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Research Article

Complementarity for Wind Power in Turkey: A Correlation Analysis Using XGBoost

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Abstract

Generation from resources such as wind power and photovoltaics is highly variable and relatively unpredictable. This variability incurs costs, especially when wind and photovoltaic generation is low due to weather conditions, necessitating substitution by other energy sources to meet demands through market forces. The extent to which thermal leg or reservoir storage hydropower plants can fill or substitute this gap is a matter of interest. This is explored in the literature through complementarity between variable renewables and alternative energy sources. To address this question, this study uses hourly data from Türkiye for the period between 2015 and 2020, predicting generation from the thermal leg and reservoir storage hydropower plants with XGBoost machine learning algorithm, based on different price and generation levels of wind power. The results indicate a positive correlation between wind power and reservoir storage hydropower, which concludes as the lack of complementarity between these sources in the Turkish context. It is observed that the feed-in-tariff system, which guarantees a price in US dollar per kWh for energy from reservoir storage hydropower, decreases the incentive for substituting wind power, thereby cancelling out the balancing role of the reservoir storage hydropower. Conversely, for positive prices, the natural gas-fueled plants appear to substitute between 63% and 116% of the loss in wind power generation, while the rest of the thermal leg substitutes for 43% to 59% of this loss in wind power, according to our calculations. These outcomes reveal a complementarity (over-substitution in this case) between wind power and the thermal leg.

Keywords: complementarity, wind power, thermal leg, reservoir storage hydropower, XGBoost, prediction.

Abbreviations and *Nomenclature*

CCGT: combined-cycle gas plants **CHP:** combined heat and power **EXIST:** Energy Exchange İstanbul **IEA:** International Energy Agency
kWh: kilowatt-hour **MWh:** megawatt-hour **OCGT:** open-cycle gas turbines **PSH:** pumped storage hydropower **PV:** photovoltaic
RESM: renewable energy support mechanism **RoR:** run of river **RSH:** reservoir storage hydropower **TETC:** Turkish Electricity Transmission Co.
VRE: variable renewable **XGBoost:** extreme gradient boosting

Introduction

Due to the ongoing climate change, the substitutes to fossil fuels are encouraged worldwide. However, electricity generation from some renewables, such as wind and photovoltaics, is highly variable and dependent on weather conditions. Moreover, due to the low marginal cost of generation, wind power is said to operate whenever the wind is on, bidding down to zero prices. Whenever generation by wind power plants decreases, it must be supplemented by fossil-fueled plants (the thermal leg) or by reservoir storage hydropower (RSH) plants to satisfy demand. In the literature, this phenomenon is examined as the complementarity between variable renewables and alternative energy sources. In this study, the complementarity between variable renewables (VRE), specifically wind power, and RSH plants, as well as the thermal leg, is investigated for Türkiye.

The complementarity between wind and solar power (Guo et al., 2023.), between hydropower and thermal power (Wang et al. 2019), between wind and hydropower (Cheng et al., 2023), between solar and hydropower (Caldeira et.al., 2023) has been studied in the literature. The complementarity within variable renewables should be distinguished from the complementarity between the variable renewables and dispatchable alternatives. In the former, all generation is exogenous, whereas in the latter, dispatchable power plants substitute for the variable renewable sources through market forces, i.e., the signals of the day-ahead price. This study investigates the complementarity in the latter context, which has never been done for Türkiye.

Substitution power depends on how well the managers of plants with alternative sources can predict generation, how dispatchable they are, and how well they optimize. Variable renewables introduce uncertainty to the power system. Integrating variable renewable resources requires flexibility of the power system. Optimization in power system by the thermal leg operators in that case have been studied by Coban and Lewicki (2023). In this paper, the mechanism for substitution is the market mechanism: the plants using alternative sources will predict the price and should include energy predictions from other plants while predicting. Thus, considering that the energy from wind power will rise that day, they can predict that the price will fall and plan to decrease their generation accordingly (and vice versa). The methodology used for prediction is a machine learning algorithm, XGBoost. We use

XGBoost to predict energy levels from RSH plants and from the thermal plants for different price and wind power levels. The scientific aim of this work is to demonstrate how alternative resources can substitute for wind power at different price levels via the market mechanism. If the substituting plants can predict the price perfectly, depending on their dispatch ability, they can adjust their output to capitalize on price changes, i.e. when the wind is not blowing, they can predict that the price will rise and increase their output. In this sense, the prediction measures how well the substituting plants respond to changes in wind power. The subject of the research was to obtain the correlation between the predicted electricity generation from selected resources, e.g. natural gas plants with the wind power to be able to demonstrate the complementarity between wind power and natural gas plants. Other than natural gas, thermal leg except for natural gas and reservoir storage hydropower plants and their complementarity with wind power was investigated. The novelty of this research is due several subjects that it investigates; this research investigates the complementarity between thermal leg including natural gas and the thermal leg except for natural gas plants separately, which was examined before only by Wang et.al (2019). In Wang et al. (2019) research, an econometric time series model is used to investigate the subject. In the current research machine learning algorithms are used for prediction, contrary to former research. Similarly, the complementarity between reservoir storage hydropower and wind power is widely investigated in the literature, but machine learning methods are used for this first time in this study. The current research is the only research that investigates the complementarity issue with Turkish data for Türkiye.

