took desire-related factors that influence wind energy diffusion into account, as this is argued to be the main driver for early path creation. Variables related to the mechanism of change – such as policies and grid connection – were not included. By using backward elimination (Heinze and Dunkler, 2017), non-significant variables were removed until only significant variables remained. This step reduced the original 15 explanatory variables from model *M3* (Zwarteveen et al., 2021b) to 9, listed in Table 1. Backward elimination excluded 6 of the 15 variables to their non-significance: the education index, electricity import dependency, energy import dependency, vested interests in oil-based electricity production, vested interests in solar energy production and the country classification (advanced economies or developing and emerging economies). The regression results of the simplified model are shown in Table 2. Binary logistic regression is non-linear, hence the regression coefficient (log odd) is not the same as the predicted probability. The size and sign of the coefficient are however related to the size and the sign of the predicted probability. The model fit (measured with the McFadden's pseudo-R squared (McFadden, 1974)) of the original model was 0.7, the simplified also achieved 0.7. This value demonstrates a substantial model fit (Chin, 1998).

The simplified regression model is used to predict the probability for stage transition to commercial wind *(P_{cw})* (UCLA, 2021):

$$P_{cw} = \frac{e^{a+b_4v_4+b_5v_5+b_9v_9+b_{10}v_{10}+b_{11}v_{11}+b_{12}v_{12}+b_{14}v_{14}+b_{15}v_{15}+b_{17}v_{17}}}{1+e^{a+b_4v_4+b_5v_5+b_9v_9+b_{10}v_{10}+b_{11}v_{11}+b_{12}v_{12}+b_{14}v_{14}+b_{15}v_{15}+b_{17}v_{17}}} \quad \text{Eq 1}$$

Table 1
The variables of the simplified model to predict the transition to commercial wind exploitation, listed with their sources (Source: adapted from (Zwarteveen et al., 2021b)).

Predictor variables		Explanation	Unit	Reference
Business case	v_4 Business case potential	Price advantage of wind energy compared to electricity price. Electricity price – levelized cost of wind energy	USD/MWh	(Euromonitor International, 2020; Global Petrol Prices, 2020; United Nations, 2020a) (International Renewable Energy Agency, 2019, 2020c)
Economic contribution	v_5 Unemployment rate	Urgency for a country to create jobs, as measured in unemployment rate	Fraction of labor force without work	The World Bank (2019a)
Environment	v_9 GHG emission	High CO_2 levels might influence choice for low CO_2 energy technology	CO_2 emissions (metric tons per capita)	The World Bank (2020)
	v_{10} Smog	High $PM_{2.5}$ levels might influence choice for low $PM_{2.5}$ energy technology	$PM_{2.5}$ air pollution, mean annual exposure in mg/m^3	The World Bank (2019b)
Spill over	v_{11} Neighbor influence	The effect of having neighbors with wind energy. Knowledge and products might spill over across borders.	Fraction of countries in geographical cluster that has adopted wind energy	International Renewable Energy Agency (2020b)
	v_{12} Globalization	Global partners with wind energy. Knowledge and products might spill over through globalized network	KOF globalization index, a composite globalization index including economic, social and political dimensions, measured per country	Gygli et al. (2019)
Vested interests	v_{14} Fossil - Gas	Existing fossil interests might have impact on wind exploitation	Gas based electricity production in kWh billion	United Nations (2020b)
	v_{15} Fossil - Coal	Existing fossil interests might have impact on wind exploitation	Coal based electricity production in kWh billion	United Nations (2020b)
	v_{17} Renewable - Hydro	Existing renewable interests might have impact on wind exploitation	Hydro based electricity production in kWh billion	United Nations (2020c)

Table 2
The regression results of the simplified model to predict the transition to commercial wind exploitation.

