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Multi-Perspective Prediction of Day-Ahead Electricity Spot Prices Via Canonical Cross-Covariance Analysis

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Electricity spot prices are influenced by numerous complex factors such as fuel costs, weather conditions, regulatory changes, and economic indicators, making accurate forecasting a major challenge in energy markets.*
- *Traditional forecasting models, including single-view machine learning and time-series approaches, often struggle with underfitting, high dimensionality, and fail to capture multivariate relationships effectively.*

WHAT THIS STUDY ADDS ON THIS TOPIC?

- *This study introduces a novel multi-view feature extraction method based on canonical correlation analysis (CCA) to improve day-ahead electricity price forecasting by effectively capturing underlying correlations between different feature groups, leading to a 14–20% reduction in prediction errors and offering a more robust, scalable, and generalizable forecasting model compared to existing approaches.*

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ABSTRACT

A wide range of factors affect the electricity market in different ways, including fuel prices, weather patterns, government policies, and consumer preferences. Traditional techniques, on the other hand, frequently struggle to extract underlying patterns effectively due to feature overlap, the fragility of descriptive identifiers, and the lack of a full holistic perspective. This study tackles these restrictions by using canonical correlation analysis to generate linear combinations of feature sets, allowing for the identification of strong determinants of power spot prices. This method enhances forecasting accuracy by incorporating multi-view feature extraction and multivariate analysis, providing an advantage in evaluating small changes in volatile markets. This method improves predictive accuracy and lowers forecasting mistakes by including multi-view feature extraction and multivariate analysis in the forecasting model. Thus, a significant advantage in price forecasting is gained by evaluating small changes in volatile markets as part of a whole. The proposed approach reduces underfitting issues in existing models that suffer from high dimensionality by using smooth and discriminative representations. Also, incurring long computational time attributed to matrix multiplication operations is effectively reduced. The average root mean square error of the proposed model is reduced by 14–20%. Multiple views in the embedding space also contribute to the prediction of asynchronous price movements under global and local information.

***Index Terms*—**Canonical correlation, electricity price forecasting, multivariate analysis, multi-view feature extraction

I. INTRODUCTION

In recent years, green energy has emerged as a crucial issue for industrialized countries, driving significant advances and legislative measures aimed at accelerating the transition to sustainable energy systems. Following a brief disturbance in 2020, the energy market has grown steadily over recent years, driven by increased demand and the expansion of generation capacity. However, electricity prices have remained variable due to various factors. The COVID-19 pandemic, along with geopolitical tensions resulting from the Russia–Ukraine conflict in 2022, has significantly contributed to long-term hikes in commodity prices. This volatility has been exacerbated by rising oil prices, often linked to geopolitical uncertainty and supply chain disruptions. Meanwhile, the decline in spot prices has been attributed to the increasing integration of renewable energy. Additionally, limitations in transmission and distribution infrastructure in different regions have also affected prices. The introduction of energy storage and the adoption of electric vehicles may further explain these fluctuations. Recently, the average spot price in the European wholesale electricity market reached €541 per megawatt-hour (MWh), up from €43 per MWh in 2021 but down from around €60 per MWh in 2019. Electricity spot prices in the United States have generally remained stable over the past decade, averaging around $30 per MWh, although they peaked at nearly $270 in 2022 due to global market dynamics. As it comes to Asia, strong economic growth and increasing energy demand have caused electricity spot prices to be higher than in Europe and the United States. In Asia, strong economic growth and increasing energy demand have driven electricity spot prices higher than those in Europe and the United States. As a result, generalizing electricity spot prices from one region to another is very difficult due to significant regional and market-specific variations. By employing a multi-view approach, this article introduces a new methodology. In the study, different views are combined to create innovative variables, resulting in a significant improvement in forecast quality through this special fusion.

A. Overview of Electricity Price Forecasting

Forecasting spot and forward prices in wholesale electricity markets are called electricity price forecasting (EPF). This process includes analyzing some fluctuating factors that affect the market. Since electricity is not storable, it has become a type of energy whose price can change depending on many influential factors. There is no doubt that weather conditions have a significant effect on electricity demand, as has been demonstrated in numerous studies [1-4]. Weather variables influence electricity consumption patterns, among other factors that influence energy demand. Various meteorological parameters (e.g., air humidity) were considered during the analysis. The analysis took into account a number of meteorological parameters (such as air humidity) in order to assess the impact of weather variables on electricity consumption patterns [5]. Additionally, different regions may expect different indoor temperatures, impacting electricity consumption [6-7]. Another determinant that correlates with prices is the calendar effect. It is also important to consider the calendar effect when determining prices [8-9]. Weekdays and weekends have different patterns of electricity demand. The cost of electricity is affected significantly by increases in gas, coal, and other fuels, which are the primary inputs into electricity production [10-11]. Some researchers have shown that coal and gas plants generate the majority of electricity, and the sensitivity to these factors varies over time [12-15]. Spot prices can also be dampened by increased storage [16-18], similarly as they are influenced by increased interconnections [19]. In addition to these, hydro and thermal generation are among the renewable energy sources, and the energy in the reservoirs is also among the factors affecting the spot price. [20-21].

Some researchers also show how the supply of electricity is largely generated from coal and gas plants, and the sensitivity towards different fundamental factors changes over time. Carbon emission trading, which prevents substitution from gas to coal when the coal price is less than the gas price, is another factor influencing electricity prices [13,22,23]. As coal prices fall below gas prices, carbon emissions costs rise, which affects other prices in the chain. Moreover, some economic indicators are related to and reflect the long-term market price [24]. In economics, financial contracts play a role in spot market bids, payments under financial contracts are made in addition to power payments, though they are tied to spot prices [25]. Another study [26] examined the hedge market, focusing on the supply of asset-backed primary issuance (i.e., firm swaps and caps). Moreover, a study [26] examined primary issuances backed by assets, specifically firm swaps and caps. It showed that the possibility of hedge contract shortages is becoming more than theoretical as Variable Renewable Energy increases.

Aside from the factors that influence electricity spot prices, successful approaches to analyzing these factors are also crucial. Since many factors affect electricity spot prices, multi-view data analysis will be more effective than other approaches in revealing the relationships. In order to analyze these relationships between the views of multi-view data and reduce their dimensions by extracting robust features, there is an increasing need for specific techniques that analyze the relationships between the views of multi-view data. The majority of preliminary studies using Canonical Correlation Analysis (CCA) are focused on the quantitative analysis of the relationships between multiple unrelated but dissimilar variables [27-31]. In an effort to uncover the hidden yet influential semantic factors responsible for the correlation, it is appropriate to find correlated functions (covariates) between the two views of the same phenomenon. Discarding the representation-specific details (noise) is expected to uncover the hidden yet influential semantic factors responsible for the correlation. For the purpose of uncovering the hidden, yet influential semantic factors responsible for the correlation, correlated functions (covariates) should be identified between the two views of the same phenomenon. Discarding representation-specific details (noise) will reveal the hidden, yet influential, semantic factors responsible for the correlation [32-35]. According to one study, it is critical to identify multiple bivariate relationships when identifying complex multivariate relationships in large-scale genomic studies [36]. A sparse CCA method was proposed by Parkhomenko that examines the relationship between two types of variables and provides sparse solutions that include only small subsets of variables of each type by maximizing the correlation between the subsets of variables of different types when selecting variables. As a result of the sparse CCA method proposed by Parkhomenko, two types of variables are analyzed and sparse solutions are provided by maximizing the correlation between subsets of variables of different types when selecting variables, resulting in solutions that contain only small subsets of each type.

