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# Renewable Energy Resources Development Effect on Electricity Price: an Application of Machine Learning Model

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***Abstract***— *Given the significant uncertainty surrounding future electricity prices, which is widely regarded as the most critical factor in this context, market participants must engage in forecasting to facilitate their exploitation and planning activities. The success of electricity market actors is dependent on the availability of more appropriate tools to address this issue. In contrast, there is a prediction of prices in the electricity market for varying periods due to the increasing use of renewable energy in global energy generation and the unsteady and disjointed configuration of renewable energy production. The fluctuating characteristics of wind energy production have increased the complexity of real-time demand management in power systems. This paper investigates the impact of renewable energy production on price forecasting using data from the Nord pool market's electricity market. The primary goal is to present a framework for forecasting market settlement prices using a hybrid wavelet-particle swarm optimization-artificial neural network (W-PSO-ANN). In two scenarios, the results showed that the proposed model accurately represents data and is more precise than the ANN and WANN models. Machine learning has demonstrated promise in predicting electricity prices, but it is not without limitations. The ANN, WANN, and W-PSO-ANN models have training phase RMSE indices of 0.09, 0.07, and 0.04 respectively. During testing, the values were 0.15, 0.11, and 0.08. This demonstrates that the proposed model outperforms previous models.*

***Keywords***—Renewable energy, electricity prices, electricity market, machine learning, wavelet, optimization model, artificial neural network, model performance.

## 1. INTRODUCTION

The energy sector is rapidly evolving, and the use of renewable energy resources is becoming increasingly popular. Renewable energy resources, such as solar and wind power have the potential to provide a reliable and sustainable source of energy for the future [1],[2]. One of the main factors that have prevented renewable energy from becoming more widespread is the cost. However, with the advancements in technology and machine learning, the cost of renewable energy is decreasing at a rapid pace [3], [4].

The energy sector plays a vital role in our daily lives, powering our homes, businesses, and industries [5]. However, traditional energy sources such as fossil fuels have posed significant challenges, including environmental pollution, resource depletion, and volatile price fluctuations [6]. Recognizing the need for sustainable and cleaner alternatives, the world has increasingly turned towards renewable energy resources [7].

Renewable energy, obtained from sources like solar, wind, hydro, and geothermal, presents a hopeful remedy for the problems linked to traditional energy production [8], [9]. These sources are both plentiful and limitless, and they have a considerably reduced environmental footprint, emitting fewer greenhouse gases and pollutants [10]. The shift towards renewable energy is propelled by multiple factors. The urgent imperative to address climate change is one of the main driving forces. Fossil fuel combustion emits carbon dioxide into the atmosphere, thereby contributing to global warming and climate-related catastrophes. Through the utilization of renewable energy sources, we have the ability to greatly diminish our carbon emissions and alleviate the impacts of climate change [11].

Another crucial factor driving the shift towards renewable energy is the desire for energy independence. Many countries heavily rely on imported oil, gas, and coal, which not only affects their economies but also makes them vulnerable to geopolitical tensions and price volatility. Developing domestic renewable energy resources can enhance energy security, reduce dependence on foreign sources, and create new job opportunities in the renewable energy sector. Furthermore, the declining costs of renewable energy technologies have made them increasingly competitive with conventional energy sources. As technology advances and economies of scale are realized, the price of renewable energy generation continues to decrease, making it more affordable and accessible for consumers and businesses alike [12]. Understanding the relationship between renewable energy resource development and electricity prices is crucial in assessing the potential impact of this revolutionizing sector. As the world increasingly turns to renewable energy sources, such as wind, solar, and hydroelectric power, it is important to delve into the

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intricate dynamics that shape electricity prices [13].

Renewable energy resource development has the potential to significantly influence electricity prices through various mechanisms. One key factor is the cost of producing energy from renewable sources compared to traditional fossil fuel-based methods. As technology advances and economies of scale are achieved, the cost of renewable energy production has been steadily declining. This trend has made renewable energy more competitive, and in some cases, even cheaper than conventional energy generation methods [14]. Furthermore, the availability and reliability of renewable energy resources play a vital role in shaping electricity prices. Unlike fossil fuel reserves, which are finite and subject to geopolitical factors, renewable energy resources are abundant and widely distributed. This decentralization of energy sources can lead to lower transmission and distribution costs, ultimately impacting electricity prices [15].