This article is organized as follows: In the introduction section mentions wind power and the importance of wind power in Turkish power system, also introduces the property of variability of the wind power as an intermittent resource. The working of the market mechanism in Turkish wholesale electricity market is discussed, and the importance of prediction is mentioned in the market mechanism. In the materials and methods section the how the data is obtained, the coverage of the data and properties of the data is discussed, the prediction method of XGBoost as a machine learning algorithm is introduced, the three models which differ by the explained variables are introduced. Results section introduces the results of the prediction and metrics and discussion and conclusion section discuss the results of the research.

Wind Power in Türkiye as a Variable Renewable Resource

In Türkiye, electricity generation from renewables has increased rapidly over the last decade. By the year 2019, 44.18% of total licensed electricity generation came from renewable resources, and 13.79% of total licensed and unlicensed electricity generation was from wind power and PV, with the remainder generated mostly from hydro resources (Enerdata intelligence, 2020). Table 1 presents the shares of each resource in total licensed energy generation in Türkiye for the year 2019. Government subsidies and regulatory incentives played a significant role in the increase in renewable generation. These incentives include the establishment of the Renewable Energy Support Mechanism (RESM) and a tariff guarantee where a set price over US cents per kWh was applied to the participants of the RESM as a subsidy (Öztürk and Serkendiz, 2018; Kurucu, 2019). The feed-in-tariff which guarantees a price of 7.3 US cents per kWh for wind and all kinds of hydropower resources, was implemented for RESM participants for 10 years beginning from the year they first participated in the mechanism (Law on Renewable Resources numbered 5346, 2005). This law was effective until 31.12.2020. We used hourly energy generation from wind power, RSH, natural gas, lignite, stone coal, imported coal, fuel oil and day-ahead electricity prices over a 5.5 year period.

Wind power, which constitutes 7.04% of Türkiye's total licensed electricity generation, is categorized as a variable and non-dispatchable renewable resource. The variability of wind power has been highlighted in many studies including Itiki et al., (2011) and De Groot, (2016). This variability decreases as more wind power plants are considered together (Milligan et al.,2009). Location also matters, as wind power plants in windy locations are less costly to integrate into the system (Katzenstein & Apt, 2012). PV energy is like wind energy in terms of dispatch ability, variability and low marginal costs. In Türkiye, as of 2020, PV energy is produced in negligible amounts as part of licensed generation.

An important source while filling the gap due to the VRE are potentially the hydropower plants. (Denault et al.,2009; Cantao et al.,2017; Chiemelu et al., 2019; Jurasz et al., 2020; Risso et al. 2018) Hydropower sources in Türkiye include run-of-river (RoR) hydropower plants, reservoir storage hydropower plants (RSH), and pumped storage hydropower plants (PSH). RoR hydropower plants are built on rivers and utilize the energy from running water. RSH is the most significant source of electricity in Türkiye, accounting for 22.64% of the total electricity in 2019. RoR hydropower is another significant source of electricity generation.

Generation from renewables, specifically from wind and PV sources, depends on external factors like weather. Once such energy is present, the marginal cost of electricity generation from these sources is equal to operational costs, which are very low or zero (Pikk & Viiding,2013). These plants are, therefore, expected to operate at their highest capacity all the time. The generation from such sources is considered inflexible, meaning they do not respond to price changes. At times when VRE sources generate low levels of electricity due to weather or seasonal conditions, the security of supply is maintained by peaking plants including RSH and the thermal leg. The remainder of the electricity demand is thus satisfied by "dispatchable power plants", which are the source of flexibility in the electricity generation system. These plants can be categorized into baseload units, mid-merit units and peaking plants, according to the flexibility of operation in ascending order. Baseload plants include nuclear power plants and part of the coal powered plants. The security of supply, on the other hand, depends on more flexible plants, which are the semi-flexible "mid-merit units" and the "peaking units". These satisfy the peak generation remaining from the base load when demand is at its peak (de Groot,2016). Such plants include reservoir storage hydropower (Van Ackere & Ochoa, 2010) and the thermal leg, which includes combined-cycle gas plants (CCGT), part of the coal powered plants, diesel turbines, and open-cycle gas turbines (OCGT) (De Groot, 2016). Gas-fired combined-cycle plants play a significant role in the flexibility of generation (Moreno & Martinez Val, 2011). The substitutability of VRE by the thermal leg is due to the dispatch ability and flexibility of fossil fuel plants. CCGT, OCGT, steam turbine, hydro power, CHP, and fuel oil plants are flexible up to 100% of their capacity almost all the time, considering 6-hour periods. Coal-powered plants are about 50% flexible in these intervals. Over a 36-hour period, it can be observed that all coal-powered plants are also flexible at 100% (IEA, 2011). Another issue affecting flexibility is the performance of the fossil-thermal leg while adjusting for changes in price.