II. MATERIALS AND METHODS

A. Dataset Analysis

In this article, electricity market data for one megawatt-hour are taken from two different markets located far apart. The market for day-ahead electricity in Türkiye and Australia's National Electricity Market (NEM), which is the major spot market for wholesale electricity in Australia, are utilized in the study. There are some electricity prices shown in Fig. 1 as a chart of fluctuation. Day Ahead Market includes all the trading and portfolio optimization activities for Day + 1.

This market allows supply-side and demand-side portfolios to plan and balance their generation and consumption needs at once using a reference price (Market Clearing Price, MCP) from the previous day. An assessment of the proposed multi-view approach is tested in this study using two case studies to verify accuracy and robustness as demonstrated in Table I.

The dataset includes Türkiye and Australia day-ahead hourly clearing prices for electricity markets from January 1, 2023 to January 1, 2024 operated by the Energy Exchange İstanbul (EXIST) a member of the Association of Power Exchanges and the Association of European Energy Exchanges, formed by the world's leading energy markets and regulatory authorities (see Appendix A) and Australian Energy Market Operator (AEMO) established to manage the NEM. As shown in Fig. 2, the autocorrelation function of electricity prices in the EXIST market indicates that the data show no stationary behavior and a correlation between successive values.

B. Dataset Analysis

The ability to forecast electricity prices effectively requires a solid understanding of how market clearing algorithms work. The dynamics of supply and demand are captured by the model based on knowledge of market clearing mechanisms. A market clearing

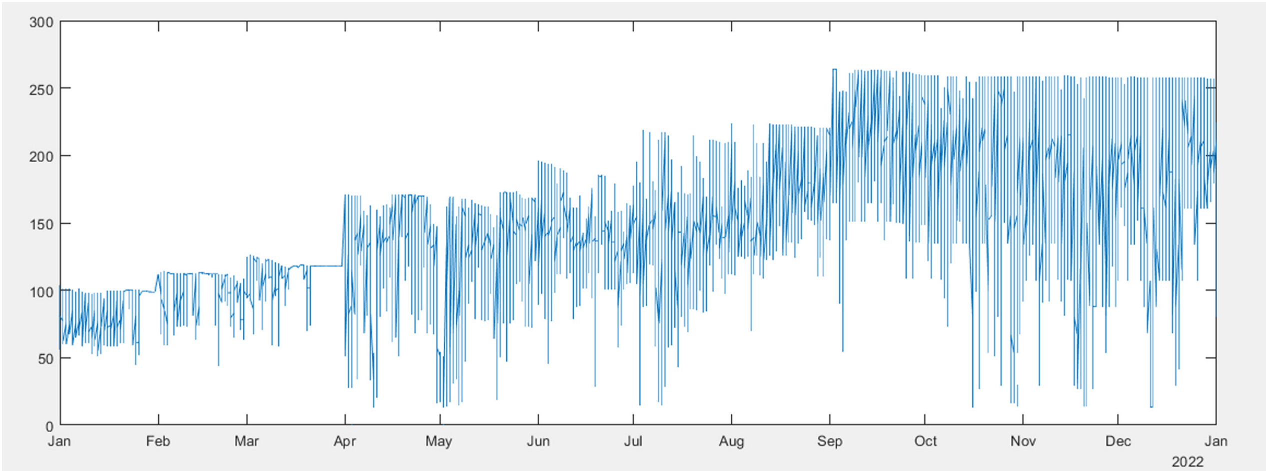

Fig. 1. Day-ahead electricity prices from January 1, 2023 to January 1, 2024.

algorithm is chosen by taking into account the characteristics of a given market. The main formulation of the study is discussed below.

1) Sets and Indices

t, T: time period and set of time periods.

I: bids for supply hourly.

J: bids for demand hourly.

I, L(i): segment index and set of segments for hourly bid i, $i \in I \cup J$.

B^s: set of supply block bids (B^{sc}: set of child supply block bids, $B^{sc} \subset B^s$).

B^d: set of demand block bids (B^{dc}: set of child demand block bids, $B^{dc} \subset B^d$).

$^{\wedge b}$: set of block bids to which block bid b is linked, $b \in B^s \cup B^d$.

TABLE I. GROUPS OF TRAINING DATASETS AND TEST DATASETS IN CASE STUDY 1 AND CASE STUDY 2

Case Study	Training Dataset	Test Dataset
Case Study 1	January 1, 2023–January 30, 2023	January 31, 2023
	March 1, 2023–March 29, 2023	March 30, 2023
	May 1, 2023–May 30, 2023	May 31, 2023
	July 1, 2023–July 30, 2023	July 31, 2023
	September 1, 2023–September 29, 2023	September 30, 2023
	November 1, 2023–November 29, 2023	November 30, 2023
Case Study 2	February 1, –February 26, 2023	February 27, 2023
	Aoril 1, 2023–April 29, 2023	April 30, 2023
	June 1, 2023–June 29, 2023	June 30, 2023
	August 1, 2023–August 30, 2023	August 31, 2023
	October 10, 2023–October 30, 2023	October 31, 2023
	December 1, 2023–December 31, 2023	January 1, 2024

F^s: set of supply flexible bids.

2) Parameters

P_{min}: price minimum for valid bids.

P_{max}: price maximum for valid bids.

P^0_{itl}, P^1_{itl}: the initial and final price of segment I of hourly bid i in period t ($P_{min} \le P^0_{itl} < P^1_{itl} \le P_{max}$ for supply bids and $P_{max} \ge P^0_{itl} > P^1_{itl} \ge P_{min}$ for demand bids).

Q^0_{itl}, Q^1_{itl}: the initial and final quantity of the segment I of hourly bid I in period t ($0 \le Q^0_{itl} \le Q^1_{itl}$ for all bids).

P_b, P_f: flexible bid f and block bid b prices.

Q_b, Q_f: flexible bid f and block bid b prices.

N_b: the number of time periods spanned by block bid b, $b \in B^s \cup B^d$.

δ_{bt}: a binary parameter equal to 1 if block bid b spans period t, 0 otherwise.

3) Decision Variables

p_t: MCP at period t.

x_{itl}: acceptance ratio of segment I of hourly bid i in period t.

y_b: 1 if block bid b is accepted, 0 otherwise.

Z_{ft}: flexibility bid f in period t is 1; otherwise, it is 0.