Machine learning algorithms are capable of processing vast amounts of historical data, including factors such as weather patterns, demand fluctuations, and generation capacity [16]. By analyzing this data, machine learning models can identify hidden patterns and relationships that may not be apparent to human analysts. This enables energy companies and policymakers to make more informed decisions regarding electricity pricing [17]. Machine learning can also factor in external variables that impact electricity prices, such as government policies, regulatory changes, and the integration of renewable energy resources. These variables introduce additional complexity, but machine learning algorithms can handle the complexity and provide insights on how these factors influence pricing dynamics [18].

Certain forms of renewable energy lack the capacity for storage, and as a result, their presence in the electricity market inevitably influences prices [19]. The variability of atmospheric conditions introduces significant fluctuations in the generation capacity of renewable energy, resulting in a high degree of complexity. The aforementioned modifications result in operational and energy production discrepancies, necessitating the independent system operator to consider them in order to maintain equilibrium between supply and demand.

This study forecasts electricity market prices for the French region in 2022 and 2023 using Nord Pool market data. Combining artificial neural networks (ANN), wavelet transform, and the particle swarm optimization (PSO) algorithm, the utilized forecasting model is a hybrid model. To address the inherent instability of time series data in the ANN, the wavelet transform is utilized. In addition, the PSO algorithm is employed to optimize network weights and improve the performance of the machine learning procedure. The obtained price forecasts for the French electricity market are then analyzed and compared to those produced by a conventional ANN model.

## 2. MATERIALS AND MEHODS

Numerous nations have recently recognized the importance of clean, cost-effective wind energy in meeting their energy needs. Therefore, these nations have devised long-lasting strategies and allocated substantial financial resources to scientific and industrial advancements in this field. As a result, the proportion of renewable energy production to total electricity production is growing; however, it is essential to recognize that renewable energy is not a constant and uninterrupted energy source. In other words, wind turbines are not consistent sources of electricity generation. Changes in wind velocity have a direct impact on the amount of energy generated, leading to regulated fluctuations in voltage and frequency of production. Furthermore, it is important to mention that wind turbines are regulated by specific maximum and minimum speed restrictions. If the wind speed exceeds the predetermined threshold, the controller mechanism will immediately disable the wind turbine. This action may potentially cause a significant disturbance to the overall stability of the national grid, requiring careful consideration and management. The potential to increase the penetration coefficient of wind energy can be attributed to several factors, such as the implementation of efficient wind turbine control mechanisms, optimization of production allocation among units, adherence to reserve limitations, and effective distribution of production power across power plant units.

Competition on the wholesale energy markets is largely determined by the current market price. Significant price volatility is the primary characteristic of daily prices. Fig. 1-(a) illustrates the daily fluctuations of the French Nord Pool electricity market. Additionally, Fig. 1-(b) depicts the amount of renewable energy produced in France during the corresponding time period. The correlation between the production of renewable electrical energy and the daily market price of electricity is depicted in Fig. 1. Clearly, when the amount of renewable electrical energy increases, the daily price of electricity decreases proportionally.