Table 1. Share of selected resources in electricity generation in Türkiye for the year 2019

Renewables Share in Total Licensed Generation in Türkiye in 2019	
Wind Power	%7,04
PV	%0,07
RSH	%22,64
Run-of-River	%7,71
Geothermal	%2,84
Other	%1
The Share of the Thermal Leg in Total Licensed Generation in Türkiye in 2019	
Natural Gas	%18,92
Lignite	%16.12
Imported Coal	%20,83
Stone Coal	%1.18
Asphaltite Coal	%0.80
Fuel Oil	%0.32
Other	%0.05
Total	%100

Source: EXIST and own calculations

Price Prediction in the Market Mechanism

Price prediction by energy producers is important because it enables electricity arbitrage and allows them to submit the most profitable bids (Diaz et al., 2019). In predicting prices, producers should consider the generation of energy from various sources. Predictions for wind energy include time series models and meteorological modelling. Within the realm of time series modelling, machine learning methods such as artificial neural networks are notable (Giebel et al., 2011). Exizidis et al., (2017) modeled how the publicization of wind power forecasts increases competitiveness in the power market. The substitutability of thermal and RSH plants will depend on their predictive power, as well as their dispatch ability. Conversely, forecast errors also prevent the substitution of VRE by alternative sources. Forecast errors for wind energy vary from 4.5-15%, and for PV from 2.3-13% (Brouwer et al., 2014). In Türkiye, wind power forecasts are made public through the transparency platform by EXIST.

The substitutability between VRE and other sources has been investigated in various studies, focusing on the impact of VRE on the electricity system. These effects include an increase in reserves and a decrease in the efficiency of thermal plants (Holttinen et al.,2012), (de Groot, 2016). Brouwer et al., (2014) reviewed the impact of VRE on generation from thermal generators. According to their study, three kinds of modelling approaches can be implemented. The first, "detailed modelling", simulates the power system in detail, including the need for extra reserves to compensate for potential shortages due to power plant failure, errors in load predictions, and errors in VRE predictions. The results point to increased reserves with higher VRE penetration, and the displacement of thermal and other plants based on ascending marginal cost order, termed "merit-order displacement". This displacement occurs over a relatively long-time interval, approximately a decade (Brouwer et al., 2014).

In "crude modelling", the impact is studied without including the mechanism of action, using aggregate values and is mostly based on a region. "Cost modelling" quantifies the impact of wind energy on the economy. An example of "cost modelling" is the work by Hirth, (2016), where the effect on the relative price of electricity from wind energy (relative to other sources) is quantified. Additionally, Coban and Lewicki (2023) investigated the optimization of the thermal leg operators when the generation by renewables is not enough to satisfy the demand.

In our study, we adopted a similar approach, focusing on the replacement of wind power by alternative sources in Türkiye. The substitution effect we considered occurs within a day. The present paper may serve as an example of "crude modelling" as mentioned by (Brouwer et al., 2014), presenting results from a general aggregate simulation model for Türkiye.

Materials and Methods

In the electricity markets of Türkiye, the period between 2000 and 2017 marked a transition to a more competitive market. A portfolio-based electricity market system was established by the authorities, managed by Energy Exchange Istanbul (EXIST). Three markets were established under the management of EXIST and the Turkish Electricity Transmission Corporation (TETC), differing by the agreement time relative to the electricity exchange time. In all the three markets, day-ahead market, intraday market and balancing power market, the price equating supply to demand is managed and set by the managing authorities. Market participants must eventually balance their portfolios, if they cannot do so in the initial markets, they try to balance in subsequent markets, meaning they must deliver or purchase the promised amounts at the promised time.

Another service provided by EXIST is the availability of electricity-related data, made public through an online "transparency platform" (EXIST, 2020). The hourly prices formed in the aforementioned markets, as well as the hourly demand and generation by all types of power plants, are made public on this platform. On the EXIST platform, energy planning from different plants is categorized according to the resource used by the plant, and energy output according to plant type is unavailable. In this paper, therefore, we categorized energy output from resource types.

All the data used was taken from the transparency platform provided by EXIST. As for price data, hourly day-ahead prices were used. Generation in MWh includes the planned generation made available by the producers in the day-ahead markets. For the generation from the thermal leg, hourly generation from stone coal, imported coal, lignite, fuel oil, imported coal, natural gas plants were obtained. Natural gas plants and generation from other fossil fuel resources were examined separately due to their different dispatch ability rates. The data from RSH plants were also obtained on an hourly basis. For the analysis, we formed three models, using time dummies, wind power, and price as explanatory variables. The explained variables in these models were: RSH, generation from natural gas, and generation from thermal sources except natural gas. Hourly data covering the period from January 1, 2015, to June 30, 2020, were used.