4) Formulation

The day-ahead electricity market involves participants submitting various bids for some periods up to the next day. The market operator then decides the matching quantities for each bid to maximize daily surplus while maintaining a balance between supply and demand. Optimal market surplus maximization is the objective function of the problem. Traders or consumers in the day-ahead market produce and consume daily surpluses, forming the daily market surplus. Producer surplus generated by hourly bids:

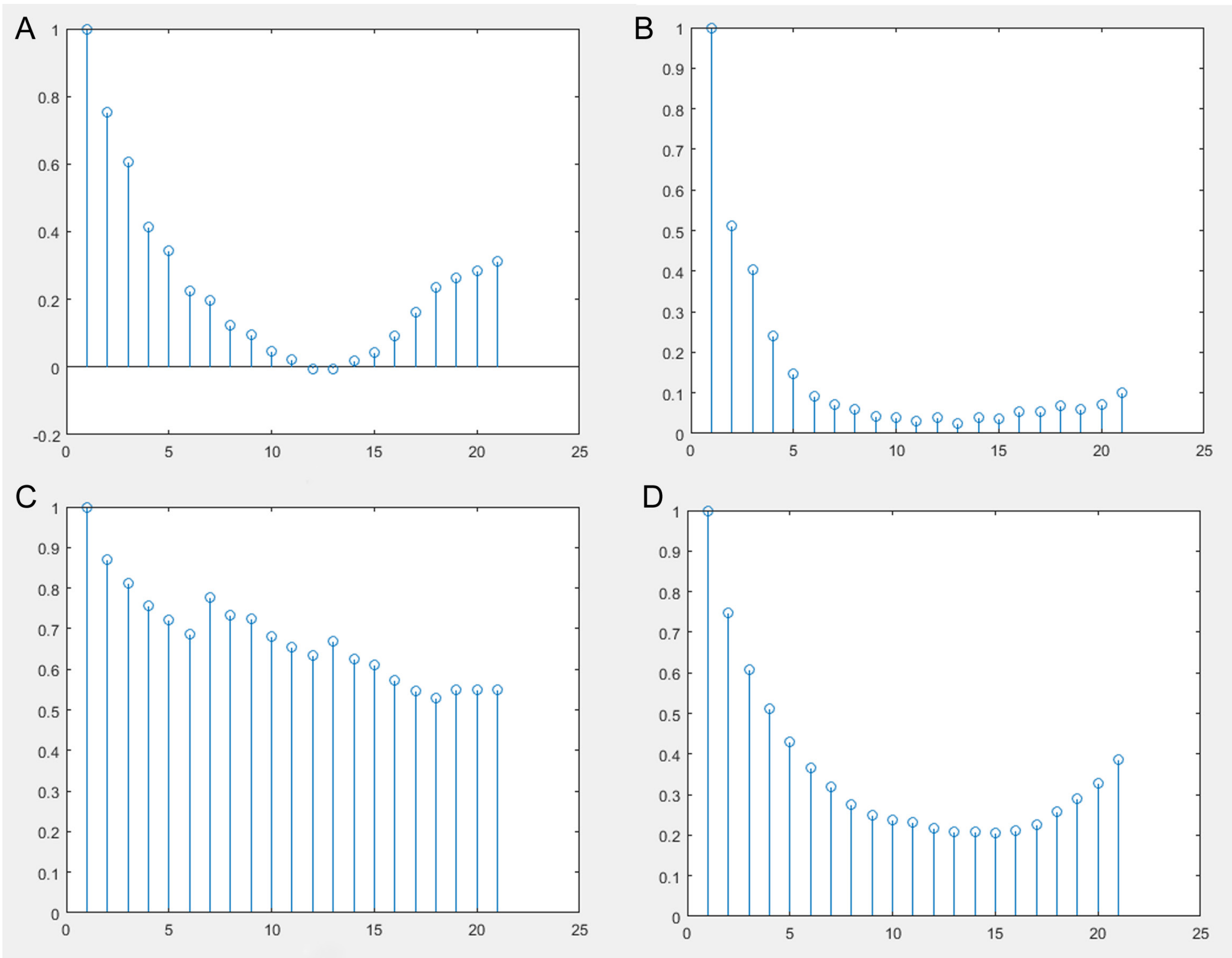

Fig. 2. Autocorrelation plot for the hourly day-ahead electricity price series (a): A price series with a high seasonal component (a period where weekday and weekend variations are significant). (b): A period with low autocorrelation, indicating more random fluctuations in prices (a period with low volatility in electricity prices). (c): A series exhibiting strong autocorrelation and long-term dependency (a period with high price stability). (d): Similar to (a) but with an inverse trend pattern (a period showing fluctuations within a specific structure). (on an autocorrelation plot, the vertical axis shows the value of the autocorrelation function (ACF), and the horizontal axis shows the lag between the time series elements).

$$\left(\sum_{t\in T} p_t \sum_{i\in J}\sum_{l\in L(i)} \left(Q^1_{itl}-Q^0_{itl}\right)^* x_{itl}\right) - \left(\sum_{t\in T}\sum_{i\in I}\sum_{l\in L(i)}\left[0,5x_{itl}\left(Q^1_{itl}-Q^0_{itl}\right)\left(2P^0_{itl}+x_{itl}\left(P^1_{itl}-P^0_{itl}\right)\right)\right]\right) \quad (1)$$

And consumer surplus generated by hourly bids:

$$\left(\sum_{t\in T}\sum_{i\in I}\sum_{l\in L(i)}\left[0,5x_{itl}\left(Q^1_{itl}-Q^0_{itl}\right)\left(2P^0_{itl}+x_{itl}\left(P^1_{itl}-P^0_{itl}\right)\right)\right]\right) - \left(\sum_{t\in T} p_t \sum_{i\in J}\sum_{l\in L(i)} \left(Q^1_{itl}-Q^0_{itl}\right)^* x_{itl}\right) \quad (2)$$

Fig. 3 illustrates producer and consumer surpluses associated with accepted supply and demand block bids, respectively. Using the average MCP of the periods (*P**) when the block bid is active, it is possible to obtain that the surplus of an accepted block bid equals the volume of the rectangle shown.

An accepted supply block bid and a block demand block bid are shown in Fig. 3; by calculating the average MCP for the periods when a block bid is active, it can be concluded that the surplus equals the volume of the rectangle shown for an accepted block bid.

Producer surplus generated by block bids:

$$\sum_{b\in B^s} y_b * Q_b * \left(\sum_{t\in T}\delta_{bt} p_t - N_b P_b\right) \quad (3)$$