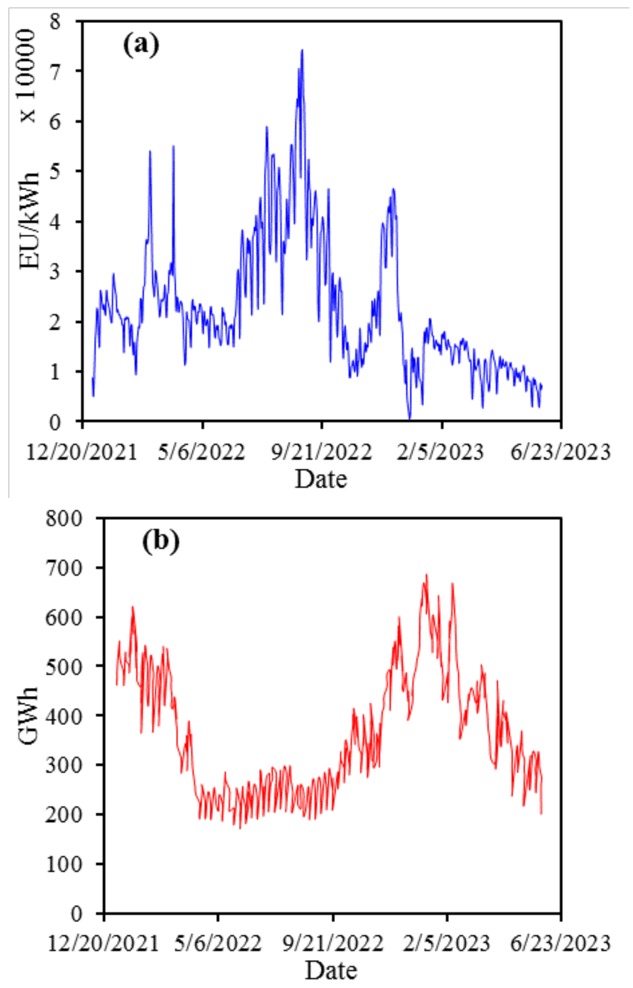


Fig. 1. a) Price changes and b) renewable energy production in the Nord Pool market in the French region.

### 2.1. Artificial Neural Network (ANN)

One of the key advantages of employing machine learning in renewable energy resource development is its capability to forecast electricity prices. By analyzing historical data and considering various influencing factors such as supply and demand dynamics, weather conditions, and market trends, machine learning models can provide accurate predictions of future electricity prices. This information can be invaluable for energy market participants, allowing them to make informed decisions and optimize their operations accordingly [20].

Artificial neural networks are widely employed as efficient functional approximation tools in many domains, such as pricing and load forecasting. In conjunction with these networks, evolutionary optimization techniques have also shown to be valuable tools. They are employed to maximize various objectives. The convergence of these two tools lies in the fact that the process of acquiring knowledge and establishing the framework of the neural network ultimately becomes an optimization challenge. In the discourse surrounding the training of neural networks, other approaches such as evolutionary optimization methods have been proposed as viable alternatives to the widely employed gradient-based methods [21]. The proper training and input methodology are crucial aspects in utilizing neural networks for price prediction. Typically, the determination of the number of network layers and neurons in each layer is dependent on empirical knowledge and iterative experimentation. The selection of these parameters is motivated by the objective of minimizing the magnitude of prediction error. In order to address the aforementioned limitation, it is recommended to enhance the model by integrating the neural network with intelligent optimization methods, therefore mitigating the risk of convergence to local minima. Hence, while considering the examination of neural network architecture, it becomes evident that gradient-based algorithms are insufficient in addressing certain inquiries. In such cases, evolutionary algorithms emerge as a viable solution for resolving this predicament. Hence, there exist two approaches for enhancing the performance of the neural network, namely: 1. Employing wavelets to address the issue of time series instability. 2. Implementing neural network weights nesting.

In the subsequent section, an elucidation of the utilization of these components inside the neural network will be provided.Artificial neural networks serve as effective functional approximation tools in several domains, such as pricing and load forecasting. Additionally, evolutionary optimization methods complement these networks as valuable tools. They are employed to maximize various objectives. The convergence of these two tools lies in the fact that the process of acquiring knowledge and establishing the framework of the neural network ultimately becomes an optimization challenge. In the discourse surrounding the training of neural networks, other approaches such as evolutionary optimization methods have been proposed as a viable alternative to the widely employed gradient-based methods [21],[22]. The training process and data input methodology play a crucial role in utilizing neural networks for price prediction. Typically, the determination of the number of network layers and neurons in each layer is dependent on empirical knowledge and iterative experimentation. Put simply, these parameters are selected in order to minimize the level of prediction inaccuracy. In order to address the aforementioned limitation, it is possible to enhance the model by integrating the neural network with intelligent optimization methods, therefore mitigating the risk of convergence to local minima. Hence, while considering the examination of neural network structure determination, it becomes evident that gradient-based algorithms are insufficient in addressing this matter. In such cases, evolutionary algorithms may be employed as a viable solution to resolve this issue. Hence, there exist two approaches for enhancing the neural network, namely: 1. Employing wavelets to address the issue of time series instability. 2. Implementing neural network weights nesting. In the subsequent section, an elucidation of the utilization of these components inside the neural network will be provided.