Variable renewables, mentioned in the literature, cover wind and PV sources. In this study, we only used wind energy as the variable resource, due to the negligible share of PV in licensed energy in Türkiye until 2021 and the unavailability of PV data at EXIST for this period. We used day-ahead generation planning data rather than actual generation since we are using day-ahead prices.
A machine learning algorithm, XGBoost, was used to analyze the data. Machine learning algorithms learn from the data to make predictions. XGBoost was chosen particularly as a machine learning algorithm that has won several algorithm competitions for making the best predictions.

XGBoost is a tree-based advanced boosting methodology. In the boosting methods of machine learning algorithms, a specific bias is iteratively reduced. The t^{th} model is built as $f_t(x) = f_{t-1}(x) + \lambda h_t(x)$ where $h_t(x)$ is the t^{th} corrective model built on the residuals and λ is the learning rate. Here, $h_t(x)$ is a tree structure (also represented by q) where w_j is the score on jth leaf with total number of leaves in q being T.

In the XGBoost algorithm, the objective is to build regression trees that minimize the objective function $\mathcal{L}$, which consists of a loss function ℓ plus the regularization term Ω. The loss function depends on the difference between the predicted values ($\hat{y}_i$) and observed values (y_i). At the t^{th} iteration, the function to be minimized is as follows:

$$\boldsymbol{\mathcal{L}^t = \sum_i^N \ell(y_i, f_t(x_i)) + \sum_t^T \Omega(h_t)} \quad \text{(Eq.1)}$$

Substituting equation (1) and using second order Taylor series approximation the above objective function can be written as

$$\boldsymbol{\mathcal{L}^t = \sum_i^N [p_i h_t(x_i) + \frac{1}{2} q_i h_t^2(x_i)] + \sum_t^T \Omega(h_t)} \quad \text{(Eq.2)}$$

Where
$\boldsymbol{p_i = \frac{\partial \mathcal{L}(y_i, f_{t-1}(x_i))}{\partial f_{t-1}(x_i)}}$ and $\boldsymbol{q_i = \frac{\partial^2 \mathcal{L}(y_i, f_{t-1}(x_i))}{\partial f_{t-1}(x_i)^2}}$.

The regularization term can be written as

$$\boldsymbol{\Omega(h_t) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^T w_j^2}.$$

Then equation (2) can be written as

$$\boldsymbol{\mathcal{L}^t = \sum_{j=1}^{T}\left[\left(\sum_{i \epsilon I_j} p_i\right) w_j + \frac{1}{2}\left(\sum_{i \epsilon I_j} h_i + \lambda\right) w_j^2\right] + \gamma T} \quad \text{(Eq.3)}$$

$\boldsymbol{\gamma}$ and $\boldsymbol{\lambda}$ are used to limit the size of the tree to be built. The optimal weight of each leaf is calculated by minimizing $\boldsymbol{\mathcal{L}^t}$ function given by equation (3) at tth iteration. Then, a "greedy" algorithm which starts from a single leaf and adds branches is employed to build a tree at each iteration t. (Chen & Guestrin, 2016)

Three models are constructed to predict the levels of RSH, natural gas power and the rest of the thermal power for different levels of wind power and price, as detailed in Table 2. Only two variables (wind speed and electricity market price) are used as explanatory variables, aside from the time dummies, due to multicollinearity and the difficulty of holding other potential explanatory variables constant while predicting.

To analyze the effectiveness of these models, the data is divided into three subsets, 70% for training, 10% for validation, and 20% for testing. The data is then trained using the XGBoost algorithm.

Table 2. Models used in training, testing and prediction processes

	Y (explained variable)	X (explanatory variables)
Model 1	RSH	Wind, price, dummy for days of the week, dummy for month of the year
Model 2	Natural gas	Wind, price, dummy for days of the week, dummy for month of the year
Model 3	Thermal except natural gas (stone coal, imported coal, fuel oil, lignite)	Wind, price, dummy for days of the week, dummy for month of the year

Results

We presented the results under three main headings: the substitution of wind power by RSH (Model 1), the substitution of wind power by natural gas plants (Model 2), and the substitution of wind power by thermal plants excluding natural gas (Model 3). The thermal leg includes imported coal, stone coal, lignite, and fuel oil. The results are presented based on data trained with wind power, price, and alternative resource (RSH, natural gas or the thermal leg) as shown in the figures. The categorical variables representing days of the week and months of the year are included in all analysis. We utilized month-of-the-year dummies as well as day-of-the-week dummies. However, in the figures, only the first Monday of the following months is presented: January, April, July, and October. Each of these months represents the season to which it belongs. We calculated the average slope of the relationship between the wind power and each of the explained variables for Models 1, 2, and 3. The average slope indicates the average rate of substitution between wind and alternative sources across different price levels.