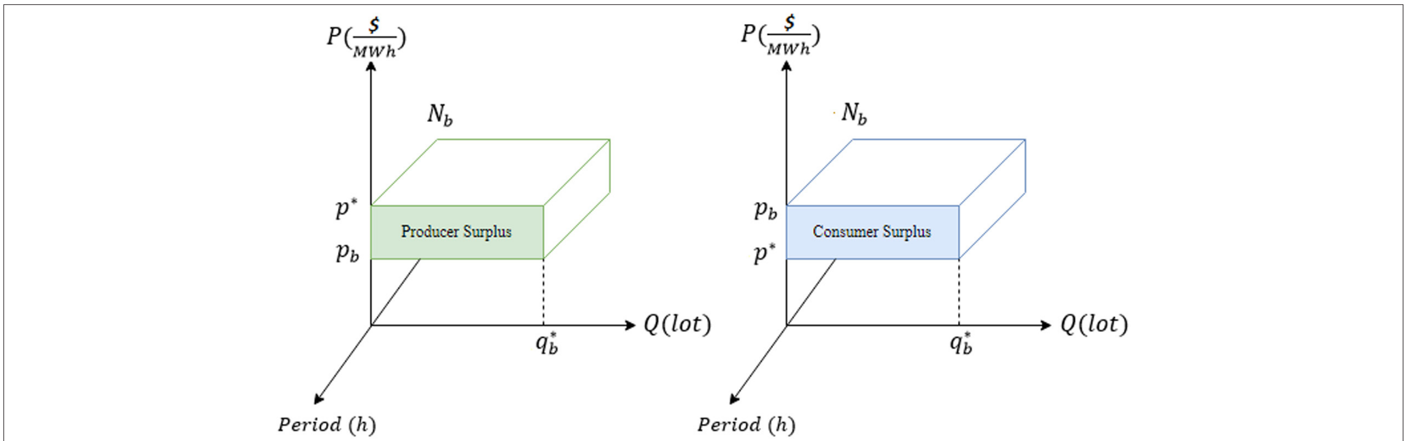

Fig. 3. Illustration of accepted supply and demand block bid surpluses.

Consumer surplus generated by block bids:

$$\sum_{b\in B^d} y_b * Q_b * \left(N_b P_b - \sum_{t\in T}\delta_{bt} p_t\right) \tag{4}$$

Producer surplus generated by flexible bid:

$$\sum_{f\in F^s} Q_f * \left(\sum_{t\in T} z_{ft} p_t - P_f\right) \tag{5}$$

III. IMPLEMENTATION & RESULTS

A. Mathematical Model of Multivariate/Multi-View Analysis

Objects can be described more comprehensively using different knowledge from different datasets or different subsets of features. By integrating diverse knowledge, the object can be described more thoroughly. It is possible to divide multi-view learning into different types according to how the information from multiple views is integrated. Subspace learning aims to obtain potential subspace shared by multiple views, such as CCA. Depending on how the information from multiple views is integrated, multi-view learning can be divided into categories. Subspace learning identifies potential subspace shared by multiple views, like CCA.

As an alternative to bivariate observations being a pair of scalars, suppose instead that it is given two different random vectors; ***X*** and ***Y***, as seen in Fig. 4. Looking deeper at data projections of low dimensions can provide a better understanding of these multivariate data structures. The use of complex multivariate relationships in large-scale datasets with multiple measures enables a deeper understanding of the analysis of these datasets. This study aims to measure linear relationships between two sets of variables (views) that can be used to extract distinctive features to identify the underlying factors that affect both sets of variables.

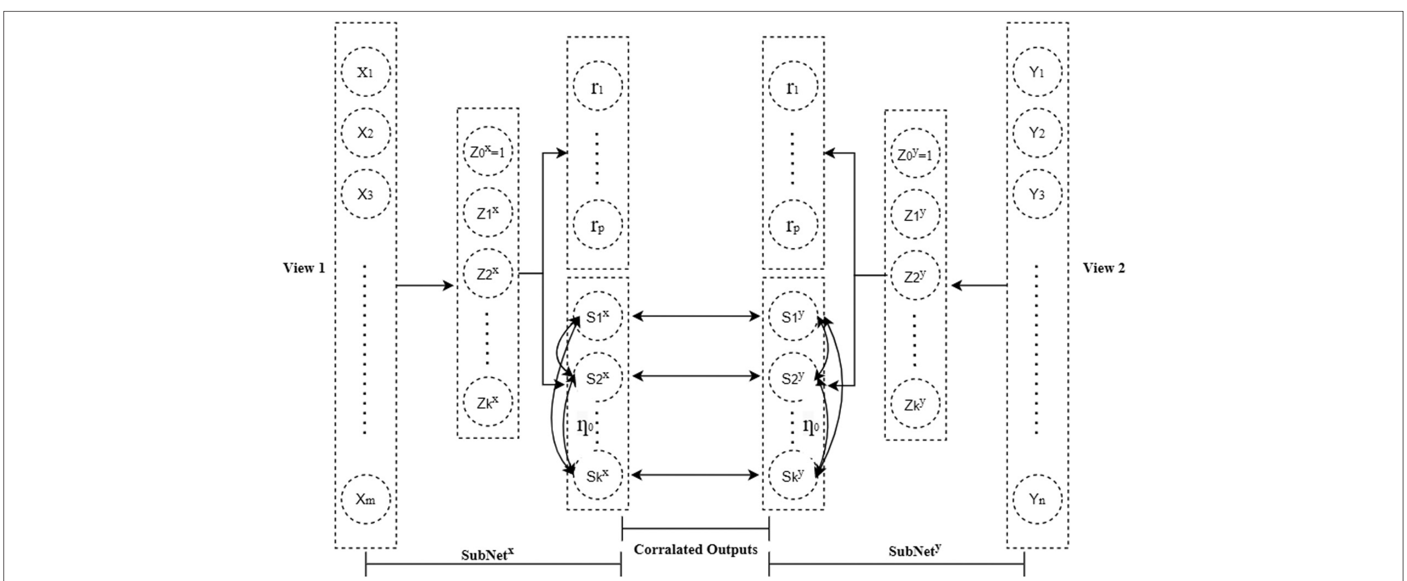

Fig. 4. Architecture of the proposed multi-view method. $X \in \mathbb{R}^{mxN}$ and $Y \in \mathbb{R}^{nxN}$ are reduced from m and *n* to *k*, respectively. An alternation of correlated outputs is used during training to maximize their correlation.

Assume there are two sets of independent variables of electricity spot prices in two centered data sets,

$$X = \left[x_1, x_2, \ldots, x_N\right] \in \mathbb{R}^{m\text{x}N}$$
$$Y = \left[y, y_2, \ldots, y_N\right] \in \mathbb{R}^{n\text{x}N} \quad (6)$$

Where *m* and *n* are the numbers of features of ***X*** and ***Y***, respectively, and *N* is the total number of samples. The target involves projecting the ***X*** and ***Y*** datasets onto basis vectors $\boldsymbol{w}_x$ and $\boldsymbol{w}_y$, respectively, such that the correlations between their projections are maximized.

$$\rho = max_{w_x w_y} corr\left(w_x^T X, w_y^T Y\right)$$
$$= max_{w_x w_y} \frac{cov\left(w_x^T X, w_y^T Y\right)}{\sigma w_x^T X \sigma w_y^T Y} \quad (7)$$

$$\rho = max_{w_x, w_y} \frac{\mathbb{E}\left[\left(w_x^T X\right)\left(w_y^T Y\right)^T\right]}{\sqrt{\mathbb{E}\left[\left(w_x^T X\right)\left(w_x^T X\right)^T\right]\mathbb{E}\left[\left(w_y^T Y\right)\left(w_y^T Y\right)^T\right]}}$$
$$= max_{w_x, w_y} \frac{\mathbb{E}\left[w_x^T X Y^T w_y\right]}{\sqrt{\mathbb{E}\left[w_x^T X X^T w_x\right]\mathbb{E}\left[w_y^T Y Y^T w_y\right]}} \quad (8)$$
$$= max_{w_x, w_y} \frac{w_x^T \mathbb{E}\left[XY^T\right] w_y}{\sqrt{w_x^T \mathbb{E}\left[XX^T\right] w_x w_y^T \mathbb{E}\left[YY^T\right] w_y}}$$

in which $\mathbb{E}$ denotes the expectation and T denotes the transpose. The covariance matrix of (X, Y) is

$$C\left(X, Y\right) = \mathbb{E}\begin{pmatrix} C_{XX} & C_{XY} \\ C_{YX} & C_{YY} \end{pmatrix} = C \quad (9)$$