### 2.2. Wavelet Artificial Neural Network (WANN) Model

The wavelet function is a function with two essential characteristics: short-term and fluctuation. $\psi\left(x\right)$ is a wavelet function if and only if its Fourier transform $\psi\left(\omega\right)$ meets the stipulation (Equation (1)) [23]:

$$\int_{-\infty}^{+\infty} \frac{\left|\psi\left(\omega\right)\right|}{\left|\omega\right|^{2}} d\omega < +\infty \tag{1}$$

This condition is known as the $\psi\left(x\right)$ wavelet acceptance condition. The Equation (1) can be considered equivalent to the Equation (2) that must be satisfied:

$$\psi\left(0\right) = \int_{-\infty}^{+\infty} \psi\left(x\right) dx = 0 \tag{2}$$

Based on this features of functions with zero mean, numerous functions can be termed wavelet functions. $\psi(x)$ is the mother wavelet function, the functions used in the analysis with two mathematical operations of transfer and scaling alter the size and location of the analyzed signal, and ultimately, the wavelet coefficients at any point in the signal ($b$) and for each value are determined. It can be derived from the scale ($a$) using the Equation (3) [24]:

$$\psi_{a,b}\left(x\right) = \frac{1}{\sqrt{a}} \psi\left(\frac{x-b}{a}\right) \tag{3}$$

The $b$ parameter represents function transition, or, in simplified terms, delay and precedence. The transfer of the wavelet function ($x$) to size $b$, represented as ($x - b$) in Fig. 2, is depicted schematically [25].

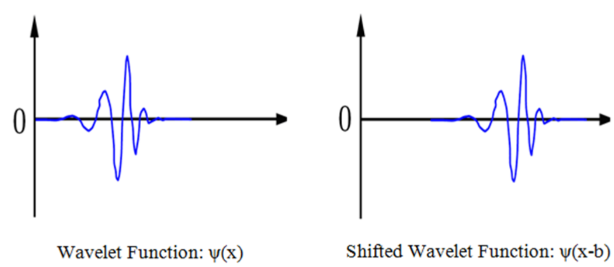


Fig. 2. The transfer of the wavelet function $\psi(x)$ to the value of b.

Finally, the continuous mode of wavelet transform (abbreviated as $CWT$) can be written in the form of Equation (4):

$$\begin{aligned} &CWT\left(a,b\right) = Wf\left(a,b\right) = \tfrac{1}{\sqrt{a}} \textstyle\int_{-\infty}^{+\infty} f\left(x\right) \psi\left(\tfrac{x-b}{a}\right) \\ &= \textstyle\int_{-\infty}^{+\infty} f\left(x\right) \psi_{a,b}\left(x\right) dx \end{aligned} \tag{4}$$

The hybrid WANN model is a specific type of wavelet-artificial intelligence model. This model leverages the strengths of both wavelet analysis and ANN to make predictions in the presence of unstable time series data. Wavelet analysis is employed in WANN models to examine the time series data prior to its input into the ANN. The hybrid model's structure has four fundamental components. The initial component involves the selection of input data for the model and encompasses entire data processing with regard to correctness and quality. In the subsequent section, the primary time series electricity prices is partitioned into subseries of varying precision and sizes through the use of wavelet modification to confine the stochastic components. The third section involves the selection of the appropriate artificial intelligence model, while the subsequent section focuses on the integration of the components of the anticipated wavelet series to provide the final output in the form of the predicted series. The WANN model is comprised of a three-layer architecture. The first layer comprises wavelet neurons that receive input from subseries derived from the application of wavelet transform on electricity prices time series.

### 2.3. Optimization of ANN Weights with PSO Algorithm

The PSO algorithm is inspired by the social behavior of animal and marine groupings. The premise of this algorithm is that every action and reaction impacts the group's movement, and as a result, every member of the group can benefit from the discoveries and abilities of other group members. This algorithm differs fundamentally from other optimization algorithms in that, in addition to a motion vector, each particle also possesses a velocity vector that forces the members of the set to change their position in the search space. This velocity vector itself becomes two vectors. It's known as Pbest and Gbest. Pbest is the best position that a particle has attained to date, and Chest is the best position that the best particle in the particle's vicinity has attained to date. In each iteration of this algorithm, each member of the set provides a solution. In search of a space D, the velocity of each particle is determined by a D-dimensional velocity vector named $V_i$=($v_{i1}$,$v_{i2}$,...,$v_{iD}$) and the location dimension of each particle is determined by a D-dimensional position vector named $x_i$=($x_{i1}$,$x_{i2}$,...,$x_{iD}$) (Equations 5 and 6). Ultimately, the population advances towards the optimal point using the subsequent relations and with intent. Optimization is decisive because, for values greater than those particles, suitable solutions may be bypassed, and for values less than those particles, suitable search is avoided. Fig. 3 shows the PSO algorithm framework [26–28].