Variables		Log odds *(b)*
a	Constant	−167.060***
	Business case	
v_4	Business case potential	0.409***
	Economic contribution	
v_5	Unemployment rate	106.740***
	Environment	
v_9	GHG emission	−1.441**
v_{10}	Smog	0.861***
	Spill over	
v_{11}	Neighbor influence	38.539***
v_{12}	Globalization	1.568***
	Vested interests	
v_{14}	Fossil – Gas	0.148***
v_{15}	Fossil – Coal	0.020**
v_{17}	Renewable - Hydro	0.121***
Specifications		**Value**
	Number of Observations	431
	Number of Groups	36
	LR $chi^2(9)$	303.71
	Log likelihood	−68.813
	Prob > chi^2	0.000
	/lnsig2u	5.641
	sigma_u	16.783
	Rho	0.988
	LR test of rho = 0: $chibar^2(01)$	127.76
	Prob≥$chibar^2$	**0.000**
	Hausman	**CNA**
	McFadden's pseudo-R squared	**0.688**

* 0.1, ** 0.05, ***0.01 significant levels, CNA = Convergence not achieved for the fixed effect model.

where a is the constant, b_i the log odd and v_i the value of the explanatory variable with the number i. The set is screened for missing data and only countries with values for all variables in Table 2 are used. In detail, only Greenland was eliminated, as it did not have a value for 3 of the 9 considered variables. Calculating the probability for stage transition with 3 missing values would result in inaccurate outcomes. Estimating the missing values is one method of solving the missing data, however dropping cases when the missing data sample is rather small is a recommended method according to Tabachnick and Fidell (2013).

As a second step, the lagging countries are clustered according to their probability for stage transition to commercial wind. Binary logistic models predict an outcome of zero or one. A grid-based clustering approach (Gan et al., 2007) followed by the 1.5 Interquartile Range (IQR) rule to determine outliers of the group (Tabachnick and Fidell, 2013) is used to determine high, low, and in-between probabilities.

Lastly, simulations are executed using the prediction model to calculate the probability for future scenarios.

3. Data and results

The 67 high wind potential countries, as defined in the introduction, and their stage in wind development (based on 2019 installation (International Renewable Energy Agency, 2020a)) are shown in Table 3. Regarding the values for the independent variables (as per Table 1) for all lagging countries, see appendix A.

The focus is on the 39 countries before commercialization. Using the simplified prediction model, the probability to exceed 500 MW of wind energy is calculated per country. Greenland was removed because of insufficient data. The results are visualized in Fig. 1 (further details, including country numbers are located in Appendix B).

Using grid-based clustering, two rough categories are defined: countries with low probability and countries with high probability (Fig. 1). With changing input variables, binary logistic models have output values close to 0 and 1 with a limited tipping phase. Hence, all outliers of both groups are considered to be part of the tipping point group (Table 4). Using the 1.5 IQR method, 9 outliers were identified, 4 from the high probability group and 5 from the low probability group. Two outliers can be visually identified as they are clearly not located on the 0% and 100% line (Fig. 1 - country number 22 and 23). The other outliers are closer to the remaining values (details in Appendix B). This illustrates that only small changes in the values of the explanatory values result in a change from very close to 0% to very close to 100% in predicted probability or vice versa.

The results of both steps in the clustering analysis split all lagging wind adopters into three groups of low, high, and tipping probability to enter full commercial wind (Table 5).

Table 3
High wind potential countries grouped into different stages of commercialization (International Renewable Energy Agency, 2020a).

Stage	Countries (2019 allocation)	
Wind energy: commercialization (>500 MW installed)	Argentina	Morocco
	Australia	Netherlands
	Brazil	New Zealand
	Canada	Norway
	Chile	Pakistan
	China	Poland
	Denmark	South Africa
	Egypt	Spain
	France	Sweden
	Germany	Turkey
	India	Ukraine
	Ireland	United Kingdom
	Japan	United States
	Mexico	Uruguay
Wind energy before commercialization (<500 MW installed)	Afghanistan	Mali
	Algeria	Mauritania
	Angola	Mongolia
	Belarus	Mozambique
	Bolivia	Namibia
	Chad	Niger
	Colombia	Nigeria
	Congo DR	Oman
	Czech Republic	Paraguay
	Eritrea	Russia
	Ethiopia	Saudi Arabia
	Greenland	Somalia
	Iceland	Syria
	Indonesia	Tanzania
	Iran	Tunisia
	Iraq	Turkmenistan
	Kazakhstan	Uzbekistan
	Kenya	Venezuela
	Libya	Zambia
	Madagascar	

Table 4
Outliers of the high and low probability groups determined with the 1.5 IQR method.