Model 1. Substitution of Wind Power by RSH

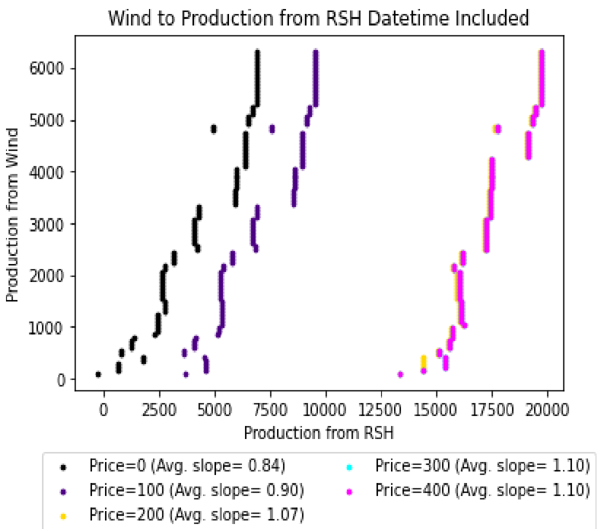

Fig. 1. The Predicted Relationship Between RSH and Wind Power in January

A substitution effect is observed for negative slopes, with values ranging from 0 to negative infinity. A slope of 0 indicates an overreaction, such as when natural gas plants increase production more than the reduction in wind power for a decrease of 1 MWh in wind power.

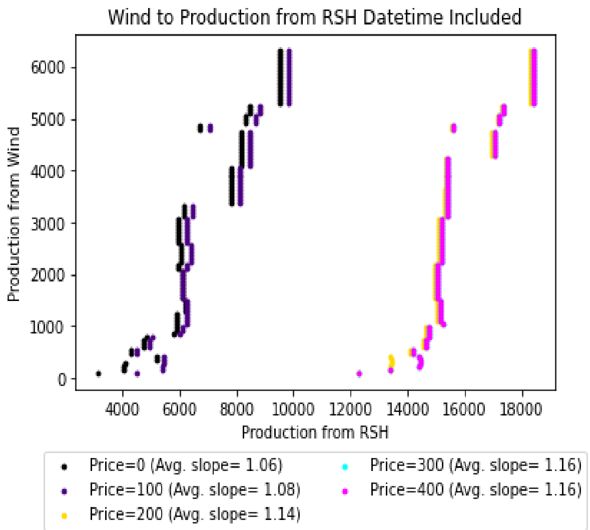

Fig. 2. The Predicted Relationship Between RSH and Wind Power in April

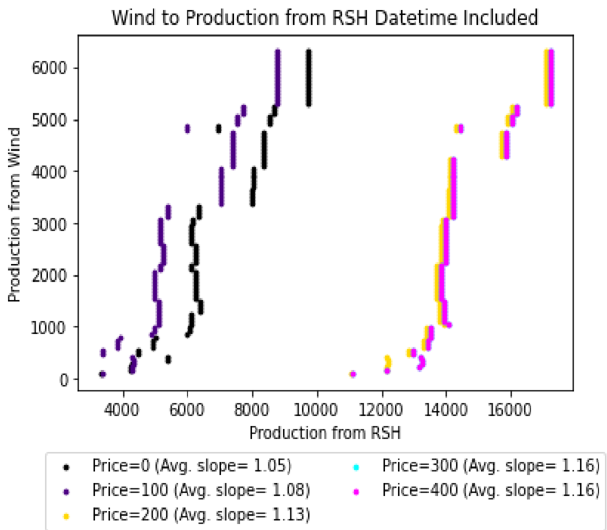

Fig. 3. The Predicted Relationship Between RSH and Wind Power in July

A slope of -1 suggests that wind power has been substituted for one-to-one basis, while a slope of negative infinity indicates no substitution between the variables. The average rate of substitution can be calculated as reciprocal of the average slope. Figures 1 to 4 show the predicted values of RSH for selected prices (for a price of 0, 100, 200, 300 and 400) for continuous values of wind power between 0 and 6500 MWh per hour. Figure 1 predicts for the month of January and the figures 2, 3 and 4 are predictions for April, July and October. In Figures 1 to 4, for all selected months of the year, it is observed that the RSH is unresponsive to changes in wind power. There is a positive correlation between wind power and RSH which is apparent in the figure and reflected by the average slope. Given the high dispatch ability of RSH plants, this unresponsiveness could be attributed to the low predictive power of RSH plants, potentially resulting from optimization failures. The model achieves an $\boldsymbol{R^2}$ of 0.79.