Substituting these covariance matrices in (8),

$$\rho = max_{w_x, w_y} \frac{w_x^T C_{XY} w_y}{\sqrt{w_x^T C_{XX} w_x w_y^T C_{YY} w_y}} \quad (10)$$

;

According to (10), rescaling of the canonical vectors does not affect the solution to the maximization problem; the problem stated in (8) can be written as follows:

$$\frac{\alpha w_x^T C_{XY} w_y}{\sqrt{\alpha^2 w_x^T C_{XX} w_x w_y^T C_{YY} w_y}} = \frac{w_x^T C_{XY} w_y}{\sqrt{w_x^T C_{XX} w_x w_y^T C_{YY} w_y}} \quad (11)$$

$$\rho = max_{w_x, w_y} \frac{w_x^T C_{XY} w_y}{\sqrt{w_x^T C_{XX} w_x w_y^T C_{YY} w_y}} \quad (12)$$

s.t. $w_x^T C_{XX} w_x = 1$

$w_y^T C_{YY} w_y = 1$

Using the Lagrange relaxation method, the problem is reduced to

$$L\left(\lambda, w_x, w_y\right) = w_x^T C_{XY} w_y - \frac{\lambda_X}{2}\left(w_x^T C_{XX} w_x - 1\right) - \frac{\lambda_Y}{2}\left(w_y^T C_{YY} w_y - 1\right) \quad (13)$$

$$XY^T\left(YY^T\right)^{-1} YX^T w_x = \lambda^2 XX^T w_x \;\; C_{XY} C_{YY}^{-1} C_{YX} w_x = \lambda^2 C_{XX} w_x$$

$$YX^T\left(XX^T\right)^{-1} XY^T w_y = \lambda^2 YY^T w_y \;\; C_{YX} C_{XX}^{-1} C_{XY} w_y = \lambda^2 C_{YY} w_y$$

which are eigenvalue problems of the form $Ax = \lambda Bx$. After obtaining the first projective directions (w_{x1} and w_{y1}), the second largest eigenvalues of the problem can be obtained by solving the following optimization problem.

$$\rho = max_{w_x, w_y} \frac{w_x^T C_{XY} w_y}{\sqrt{w_x^T C_{XX} w_x w_y^T C_{YY} w_y}} \quad (14)$$

s.t. $w_x^T C_{XX} w_x = 1$

$w_y^T C_{YY} w_y = 1 \;\; w_{x1}^T C_{XX} w_x = 0 \;\; w_{y1}^T C_{YY} w_y = 0$

B. Multi-View Features Extraction and Processing

An important requirement to have good robustness is the selection of multiple features. Recognizing latent harmony requires canonical covariates on these features after grouping them in views. In the study, as shown in Table II below, the specific features included in the separate views describing electricity market prices are listed as follows.

It is shown in Table III how the division procedures were implemented during the extraction phase of the data, in order to determine the character of the data by extracting the correlation between the canonical variables created among them.

As shown in the schematic in Fig. 4, a systematic approach of grouping cross-view features and creating canonical features with high distinctiveness and broad evaluation ability is presented. A new set of canonical covariants was created after the features in several views were grouped together. The correlations created between canonical covariates will result in a higher discrimination success than discriminating the view features alone. By doing so, both the correlation within the view and the correlation between views based on feature groups can be captured. Thus, it is then possible to reduce the size of the new determinant variable space, thereby simplifying the calculation process.

C. Performance Metrics

There are three performance criteria utilized in the paper, including root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The equations are given as follows,

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \check{y}_i\right)^2} \quad (15)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \check{y}_i\right| \quad (16)$$

TABLE II. FEATURES REPRESENTED IN THE VIEWS ARE DIVIDED INTO SPECIFIC FEATURE GROUPS

Views in Multi-View Analysis	Features in the Views
AEMO_View_1	Electricity_dayahead_market_prices
AEMO_View_2	Weather_data_features
AEMO_View_3	Demand_supply_data_features
AEMO_View_4	Economic_indicators_features
AEMO_View_5	Infrastructure_data_features
AEMO_View_6	Regulatory_info_features
EXIST_View_1	Electricity_dayahead_market_prices
EXIST_View_2	Weather_data_features
EXIST_View_3	Demand_supply_data_features
EXIST_View_4	Economic_indicators_features
EXIST_View_5	Infrastructure_data_features
EXIST_View_6	Regulatory_info_features
EXIST_View_7	EV_cars_data_features
EXIST_View_8	Inflation_rates_features

AEMO, Australian Energy Market Operator; EXIST, Energy Exchange Istanbul.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|1-\frac{\check{y}_i}{y_i}\right| \tag{17}$$

Where y_i and $\check{y}_i$ are the true and forecast values of variables and N is the total number of forecasting samples.

IV. IMPLEMENTATION & RESULTS

In a preliminary analysis, the impact of the multi-view approach on the forecasting results was investigated for the CCA-utilized model as seen in Fig. 5. In comparison to existing studies, the major contribution of the work is the identification of complex multivariate relationships among independent spot price variables in large-scale forecasting studies of electricity spot prices yields valuable insights into how to forecast the prices as seen in Table IV.

In this paper, a method of creating distinct covariates from multi-view data while maintaining their local consistency was pesented.

TABLE III. DIVISION METHODOLOGY OF THE SYSTEM

Datasets	Samples	No. Views	No. Training	No. Test
AEMO_CaseStudy_1	2160	6	1728	432
EXIST_ CaseStudy_1	4320	8	3456	864
AEMO_CaseStudy_2	2160	6	1728	432
EXIST_ CaseStudy_2	4320	8	3456	864

AEMO, Australian Energy Market Operator; EXIST, Energy Exchange Istanbul.