Group	Outliers
High probability group	Namibia
	Iceland
	Kenya
	Tunisia
Low probability group	Libya
	Paraguay
	Iran
	Bolivia
	Belarus

Table 5
Lagging countries and their predicted probability to start wind power commercialization (which is to exceed 500 MW of installed capacity).

Low	Tipping point	High
Turkmenistan	Namibia	Indonesia
Angola	Iceland	Eritrea
Ethiopia	Kenya	Nigeria
Kazakhstan	Tunisia	Colombia
Uzbekistan	Libya	Mali
Oman	Paraguay	Saudi Arabia
Syria	Iran	Niger
Venezuela	Bolivia	Chad
Congo DR	Belarus	Somalia
Madagascar		Mauritania
Afghanistan		Russia
Zambia		Czech Republic
Tanzania		
Iraq		
Mongolia		
Mozambique		
Algeria		

4. Discussion

This paper considered 39 high wind potential countries with less than 500 MW wind energy capacity installed. It used a binary prediction model to estimate the probability of breaking this threshold, entering full commercial wind exploitation. After the screening for missing data, 38 countries remained. The 38 countries were split into 3 groups, low, high, and tipping probability. But what are the implications of the distribution of the countries in these groups?

4.1. Low probability

17 countries have a low probability of entering full commercial wind utilization. This is the largest group in Table 5. It contains 8 countries from Africa, 4 from Central Asia, 4 from the Middle East, and 1 from Latin

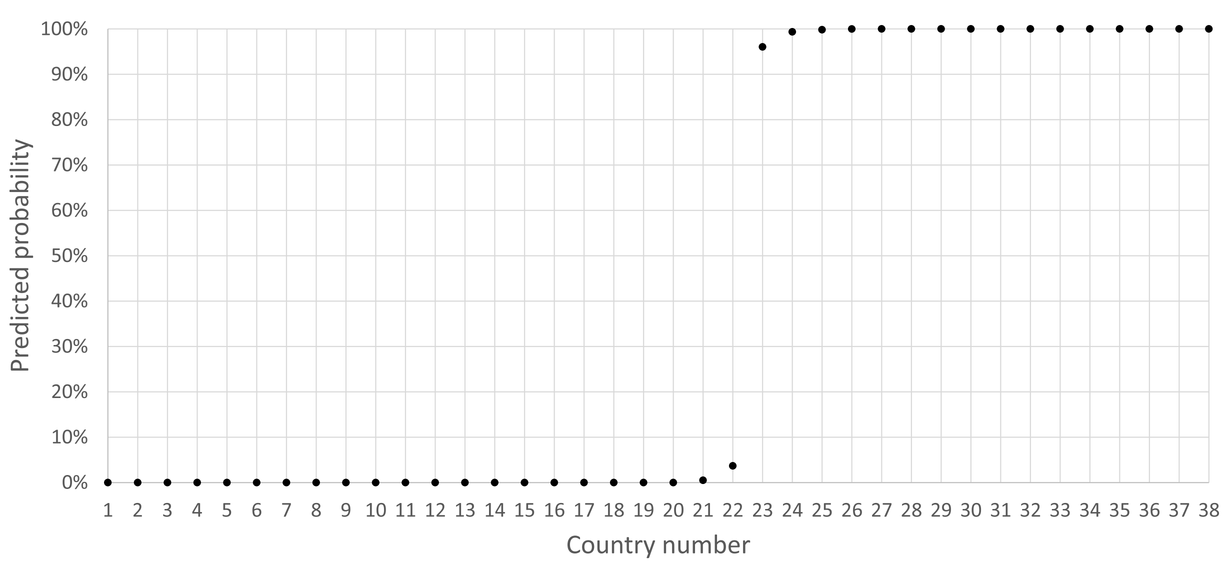

Fig. 1. Predicted probability of exceeding 500 MW of wind power, visualized per country (country numbers according to Appendix B). Grid based clustering, using steps of 10%, results in 22 countries in the low probability group and 16 countries in the high probability group.