$$\begin{aligned} &v^i[t+1] = wv^i[t] + \\ &c_1\mathrm{rand}_1\left(x^{i,pbest}[t] - x^i[t]\right) + \\ &c_2\mathrm{rand}_2\left(x^{gbest}[t] - x^i[t]\right) \end{aligned} \tag{5}$$

$$x^i[t+1] = x^i[t] + v^i[t+1] \tag{6}$$

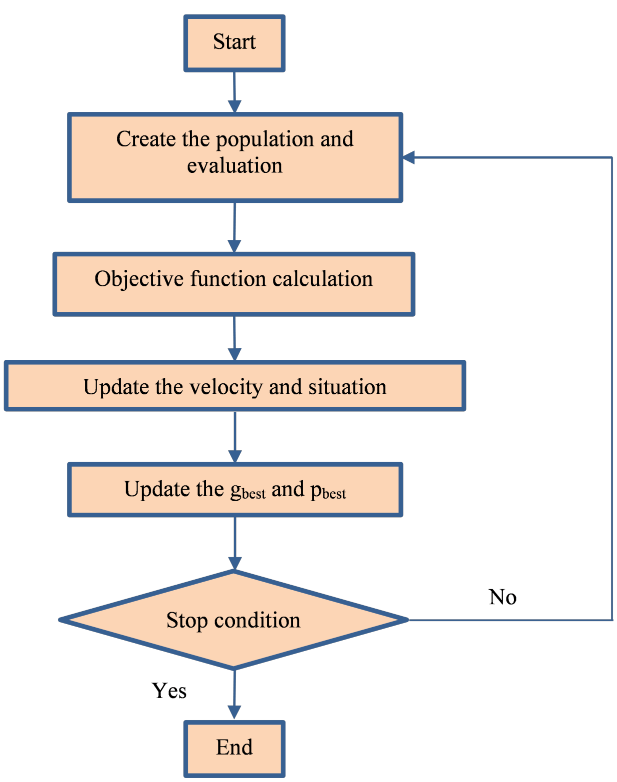


Fig. 3. PSO algorithm framework.

Before optimizing the weights, it is necessary to ascertain the corresponding cost function. The variable, in this context, corresponds to a specific row in the population matrix. It is represented as a row vector that contains the weights of the network. In fact, this vector is used to construct the neural network being discussed. For this purpose, a function is created with the main task of producing a network according to the specified number of layers and neurons in each layer. The evaluation phase commences, taking into account the diverse values of this variable. The simulated network's output and the mean squared error value are computed by measuring the discrepancy between the model's output and the actual output, which is stored as the cost function.

Statistical measures are employed in order to assess the performance of models. Statistical metrics, namely Mean Average Error ($MAE$), Root Mean Square Error ($RMSE$), and correlation coefficient ($R$), have been employed to verify and quantitatively evaluate the performance of the proposed models (Equations (7)-(9)). In the aforementioned relationships, the variables $X_i$ and $Y_i$ represent the observed and predicted parameters, respectively, based on a given set of $N$ observational data. The symbols $\bar{X}$ and $\bar{Y}$ represent the average observational and predicted values, respectively. The evaluation of the models' performance was conducted using error indices [29].

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{\mathrm{N}} |X_i - Y_i| \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2} \tag{8}$$

$$\mathrm{R} = \frac{\sum\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right)}{\sqrt{\sum\left(X_i - \bar{X}\right)^2 \sum\left(Y_i - \bar{Y}\right)^2}} \tag{9}$$

The hybrid wavelet-particle swarm optimization artificial neural network (W-PSO-ANN) was developed to address the limitations of conventional optimization algorithms by capitalizing on the complementary strengths of these individual techniques. By combining the multiresolution analysis capabilities of the wavelet transformation with the capability of particle swarm optimization and the learning capability of artificial neural networks, the proposed hybrid model aims to improve the accuracy and efficiency of the optimization process while ensuring its robustness and adaptability to complex and nonlinear datasets. This integration enables a more exhaustive exploration of the solution space, resulting in faster convergence and greater precision in locating optimal solutions. Consequently, the W-PSO-ANN method represents a strategic approach to overcoming the challenges posed by conventional optimization techniques, ultimately providing a more effective and trustworthy solution for complex problems.

## 3. RESULTS AND DISCUSSION

In this study, an advanced neural network, wavelet transform, and PSO algorithm were used to predict the electricity market price. The wavelet transform has been used to overcome the instability of the time series and in the optimization of the network structure, the bat algorithm has been used due to its continuous nature in the discussion of determining the weights of the network. The most appropriate response in the discussion of structure optimization is a three-layer feed-forward network with 27 neurons in its hidden layer. The training stage utilized 80% of the data, while the remaining 20% was allocated for testing the models.