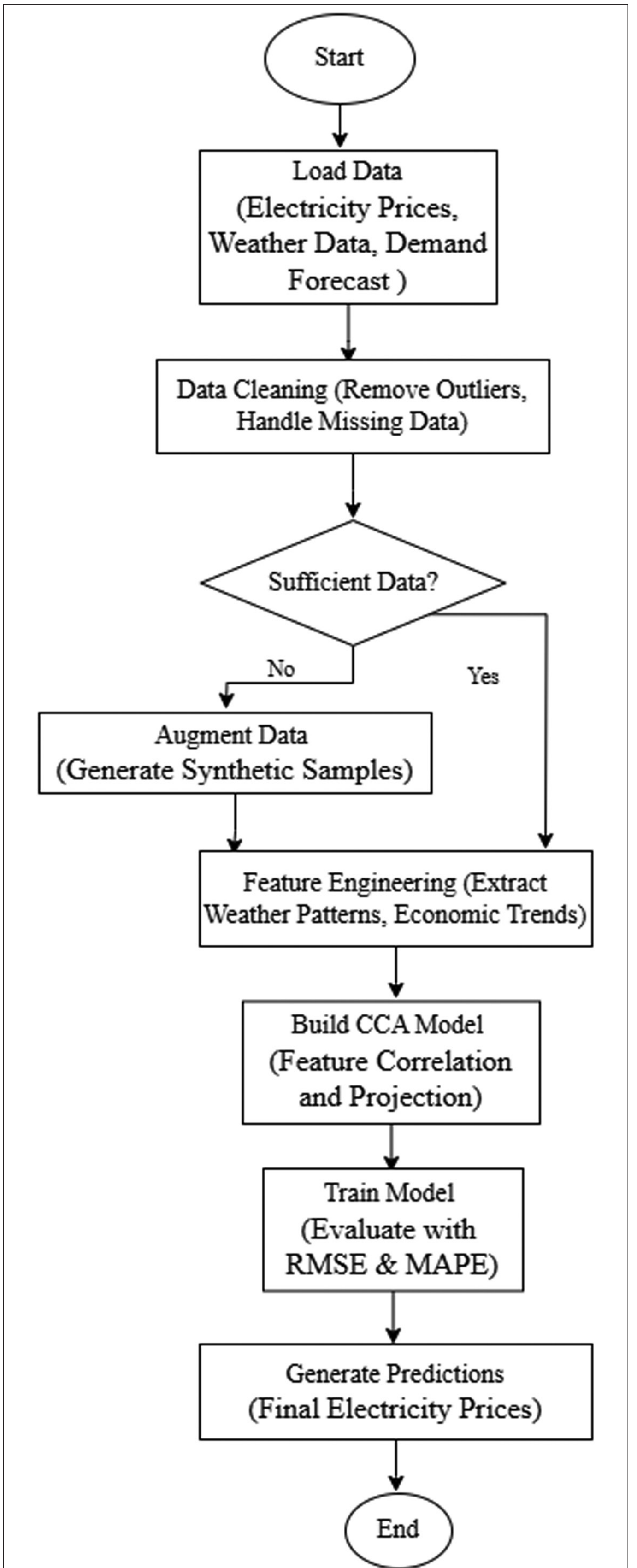

Fig. 5. Flowchart for the proposed approach.

TABLE IV. DEMONSTRATING THE SUPERIORITY OF THE MULTI-VIEW APPROACH OVER THE SINGLE-VIEW APPROACH WITH ROOT MEAN SQUARE ERROR AND MEAN ABSOLUTE PERCENTAGE ERROR VALUES

	View1		View2		View3		View4		View5		View6		Multi-View	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
CCA-utilized (proposed)	1.121	0.706	0.925	0.802	0.916	0.745	1.152	1.126	1.012	0.822	0.951	0.701	0.789	0.025

CCA, canonical correlation analysis; MAPE, mean absolute percentage error; RMSE, root mean square error.

This approach has the advantage of requiring relatively small amounts of data.

A fusion of features at the feature extraction level enhances pattern recognition, which leads to well-fitting electric price forecasts with as low or lower forecast error than other models for electricity prices known in the literature. The proposed new canonical covariates have been confirmed by their use in deep neural networks. For each hour of the day, the calculations were carried out separately. A better assessment of predictions for extreme price levels is obtained by sorting them out and calculating RMSE, MAPE, and MAE. Table V shows the average error is about a quarter as low for the complete sample. A notable indicator of the January to December results is the small error rate. Simulations performed to extract the optimal multi-view parameters of independent spot price input variables were carried out for data from each of the case studies. The data is tested on each last day of the month to obtain the most robust scores.

TABLE V. GROUPS OF TRAINING DATASETS AND TEST DATASETS

Methods	Forecasting Timing	Performance Evaluation Criteria	Evaluation Scores	Best Models
Shao et al. [37]	1-h ahead	MAPE	0.027	EEMD-BİLSTM-MRMR
		RMSE	1.347	EEMD-BİLSTM-MRMR
	24-h ahead	MAPE	0.243	MLP
		RMSE	28.962	MLP
Cruz et al. [38]	24-h ahead	MAPE	0.048	MLP
		RelMAE (RelativeMAE)	0.54	PER
Lago et al. [39]	24-h ahead	sMAPE (SymmetricMAE)	0.123	DNN
Diongue et al. [40]	24-h ahead	RMSE	3.36	Model M2
Lehna et al. [41]	24-h ahead	RMSE	6.59	VAR
		MAE	5.491	VAR
	7-d ahead	MAE	6.50	LSTM
		RMSE	8.401	LSTM
Unsihuay-Vila et al. [42]	7-d ahead	MAPE	0.745	PREDICT2-ES
Jiang et al. [43]	24-h ahead	MAPE	1.913	Designed Model
		MAE	0.6757	Designed Model
		RMSE	0.9855	Designed Model
Wang et al. [44]	24-h ahead	RMSE	0.707	RF-IMD-ICEEMD-VMD-Bi-LSTM
		MAPE	1.618	RF-IMD-ICEEMD-VMD-Bi-LSTM
		MAE	0.506	RF-IMD-ICEEMD-VMD-BI-LSTM
Proposed System	**24-h ahead**	**RMSE**	**0.669**	**CCA-Utilized**
		MAE	**0.493**	**CCA-Utilized**

MAE, mean absolute error; MAPE, mean absolute percentage error; RMSE, root mean square error.

On the other hand, in a multi-view approach, given two different representations of the same underlying phenomenon, CCA-utilized extracted features explained the correlation more descriptively. Asynchronous price movements with latent and distinctive characteristics can be revealed by the interpretability of different information in multiple views. The valuable information emerging from the multi-view approach reveals the contribution to the literature.

As a result of the CCA's distinguishing multi-view characteristics, it is concluded that they are valuable and attractive for day-ahead EPF. Compared to classic time-series models used in the literature for day-ahead forecasting, these models outperform them.

V. CONCLUSION

Canonical correlation analysis-utilized approach reveals highly correlated spot price feature groups in the reduced subspace, as well as more discriminative features characterized by canonical covariates' correlation scores. Incorporating these new discriminative variables directly leads to improved electricity price forecast accuracy. The proposed model aimed at measuring linear relationships between two sets of variables (views) that can be used for feature extraction in forecasting problems with multi-view data achieved the lowest MAPE and RMSE values for most of the days. Among the forecasting models tested, the proposed model which measured linear relationships between two sets of variables (views) that can be used for feature extraction in multi-view data forecasting had the lowest MAPE and RMSE values. A high degree of generalization is achieved by learning predictive models with minimal dimensionality by identifying and extracting salient features from data. The approach is also effectively useful for extracting dependence (mutual information) between two given views. Single-view (regular) models suffer from generalization problems due to the sample covariance matrix used for its computation, which can be affected by outliers and noisy samples. It is also an effective method for extracting information about the relationship between two views (mutual information). Because of the sample covariance matrix used for its computation, which is affected by outliers and noisy samples, single-view (regular) models are susceptible to generalization problems.