America. It is unlikely that these countries will install wind turbine capacity exceeding 500 MW in the near future. However, some of the countries have already reached the early commercialization stage, for example Ethiopia with 324 MW wind installed in 2019 (International Renewable Energy Agency, 2020a).

4.2. High probability

With 12 countries, the high probability group is the second largest group in Table 5. 7 are from Africa, 2 from Europe, 1 from the Middle East, 1 from Latin America, and 1 from the Indo Pacific region. No country from Central Asia is present in this promising list. The high probability indicates that it is likely that the accumulated installed wind capacity will soon exceed the 500 MW. Signs can already be witnessed, examples are the 1000 MW signed wind projects in Russia (Lee, 2021), the finalized tender of 400 MW in Saudi Arabia and the plans for a second tender (Aguinaldo, 2020), and the plans to build multiple wind farms exceeding 500 MW in combined capacity in Colombia (Azzopardi, 2021). However, the prediction model has a model fit of 0.7, meaning the chosen explanatory variables only explain 70% of the variation in the dependent variable. There are other factors explaining the remaining 30% in variation of the dependent variable. Some countries in the high probability list have not installed any wind power yet. As proposed by Zwarteveen et al. (2021a), it is likely that the 'mechanism of change' (e.g. grid availability and feed in tariff policies) and 'disturbing factors' (such as war) also influence the probability for significant wind growth.

4.3. Tipping probability

The countries with tipping probability form with a count of 9 the smallest group in Table 5. Depending on how the values of the variables of table A-1 (Appendix A) change, these countries can quickly develop into either low or high probability countries. Within the group, Iran is the country with the largest population, an indication of total energy demand (Yoo and Lee, 2010) and total environmental impact (Chertow, 2000). To understand the sensitivity, simulation of Iran's probability to exceed 500 MW of wind energy is shown in Fig. 2.

It can be seen that small changes in the individual variables result in disproportionate changes in probability. Table 6 shows two scenarios: globalization of Iran and a further isolation of Iran, scenarios that are potentially the outcome of the US ambitions on reaching a new nuclear deal (Wadhams and Wainer, 2021). For the globalization scenario, higher electricity prices resulting in a better business case, a higher globalization factor, lower unemployment and higher smog caused by higher productivity has been chosen. The rationale is that an increase in globalization results in an uptake of economic activity with an improvement of free-market mechanisms. This scenario results in a high probability. For the opposite scenario, the isolation scenario, a lower globalization factor, and a higher unemployment has been chosen. This results in a low probability.

4.4. Implications for the OEM

Countries with high wind potential and low wind installed capacity form significant business opportunities for wind power OEMs. However, entering new markets comes at a cost. Opening a local business, localization of supply chains, hiring, and training of new employees result in financial barriers. Having certainty about how the market develops is key when taking the decision on market entry and market development. The categorization in Table 5 is a valuable support in taking these decisions. It provides focus on countries that have a high probability of entering full commercial wind utilization. A market entry into these markets is likely to bring volume related benefits. It also provides a list of countries that are less likely to develop a solid wind business in the near future. Entering these markets comes at a risk of potentially winning one project, without a succession of other projects. This would be costly. The tipping countries in the middle indicate that given the right circumstances, the group of the high probability countries can grow. Being a first mover could bring some competitive benefits. The downside is that, if the circumstances change, these countries can also become low probability countries. It is worth noting that Table 6 is the categorization with the latest available data. However, next year, the explanatory variables will have different values and therefore the consistency of the 3 groups is likely to be different. To determine the fitting market entry and market development strategy, up-to-date values are to be used for a country specific simulation, combined with an understanding of the factors 'mechanism of change' and 'disturbing factors' (section 4.2). The complete decision model is shown in Fig. 3.

A market entry strategy should take the existence of potential competitors into account (Buckley and Casson, 1998). A first mover market entry results in a monopoly position, however it can introduce a high cost. As such the OEM growth strategy should consider the competitive strategy related to market entries. Based on the country analysis and the OEM growth strategy, the two decisions (market entry today yes/no, wind market development yes/no) can be made. Together, these two decisions shape the OEM country strategy, as further detailed in Fig. 4.