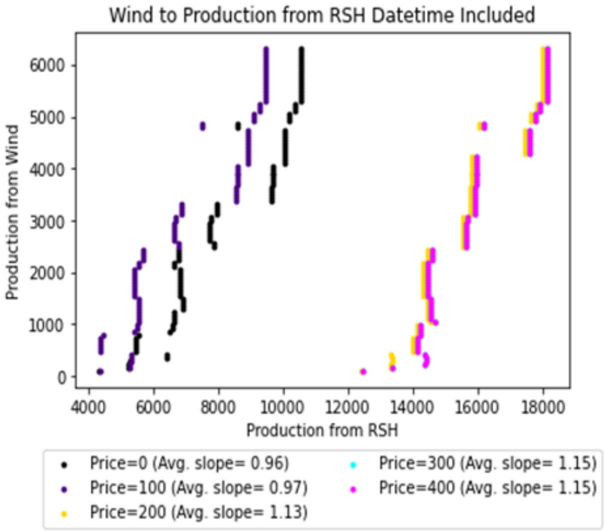

Fig. 4. The Predicted Relationship Between RSH and Wind Power in October

Model 2. Substitution of Wind Power by Natural Gas

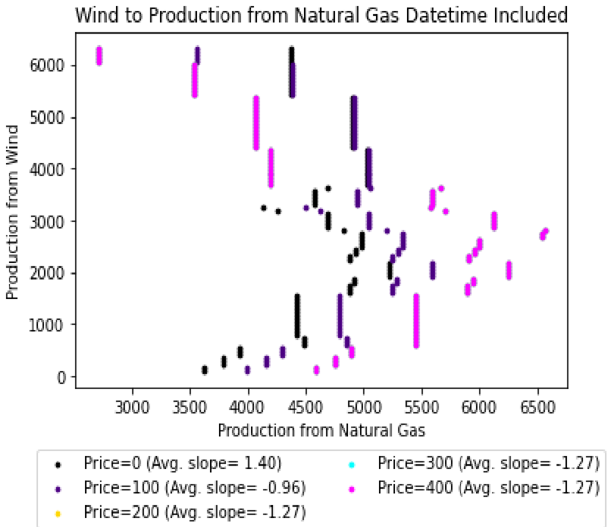

Fig. 5. The Predicted Relationship Between Natural Gas Power and Wind Power in January

Figures 5 to 8 show the predicted values of natural gas power for selected prices (for a price of 0, 100, 200, 300 and 400) for continuous values of wind power between 0 and 6500 MWh per hour. Figure 5 predicts for the month of January and the figures 6, 7 and 8 are predictions for April, July, and October. In Figure 5 to 8, a negative slope is observed, indicating a substitution effect between wind power and generation from natural gas plants.

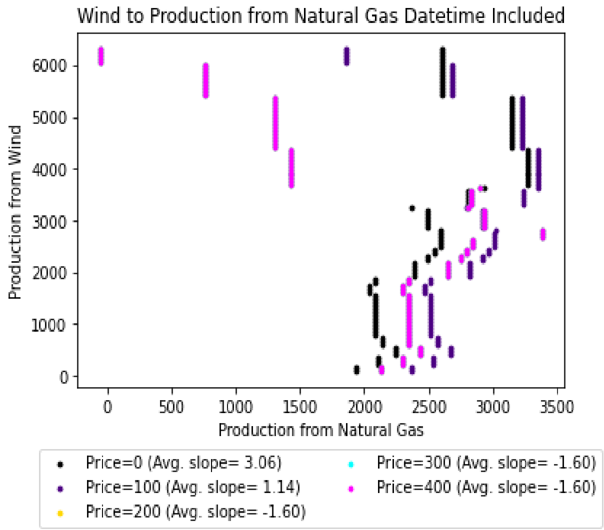

Fig 6 The Predicted Relationship Between Natural Gas Power and Wind Power in April

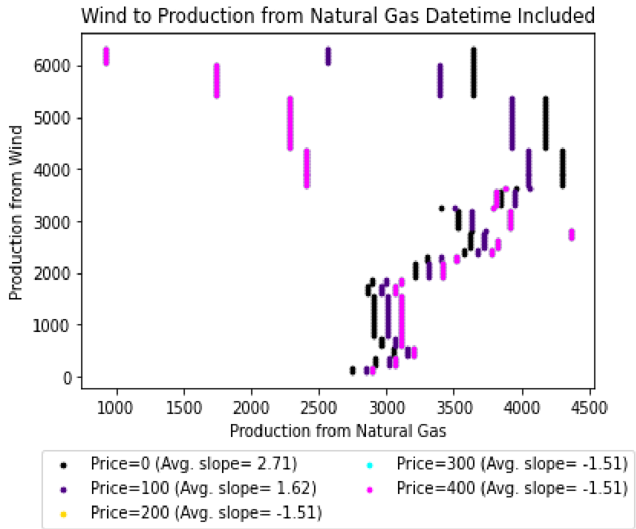

Fig. 7. The Predicted Relationship Between Natural Gas Power and Wind Power in July

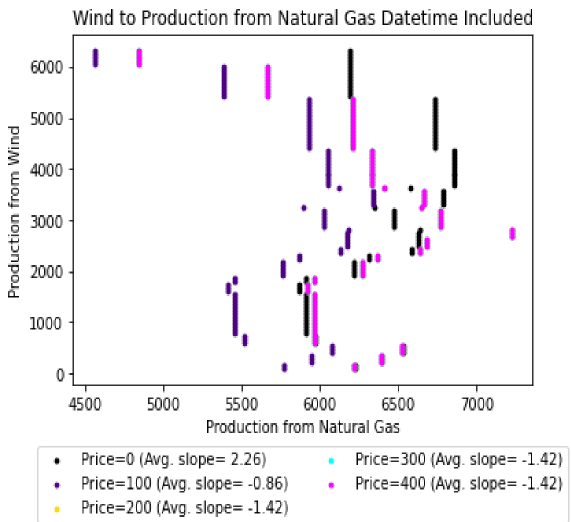

Fig. 8. The Predicted Relationship Between Natural Gas Power and Wind Power in October