Comparing the results of the developed model to other models in the literature, multiple views are successfully used to extract discriminative features by the CCA-utilized approach, reducing its RMSE by 20%. Furthermore, the RMSE values were decreased from 4.15 (literature average) to 0.78, a greater improvement than in other literature on EPF. In the multi-view performance evaluation, the RMSE values were 0.669 and the MAE values were 0.493. The lower error values suggest better prediction stability, reducing deviations and improving reliability for energy market applications. This demonstrates that the CCA-Utilized approach effectively minimizes forecasting errors, making it a robust choice for electricity price prediction. As compared to literature results derived from independent variables of observed data, these values have significant advantages. In the further phase, a more extensive database will be used to validate the effectiveness of the proposed model, with different effects that can improve its robustness.

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REFERENCES

1. L. Hernandez et al., "A study of the relationship between weather variables and electric power demand inside a smart grid/smart world framework," *Sensors*, vol. 12, no. 9, p. 11571–11591, 2012. [CrossRef]
2. H. Yi-Ling, M. Hai-Zhen, D. Guang-Tao, and S. Jun, "Influences of urban temperature on the electricity consumption of Shanghai," *Adv. Clim. Change Res.*, vol. 5, no. 2, p. 74–80, 2014. [CrossRef]
3. D. Jose, M. Mathew, and A. Krishnan, "Weather dependency of electricity demand: A case study in warm humid tropical climate," In 2016 3rd int. Conf. Electr. Energy syst. IEEE, 2016, p. 102–105. [CrossRef]
4. K. Chapagain, and S. Kittipiyakul, "Performance analysis of short-term electricity demand with atmospheric variables," *Energies*, vol. 11, no. 4, p. 818, 2018. [CrossRef]
5. Z. Zhang, Y. Zhang, and L. Jin, "Thermal comfort in interior and semi-open spaces of rural folk houses in hot-humid areas," *Build. Environ.*, vol. 128, p. 336–347, 2018. [CrossRef]
6. M. Luo, Z. Wang, G. Brager, B. Cao, and Y. Zhu, "Indoor climate experience, migration, and thermal comfort expectation in buildings," *Build. Environ.*, vol. 141, p. 262–272, 2018. [CrossRef]
7. V. Galassi, and R. Madlener, "Shall I open the window? Policy implications of thermal-comfort adjustment practices in residential buildings," *Energy Pol.*, vol. 119, p. 518–527, 2018. [CrossRef]
8. K. Gaur, H. Kumar, R. P. K. Agarwal, K. V. S. Baba, and S. K. Soonee, "Analysing the electricity demand pattern," in 2016 Natl. Power Syst. Conf. IEEE, 2016, p. 1.e6. [CrossRef]
9. P.-A. Cornillon, N. Hengartner, V. Lefieux, and E. Matzner-Løber, "Fully nonparametric short term forecasting electricity consumption," in *Modeling and stochastic learning for forecasting in high dimensions. Lecture notes in statistics()*, vol. 213, A. Antoniadis, J.-M. Poggi, and T. Jasinski, Ed.. Cham: Springer, p. 79.e93, 2015. [CrossRef]
10. R. Q. Grafton, X. Shi, and I. Cronshaw, "Making cents'' of the eastern Australian gas market," *Econ. Pap. J. Appl. Econ. Policy*, vol. 37, pp. 42–54, 2018.
11. P. Simshauser, and T. Nelson, "The Australian east coast gas supply cliff," *Econ. Anal. Policy*, vol. 45, pp. 69–88, 2015. [CrossRef]
12. C. Gao, E. Bompard, R. Napoli, and H. Cheng, "Price forecast in the competitive electricity market by support vector machine," *Phys. A: Stat Mech. Appl.*, vol. 382, 98.e113, 2007. [CrossRef]
13. L. I. Hagfors, D. Bunn, E. Kristoffersen, T. T. Staver, and S. Westgaard, "Modeling the UK electricity price distributions using quantile regression," *Energy*, vol. 102, p. 231–243, 2016. [CrossRef]
14. X. R. Li, C. W. Yu, S. Y. Ren, C. H. Chiu, and K. Meng, "Day-ahead electricity price forecasting based on panel cointegration and particle filter," *Elec. Power Syst. Res.*, vol. 95, 66.e76, 2013. [CrossRef]
15. R. K. Agrawal, F. Muchahary, and M. M. Tripathi, "Ensemble of relevance vector machines and boosted trees for electricity price forecasting," *Appl. Energy*, vol. 250, p. 540–548, 2019. [CrossRef]
16. A. S. M. Khan, R. A. Verzijlbergh, O. C. Sakinci, and L. J. De Vries, "How do demand response and electrical energy storage affect (the need for) a capacity market?," *Appl. Energy*, vol. 214, pp. 39–62, 2018. [CrossRef]
17. P. D. Lund, J. Lindgren, J. Mikkola, and J. Salpakari, "Review of energy system flexibility measures to enable high levels of variable renewable electricity," *Renew. Sustain. Energy Rev.*, vol. 45, pp. 785–807, 2015. [CrossRef]
18. M. McPherson, and S. Tahseen, "Deploying storage assets to facilitate variable renewable energy integration: The impacts of grid flexibility, renewable penetration, and market structure," *Energy*, vol. 145, pp. 856–870, 2018. [CrossRef]
19. J. Riesz, J. Gilmore, and I. MacGill, "Assessing the viability of energy-only markets with 100% renewables," *Econ. Energy Environ. Policy*, vol. 5, no. 1, pp. 105–130, 2016. [CrossRef]
20. J. C. Reston Filho, M. Affonso, de C., and R. C. L. de Oliveir, "Short-term energy price prediction multi-step-ahead in the Brazilian market using data mining," in *Advances in Data Mining Knowledge Discovery and Applications*, A. Karahoca, Ed.. InTech, 2012, p. 219.e34. [CrossRef]
21. J. Andrade, J. Filipe, M. Reis, and R. Bessa, "Probabilistic price forecasting for day-ahead and intraday markets: Beyond the statistical model," *Sustainability*, vol. 9, no. 11, p. 1990, 2017. [CrossRef]