Four different approaches to new wind markets are proposed:

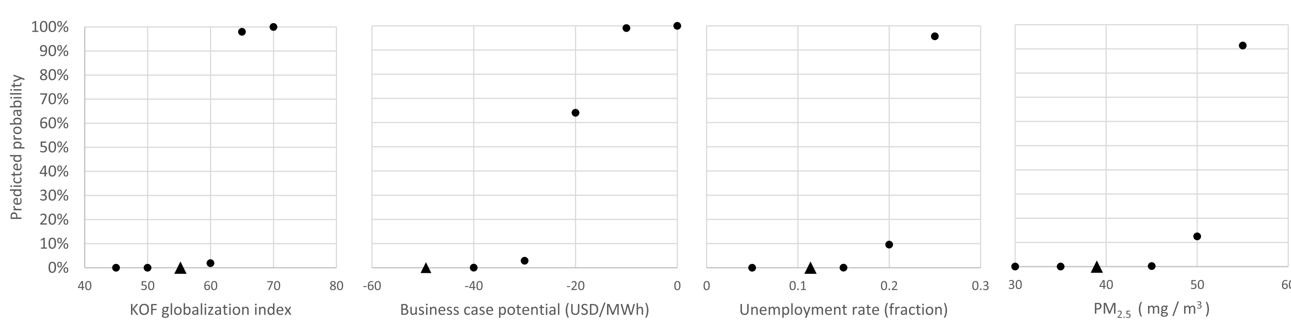

Fig. 2. Predicted probability simulation, visualized for the tipping country Iran. The triangles highlight the current value of the variables.

Table 6
Simulation scenarios and outcome for Iran.

Scenario	Business case potential	Globalization	Unemployment rate	Smog	Probability	Probability Group
Global	−30	60	0.08	60	99.999999%	High
Isolate	−50	50	0.15	40	0.000027%	Low
Today	−49.3942	55.2214	0.11382	38.9788	0.001072%	Tipping

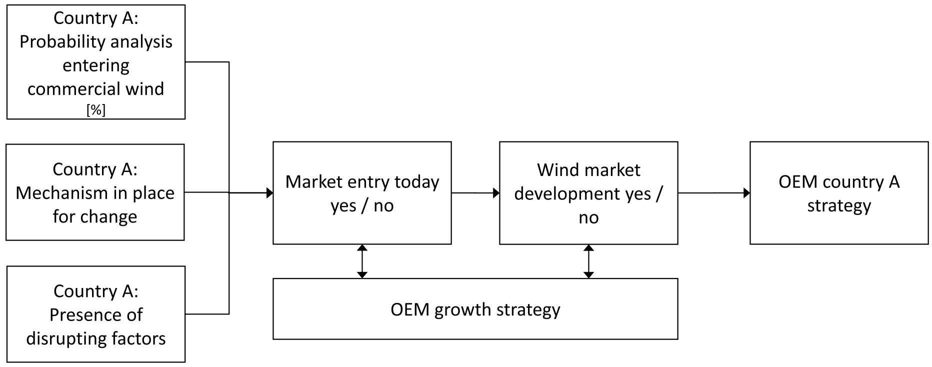

Fig. 3. Combining the country analysis with the OEM strategy to make the specific market entry and development decisions.