However, when the price is low (i.e. price=0), the substitution effect is absent. For April and July, even when the price reaches 100, a substitution effect is not evident from the average slope. In contrast, for January and October, the highest substitution rates are observed at a price of 100, with the average substitution exceeding 100% of wind power: 104% in January and 116% in October. For prices of 200 and above, the substitution effect decreased to %79 in January, 70% in October, 66% in July, and 63% in April. At lower values of wind power, substitution is absent, that is probably because the total demand is not yet satisfied. At higher values for wind generation, natural gas plants appear to increase generation across all price levels. That is observed probably because the demand is satisfied at higher levels and as wind generation increases natural gas plants cut the generation off and vice versa when the wind generation decreases. Model 2 achieves an $\boldsymbol{R}^2$ value of 0.91.

Model 3 Substitution of Wind Power by the Thermal Leg Except for Natural Gas

Figures 9 to 12 show the predicted values of the thermal leg except for natural gas plants for selected prices (for a price of 0, 100, 200, 300 and 400) for continuous values of wind power between 0 and 6500 MWh per hour. Figure 9 predicts for the month of January and the figures 10, 11 and 12 are predictions for April, July, and October.

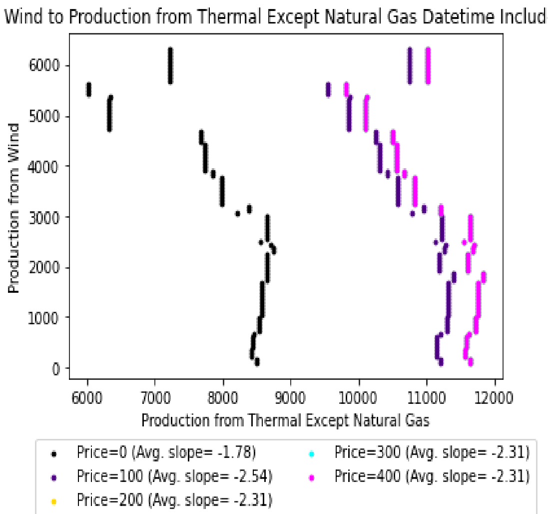

Fig. 9. The Predicted Relationship Between the Thermal Leg and Wind Power in January

In Figures 9 to 12, the substitution effect of wind power by the thermal leg varies between 35% and 56% when the price is equal to 0. At higher prices, a higher level of substitution is observed, ranging from %43 to %52 when the price is 100. For price levels of 200 and above, the highest level of substitution occurs in July, at 59%. For the other months, the replacement levels are 52% for October, 48% for April, and 43% for January. Thus, wind power appears partially to be substituted by the thermal leg. The model achieves an $\boldsymbol{R}^2$value of 0.94.

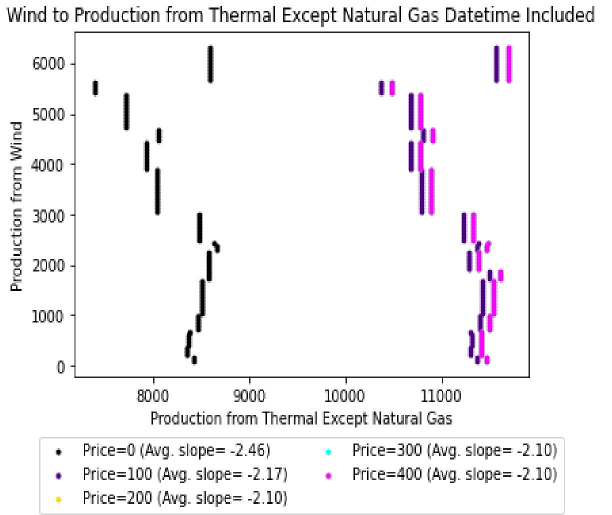

Fig. 10. The Predicted Relationship Between the Thermal Leg and Wind Power in April

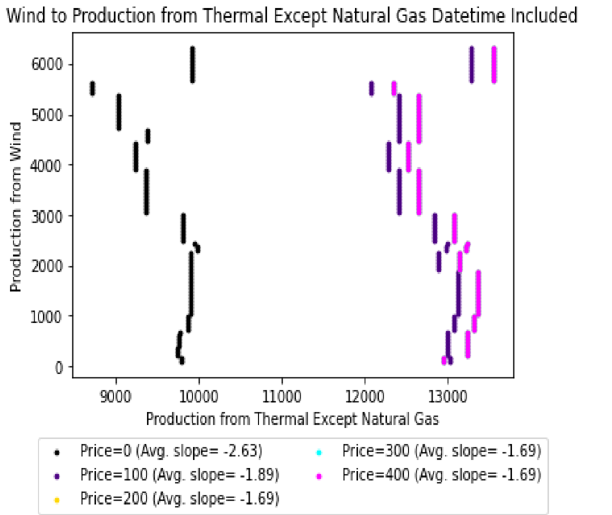

Fig. 11. The Predicted Relationship Between the Thermal Leg and Wind Power in July