The initial step in developing a machine learning-based forecast involves the normalization of data. It has the potential to enhance the training process. The provided data is within the range of 0 and 1 [30]. The presentation of normalization data is depicted in Equation (10):

$$T = \frac{z_i - z_{\min}}{z_{\max} - z_{\min}} \tag{10}$$

Table 1. Machine learning models performance.

| Stage | Model | Efficiency criteria | | | P-Value |
|---|---|---|---|---|---|
| | | MAE | RMSE | R | |
| Train | ANN | 0.44 | 0.09 | 0.47 | 0.017 |
| Test | | 0.47 | 0.15 | 0.44 | 0.021 |
| Train | WANN | 0.38 | 0.07 | 0.43 | 0.03 |
| Test | | 0.41 | 0.11 | 0.49 | <0.001 |
| Train | W-PSO-ANN | 0.30 | 0.04 | 0.36 | 0.011 |
| Test | | 0.35 | 0.08 | 0.39 | <0.001 |

where, $T$ represents the normalized data value, $Z_i$ represents the data before normalization, and $Z_{min}$ and $Z_{max}$ represent the pre-normalization minimum and maximum data values, respectively.

This study presents the findings in two separate scenarios. The initial scenario fails to consider the possible impact of renewable energy on the electricity market prices. In contrast, the following scenario incorporates models that specifically take into account the influence of renewable energy.

During a time period in which the price of the market is at its highest point, the outcomes pertaining to the omission of incorporating renewable energy injection into the market are investigated and analyzed. As was mentioned earlier, it is anticipated that the introduction of renewable energy sources into the market will result in a decrease in the cost of electricity. On the other hand, if the surplus electric energy that is generated from renewable sources is left unused within the circuit, then it is anticipated that the price of electricity will rise. Therefore, taking into consideration this one particular fact, the data that is pertinent can be derived from the time series. A comparison of the results that were observed and those that were predicted by the ANN, WANN, and W-PSO-ANN models is presented in Fig. 4. This figure demonstrates that the proposed model was successful in accurately representing the real data, and that it outperformed both the traditional ANN model and the WANN model in terms of accuracy.

In the context of the evaluation of renewable energy sources, Fig. 5 provides a comparative analysis of the outcomes that were observed and those that were predicted based on the ANN model, the WANN model, and the W-PSO-ANN model. The presented figure demonstrates that the proposed model effectively captures the actual data and demonstrates greater accuracy compared to both the traditional ANN model and the WANN model. This can be inferred from the fact that the figure was presented.

The statistical performance characteristics of the machine learning models are presented in Table 1. In light of the information that has been laid out in the table, it is clear that the proposed model outperforms both the traditional ANN model and the WANN model in terms of the performance indicators that have been considered. The normalized root mean square error (RMSE) indices for the ANN model, the WANN model, and the W-PSO-ANN model during the training phase are respectively 0.09, 0.07, and 0.04, respectively. During the testing phase, the corresponding values are 0.15, 0.11, and 0.08 respectively. This is similar to the previous example. The conclusion that can be drawn from this is that the model that has been proposed is superior to the models that have come before it.

## 4. CONCLUSIONS

During the implementation of new regulations, competitive electricity markets have substituted traditional power systems. Given the current circumstances, understanding market dynamics and accurately forecasting electricity prices is crucial. This task is challenging yet fundamental for all stakeholders. Examples of these activities include the regulation of short-term strategies, the regulation of mid-term or long-term contracts, short-term planning, and development planning. Using Nord Pool market data, this study forecasts electricity market prices for the French region in 2022 and 2023. The utilized forecasting model is a hybrid consisting of hybrid ANN, wavelet transform, and PSO algorithm. The wavelet transform is utilized to address the inherent instability of time series data in ANN. Additionally, the PSO algorithm is used to optimize network weights and enhance the performance of the machine learning procedure. The obtained price forecasts for the French electricity market are subsequently analyzed and compared with those generated by a conventional ANN model. The while The results of this study are presented in two separate scenarios. The initial scenario does not account for the potential impact of renewable energy on electricity market prices. In contrast, the scenario that follows includes models that explicitly account for the impact of renewable energy. In two scenarios, the results demonstrated that the proposed model more precisely represents the actual data than both the traditional ANN and WANN models. Predicting electricity prices with machine learning has shown great promise, but it is not without its challenges and limitations. During the training phase, the $RMSE$ indices for the ANN, WANN, and W-PSO-ANN models are 0.09, 0.07, and 0.04, respectively. During the testing phase, the corresponding values are 0.15, 0.11, and 0.08, respectively. This demonstrates that the proposed model is superior to those that came before it.