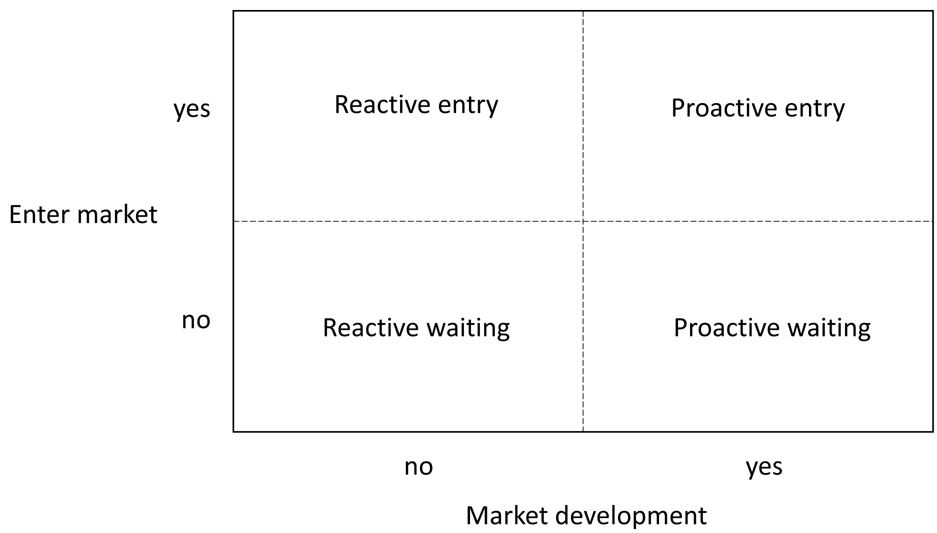

Fig. 4. The OEM country strategy for new markets, split into 4 approaches.

- Reactive entry: enter the market and continue to respond to opportunities. The market develops by itself or the market does not develop by itself but either way the OEM should wait for tenders and respond to them competitively. By having a presence in the market, the speed of responding to tenders is high.
- Proactive entry: enter the market and improve the adoption probability by influencing the values of the explanatory variables, such as the business case potential or globalization. Potential supporting strategies to maximize impact could be joint ventures, licensing, acquisitions, developing wind projects, and (co) finance wind projects (Lacal-Arántegui, 2019).
- Reactive waiting: monitor the conditions of a country, reassess periodically the market entry decision.
- Proactive waiting: improve the adoption rate by influencing the values of the explanatory variables and reassess periodically the market entry decision. Potential supporting strategies to maximize early impact could be collaborate with industry organizations and trade networks.

Depending on the company growth strategy and the competitive environment, per country the OEM can select the fitting approach. Taking the earlier example of Iran: the probability analysis shows a tipping probability regarding the commercialization of wind energy (Table 6). Even though a feed-in-tariff is in place (Hosseinioun and Bashiri, 2020), the last large wind farm exceeding 50 MW was installed in 2016 (International Renewable Energy Agency, 2020b). Hence the current mechanism of change is not very effective. The present US sanctions (Wadhams and Wainer, 2021) form a disrupting factor, highly limiting international investments in or export to Iran. Assuming an aggressive but frugal growth strategy of a wind power OEM, reactive entry would introduce costs without soon to be expected revenues. A pro-active entry would introduce even higher costs to lobby regarding e.g. clean air initiatives. And with the current US sanctions in place, it is not likely that a significant wind energy growth, for which export to Iran is necessary, can take place. This leaves two options: pro-active waiting and re-active waiting. Given the large amount of high probability countries and the OEMs desire for frugal market entry, focussing on the existing high probability countries would make the best use of corporate resources. This results in a re-active waiting market strategy for Iran. A new assessment for the market entry and market development strategy is to be made if alterations to the current US sanctions occur.

4.5. Policy implications

The implications for policy follow the three input elements presented in Fig. 3. Firstly, the presence of disrupting factors should be minimized. Sudden significant effects such as war or disasters form blocking factors for wind energy growth (Zwarteveen et al., 2021a). Efforts need to be put in place to ensure political stability (Friebe et al., 2014). Secondly, an effective mechanism of change is needed. Multiple effective mechanisms to stimulate wind power growth can be selected (Friebe et al., 2014; Keeley and Matsumoto, 2018; Polzin et al., 2015). However, constancy is needed to secure long-term market entry investments, hence uncertainty in policies, resulting in boom-bust cycles, should be avoided (Barradale, 2010). Lastly, policy makers should simulate the probability for their country to enter the commercial wind stage. This is novel. It would enable the country to forecast and adjust the attractiveness for OEMs (and other players in the wind industry) to enter their market. Table 1 shows the 9 factors influencing the probability to enter the commercial wind stage. These factors highlight the importance of integrating the wind energy policy with economic policy (electricity pricing), the foreign trade policy (neighbor influence and globalization efforts) and the generic energy policy (diversification of energy generation portfolio). The first step would be to calculate the current probability for commercial wind adoption, by using equation (1). If this results in low or tipping probability, scenarios are to be created for future values of the influencing factors. Iterations should be executed until the probability is high. The last step is to work backwards from the values of the influencing factors of the high probability scenario to policies to achieve those. Creating long term integrated policies enable the simulation of future adoption probability for commercial wind and allow for long term holistic socio-economic and environmental scenarios.