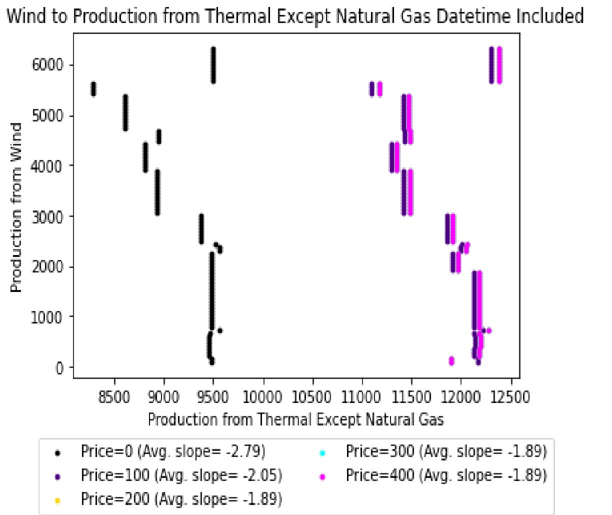

Fig. 12. The Predicted Relationship Between the Thermal Leg and Wind Power in October

Discussion and Conclusion

Results from Model 1 indicate the absence of a substitution effect, as suggested by the positive average slope, pointing to a positive correlation between RSH and wind power.
Results from Model 2 and Model 3 demonstrate that wind power is substituted at a higher rate by natural gas plants and at a lower rate by the rest of the thermal leg. An important conclusion from these two models is that the total substitution by the thermal leg exceeds the loss in wind power. Table 3 presents the total substitution of wind power by the thermal leg, excluding the natural gas plants. For prices of 200 and above, wind power is observed to be over-substituted.

Table 3: The average rates of substitution of the wind power by the thermal leg excluding the natural gas plants.

	January	*April*	*July*	*October*
Price=0	%56	%41	%38	%36
Price=100	%143	%46	%53	%165
Price=200	%121	%109	%125	%123
Price=300	%121	%109	%125	%123
Price=400	%121	%109	%125	%123

Another point to note is that in Model 2, concerning natural gas plants, substitution is apparent particularly for wind power levels greater than 2000MWh. Below this level, substitution is not apparent, or there is a concern about a positive correlation. Since the average slope is calculated for wind power values ranging from 0 to 6000 MWh, the slope and the average rate of substitution for values between 2000 and 6000 MWh would be significantly higher.

Comparatively, the literature primarily focuses on the concept of "merit order replacement", considering the long-term replacement of the thermal leg by wind power. Conversely, this paper approaches from the perspective of the replacing the relatively unstable wind power with alternative sources.

The findings indicate that, a positive correlation between RSH and wind power is observed. Also, from the higher generation levels by the RSH plants at higher price levels, we observe that the price mechanism is acting. Despite RSH plants being fully dispatchable, they do not effectively substitute for wind power, likely due to prediction and optimization failures. This may also be due to similarity of seasonal variations of wind and the water levels in hydropower plants.

Consequently, the only candidates for substitution are left as thermal plants. Due to their higher dispatch ability, natural gas plants emerge as better candidates for substituting wind power. A negative correlation between wind power and natural gas is observed only for higher levels of wind power. That may be due to the demand being satisfied at higher values of wind and at such higher values of wind the natural gas plants are decreasing the generation as wind power increases. Also, at higher price levels, it appears that the negative correlation between wind and natural gas is even greater, that is natural gas plants are even more sensitive to changes in wind power at higher prices. As natural gas plants are more dispatchable, for higher levels of wind power, we observe complementarity between wind and natural gas, that is natural gas is substituted for wind power. This points to a possible action by natural gas plants according to wind power and wind power predictions.

For reasons of unpredictability, wind power is substituted to a lesser extent by the thermal leg, more so by natural gas plants, and least by the rest of the thermal leg. Generally, a negative correlation is observed between wind power and the generation from thermal leg for all values of wind power. For higher values of price, a higher generation level is observed. But the correlation is relatively milder extent compared to natural gas. As a conclusion, the thermal leg substitutes for the wind power at a lower extent compared to natural gas. This is observed possibly due to lower dispatch ability levels of the rest of the thermal leg. The results of this research are somehow like Wang et.al. (2019). In the latter research it has been shown that the thermal leg is substituting for the selected renewable resource, that is hydropower in the long run, but in the short run, the results pointed out to a competition between hydropower and the thermal leg. Another significant finding is that the thermal leg tends to over-substitute for the loss in wind power, with substitution by the thermal leg ranging from 109% to 125% of the loss in wind power.

The complementarity has not been studied using the Turkish data and further research must be done to investigate the complementarity between renewable resources as well as investigating how well the thermal leg is responding to changes in intermittent resources using different methods, including econometrical methods.

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