These considerations must be taken into account when employing machine learning algorithms for this purpose. The availability and quality of data is one of the major challenges. To accurately forecast electricity prices, machine learning models require voluminous historical data. Obtaining such information can be difficult, especially in regions where data collection and reporting practices are not well-established. The energy industry's dynamic nature is a further obstacle. Numerous factors, including weather conditions, market demand, government policies, and technological advancements, impact electricity prices. These variables can fluctuate rapidly and unpredictably, making it challenging for machine learning models to capture and adapt to these changes.

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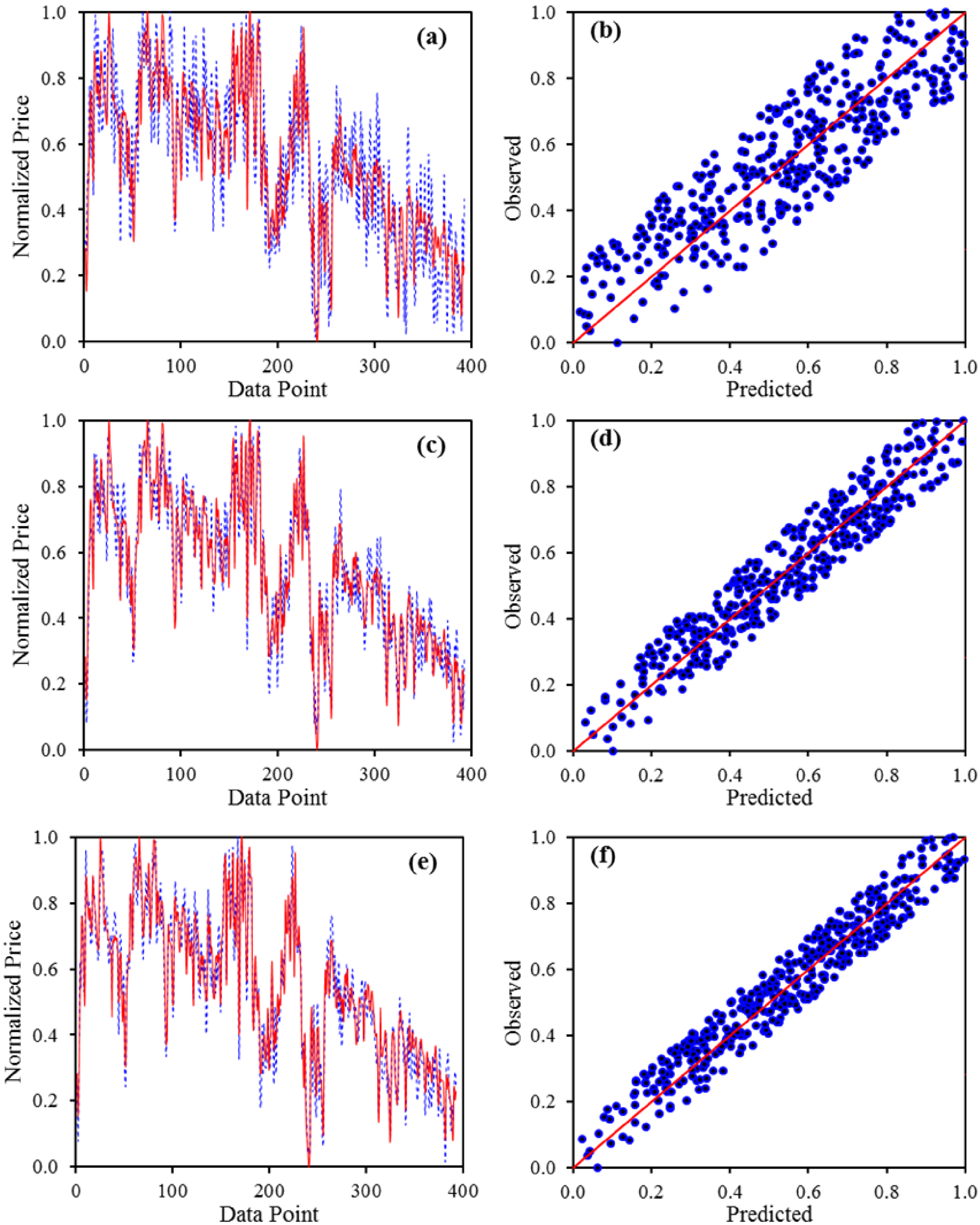


Fig. 4. A comparison between the real and predicted data between a) classic ANN, b) WANN, and c) W-PSO-ANN model in non-renewable consideration scenario.