4.6. Limitations

This study only considered the 67 highest wind potential countries. Further research is needed to determine if the model could also be applied to other countries with moderate wind resources. The model fit might be less accurate (currently it is 0.7), however by combining it with the mechanism of change and disturbances, the approach is likely to be of significant value to OEMs.

The categorization of the countries was based on the latest available data from the dataset of Zwarteveen et al. (2021b). However, the data for some variables dates to 2016. This dataset was chosen since it provided the latest, consistent data for all countries. For analysis of specific country, contemporary data could be used.

It should also be noted that onshore and offshore were both considered in the models. With the current growth of offshore extending into emerging markets such as Vietnam (Afanasiev, 2021), further research could focus on a specific offshore model.

Furthermore, the focus of this paper was on OEMs, however the findings might also be useful for international developers and international independent power producers who need to choose between different markets to place their investment.

5. Conclusions

The aim of this paper was to estimate the probability that late adopters of wind energy would begin significant wind utilization. Using a binary logistic probability model, 39 high wind potential countries with currently less than 500 MW installed were categorized into 3 groups: high probability, tipping probability, and low probability to enter commercial wind exploitation. Simulation showed that countries with tipping probability can either move quickly to the low or high probability group.

By combining the outcome of the prediction model with information on the mechanism of change and potential disturbing factors, the wind power OEM can make informed decisions on market entry and market development for new wind markets.

The broader implication for addressing the private investment gap to achieve the SDGs is that a thorough understanding of the local market conditions is needed to calculate the likelihood of long-term success. Simulating the probability of entering the commercialization stage based on path creation theory is a helpful method to de-risk investments related to market entries of sustainable technology. The triple bottom line should be considered simultaneously both from a private company and the local countries point of view. Regarding the economic value, only a reliable profitable business case both for the company (favourable risk-return balance) as well as for the country (local value creation resulting in employment) is needed to close todays significant SDG financing gap.

CRediT authorship contribution statement

Jan Willem Zwarteveen: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft. **Andrew Angus:** Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

• The main author is employed by Siemens Gamesa Renewable Energy.

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Appendix A. Variable values

Table A

1. Explanatory variables and their values per country (dataset (Zwarteveen et al., 2021b)). Greenland removed due to missing data.

Country	v4	v5	v9	v10	v11	v12	v14	v15	v17
Afghanistan	−16.9421	0.11118	0.245101	56.9108	0.6	38.1618	0	0.107	0.829
Algeria	−25.9565	0.11704	3.69916	38.884	0.555556	56.778	74.894	0	0.638
Angola	−43.9855	0.06886	1.20286	32.3885	0.545455	41.4786	0	0	7.653
Belarus	1.08692	0.04595	6.13371	18.7656	1	68.619	33.507	0	0.405
Bolivia	37.1449	0.03498	1.95851	21.569	0.857143	59.156	7.189	0	2.234
Chad	172.362	0.01891	0.069756	66.0292	0.555556	41.0539	0	0	0
Colombia	64.1883	0.09707	2.03038	16.5272	0.857143	65.0934	10.822	3.153	56.648
Congo DR	−7.92757	0.04236	0.025645	44.9093	0.545455	45.2509	0.002	0	9.482
Czech Republic	127.29	0.01933	9.6739	16.0712	1	85.6801	3.747	41.206	3.04
Eritrea	145.319	0.05144	0.210687	48.0302	0.666667	30.3343	0	0	0
Ethiopia	−43.9855	0.02081	0.143525	38.9787	0.454545	44.6341	0	0	12.957
Iceland	46.1593	0.02842	6.15468	6.48115	1	72.2403	0	0	14.059
Indonesia	28.1304	0.04687	2.15376	16.5027	1	63.3752	50.511	187.645	18.6324
Iran	−49.3942	0.11382	8.3167	38.9788	0.4	55.2214	257.955	0	15.051
Iraq	−34.971	0.12822	5.1914	61.6362	0.6	44.1386	27.761	0	2.176

(continued on next column)

Table A (*continued*)

Country	v4	v5	v9	v10	v11	v12	v14	v15	v17
Kazakhstan	−25.9565	0.0459	13.8927	13.8243	0.4	64.6785	18.466	71.851	11.21
Kenya	100.246	0.02642	0.365117	28.5784	0.454545	55.9294	0	0	2.7768
Libya	−43.9855	0.18563	7.78851	54.2547	0.666667	55.445	22.834	0	0
Madagascar	37.1449	0.01758	0.156877	22.5423	0.545455	50.0556	0	0.116389	0.7885
Mali	127.29	0.07224	0.176967	38.5266	0.666667	48.7162	0	0	1.105
Mauritania	226.449	0.09548	0.657914	47.423	0.555556	52.2851	0	0	0
Mongolia	−16.9421	0.06011	8.30017	40.1129	0.4	66.5354	0	5.69417	0
Mozambique	37.1449	0.03241	0.285402	21.2987	0.545455	54.7181	2.93	0	14.06
Namibia	46.1593	0.20273	1.79304	25.3588	0.454545	59.1722	0	0.066	1.593
Niger	46.1593	0.00475	0.097016	94.0538	0.666667	47.6051	0	0.23034	0
Nigeria	1.08692	0.08096	0.647285	71.7982	0.454545	56.1364	26.67	0	5.527
Oman	−34.971	0.02671	14.1671	41.1152	0.6	62.9017	35.088	0	0
Paraguay	−7.92757	0.04809	1.09287	11.9091	1	63.1461	0	0	59.5634
Russia	−7.92757	0.04585	11.9994	16.1602	0.4	72.5747	518.659	168.046	187.131
Saudi Arabia	−16.9421	0.05927	17.3676	87.9454	0.4	66.1004	209.69	0	0
Somalia	848.449	0.11351	0.045496	32.0346	0.454545	31.2857	0	0	0
Syria	−43.9855	0.0837	1.65177	43.7573	0.6	51.459	10.559	0	0.754
Tanzania	19.1159	0.0198	0.225685	29.0766	0.545455	51.2824	4.227	0	2.35
Tunisia	1.08692	0.16022	2.6484	37.656	0.555556	68.0515	19.715	0	0.017
Turkmenistan	−43.9855	0.03913	12.4736	21.7677	0.6	41.1237	22.534	0	0
Uzbekistan	−34.971	0.05917	2.88279	28.4559	0.6	47.266	49.2737	3.249	8.42737
Venezuela	−34.971	0.08801	5.50071	17.0086	0.857143	53.6092	36.507	0	64.847
Zambia	−25.9565	0.11425	0.314183	27.438	0.545455	57.0869	0	1.335	12.198
Year of data	2019	2019	2016	2017	2019	2017	2017–2018	2017–2018	2017–2018

Appendix B. predicted probability

Table B
1. Predicted probability of exceeding 500 MW of wind power per country

County number	Country	Predicted probability of exceeding 500 MW
1	Turkmenistan	0.000000%
2	Angola	0.000000%
3	Ethiopia	0.000000%
4	Kazakhstan	0.000000%
5	Uzbekistan	0.000000%
6	Oman	0.000000%
7	Syria	0.000000%
8	Venezuela	0.000000%
9	Congo DR	0.000000%
10	Madagascar	0.000000%
11	Afghanistan	0.000000%
12	Zambia	0.000000%
13	Tanzania	0.000000%
14	Iraq	0.000000%
15	Mongolia	0.000000%
16	Mozambique	0.000000%
17	Algeria	0.000020%
18	Libya	0.000109%
19	Paraguay	0.000804%
20	Iran	0.001072%
21	Bolivia	0.508415%
22	Belarus	3.690523%
23	Namibia	96.029546%
24	Iceland	99.363971%
25	Kenya	99.830275%
26	Tunisia	99.995971%
27	Indonesia	99.999319%
28	Eritrea	99.999486%
29	Nigeria	99.999792%
30	Colombia	100.000000%
31	Mali	100.000000%
32	Saudi Arabia	100.000000%
33	Niger	100.000000%
34	Chad	100.000000%
35	Somalia	100.000000%
36	Mauritania	100.000000%
37	Russia	100.000000%
38	Czech Republic	100.000000%

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