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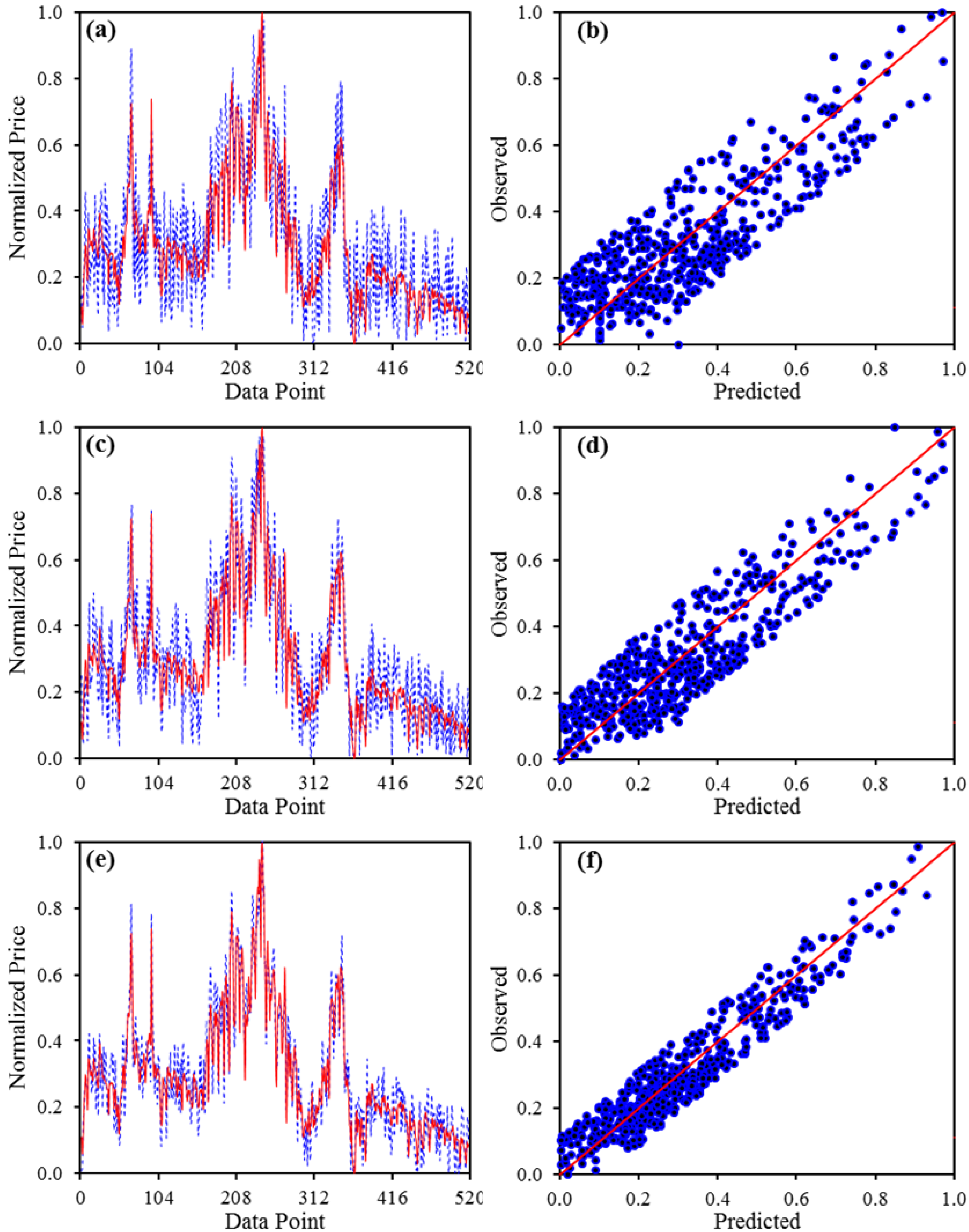


Fig. 5. A comparison between the real and predicted data between a) classic ANN, b) WANN, and c) W-PSO-ANN model in renewable consideration scenario.

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