22. R. A. de Marcos, A. Bello, and J. Reneses, “Electricity price forecasting in the short term hybridizing fundamental and econometric modeling,” *Elec Power Syst. Res*, vol. 167, 240.e51, 2019.
23. C. García-Martos, J. Rodríguez, and M. J. Sánchez, “Modelling and forecasting fossil fuels, CO2 and electricity prices and their volatilities,” *Appl. Energy*, vol. 101, pp. 363–375, 2013. [CrossRef].
24. C. Gao, E. Bompard, R. Napoli, and H. Cheng, “Price forecast in the competitive electricity market by support vector machine,” *Phys. A: Stat Mech. Appl.*, vol. 382, 98.e113, 2007.
25. E. J. Anderson, X. Hu, and D. Winchester, “Forward contracts in electricity markets: The Australian experience,” *Energy Policy*, vol. 35, no. 5, pp. 3089–3103, 2007. [CrossRef]
26. P. Simshauser, “On intermittent renewable generation & the stability of Australia’s National Electricity Market,” *Energy Econ.*, vol. 72, pp. 1–19, 2018. [CrossRef].
27. O. Varis, “Associations between lake phytoplankton community and growth factors — A canonical correlation analysis,” *Hydrobiologia*, vol. 210, No. 3, pp. 209–216, 1991. [CrossRef]
28. A. Bartos, A. Fekete, and B. Sarvari, “Study of ecological factors and nutrient content variables in wheat applying canonical correlation analysis,” *Enytermeles*, vol. 40, No. 2, pp. 111–124, 1991.
29. J. B. Wade, L. M. Dougherty, R. P. Hart, A. Rafii, and D. D. Price, “A canonical correlation analysis of the influence of neuroticism and extraversion on chronic pain, suffering, and pain behavior,” *Pain*, vol. 51, No. 1, pp. 67–73, 1992. [CrossRef]
30. M. E. Finkenberg, J. M. Dinucci, S. L. Mccune, and E. D. Mccune, “Personal incentives for exercise and body esteem: A canonical correlation analysis,” *J. Sports Med. Phys. Fitness*, vol. 34, No. 4, pp. 398–402, 1994.
31. T. Cserhati, and E. Forgacs, “Use of canonical correlation analysis for the evaluation of chromatographic retention data,” *Chemom. Intell. Lab. Syst.*, vol. 28, no. 2, pp. 305–313, 1995. [CrossRef]
32. D. R. Hardoon, S. Szedmak, and J. Shawe-Taylor, “Canonical correlation analysis: An overview with application to learning methods,” *Neural Comput.*, vol. 16, no. 12, pp. 2639–2664, 2004. [CrossRef]
33. S. Becker, “Implicit learning in 3d object recognition: The importance of temporal context,” *Neural Comput.*, vol. 11, no. 2, pp. 347–374, 1999. [CrossRef]
34. O. V. Favorov, and D. Ryder, “SINBAD: A neocortical mechanism for discovering environmental variables and regularities hidden in sensory input,” *Biol. Cybern.*, vol. 90, no. 3, pp. 191–202, 2004. [CrossRef]
35. O. V. Favorov, D. Ryder, J. T. Hester, D. G. Kelly, and M. Tommerdahl, “The cortical pyramidal cell as a set of interacting error backpropagating networks: A mechanism for discovering nature’s order,” in *Theories of the Cerebral Cortex*, R. Hecht-Nielsen, and T. McKenna, Ed. London: Springer, 2003, pp. 25–64.
36. E. Parkhomenko, D. Tritchler, and J. Beyene, “Sparse canonical correlation analysis with application to genomic data integration,” *Stat. Appl. Genet. Mol. Biol.*, vol. 8, no. 1, pp. Article 1, 2009. [CrossRef]
37. Z. Shao, Q. Zheng, C. Liu, S. Gao, G. Wang, and Y. Chu, “A feature extraction-and ranking-based framework for electricity spot price forecasting using a hybrid deep neural network,” *Electr. Power Syst. Res.*, vol. 200, 107453, 2021. [CrossRef]
38. A. Cruz, A. Muñoz, J. L. Zamora, and R. Espínola, “The effect of wind generation and weekday on Spanish electricity spot price forecasting,” *Electr. Power Syst. Res.*, vol. 81, no. 10, pp. 1924–1935, 2011. [CrossRef]
39. J. Lago, F. De Ridder, and B. De Schutter, “Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms,” *Appl. Energy*, vol. 221, pp. 386–405, 2018. [CrossRef]
40. A. K. Diongue, D. Guegan, and B. Vignal, “Forecasting electricity spot market prices with a k-factor GIGARCH process,” *Appl. Energy*, vol. 86, no. 4, pp. 505–510, 2009. [CrossRef]
41. M. Lehna, F. Scheller, and H. Herwartz, “Forecasting day-ahead electricity prices: A comparison of time series and neural network models taking external regressors into account,” *Energy Econ.*, vol. 106, 105742, 2022. [CrossRef]
42. C. Unsihuay-Vila, A. C. Zambroni de Souza, J. W. Marangon-Lima, and P. P. Balestrassi, “Electricity demand and spot price forecasting using evolutionary computation combined with a chaotic nonlinear dynamic model,” *Int. J. Electr. Power Energy Syst.*, vol. 32, no. 2, pp. 108–116, 2010. [CrossRef]
43. P. Jiang, Y. Nie, J. Wang, and X. Huang, “Multivariable short-term electricity price forecasting using artificial intelligence and multi-input multi-output scheme,” *Energy Econ.*, vol. 117, 106471, 2023. [CrossRef]
44. K. Wang, M. Yu, D. Niu, Y. Liang, S. Peng, and X. Xu, “Short-term electricity price forecasting based on similarity day screening, two-layer decomposition technique and Bi-LSTM neural network,” *Appl. Soft Comput.*, vol. 136, 110018, 2023. [CrossRef]

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APPENDIX A.

Date	Hour	Total (MWh)	Natural Gas	Dam	Lignite	Stream	İmported Coal	Wind	Sun	Fuel Oil	Geothermal	Asphaltite Coal	Stone Coal	Biomass	Naphtha	LNG	International	Waste Heat
01.01.2022	00:00	30.983,59	9.211,47	3.537,80	5.891,30	787,59	7.106,15	1.671,13	0,00	24,10	1.302,78	194,30	561,62	772,31	0,00	0,00	-180,66	103,70
01.01.2022	01:00	29.672,68	8.336,79	3.337,10	5.680,95	824,39	6.935,63	1.698,46	0,00	24,20	1.305,23	192,09	581,21	771,35	0,00	0,00	-116,16	101,44
01.01.2022	02:00	28.282,42	7.688,36	2.514,12	5.726,78	684,64	7.011,94	1.707,50	0,00	24,90	1.307,08	192,09	575,07	758,44	0,00	0,00	-12,92	104,42
01.01.2022	03:00	27.135,73	7.004,94	1.991,23	5.778,74	607,99	6.806,22	1.723,35	0,00	23,00	1.311,12	192,09	591,10	777,94	0,00	0,00	222,66	105,35
01.01.2022	04:00	26.491,49	6.969,12	1.717,93	5.770,87	569,12	6.640,47	1.514,91	0,00	23,30	1.313,74	189,88	581,16	778,31	0,00	0,00	321,02	101,66
01.01.2022	05:00	26.282,82	7.093,48	1.586,00	5.710,69	560,25	6.610,38	1.326,99	0,00	23,10	1.313,42	189,88	575,39	774,83	0,00	0,00	412,75	105,66
01.01.2022	06:00	26.769,41	7.288,76	1.492,08	5.769,20	603,94	6.816,83	1.391,01	2,42	22,90	1.316,74	189,88	587,67	760,46	0,00	0,00	424,11	103,41
01.01.2022	07:00	26.905,62	7.324,37	1.546,65	5.777,13	659,06	7.131,90	1.302,22	14,31	22,90	1.314,67	192,09	570,23	758,15	0,00	0,00	191,50	100,44
01.01.2022	08:00	27.298,85	7.850,65	1.348,24	5.798,71	771,80	6.929,08	1.222,87	73,23	24,50	1.314,75	189,88	587,37	726,39	0,00	0,00	358,71	102,67
01.01.2022	09:00	28.302,24	8.492,64	1.447,72	5.647,66	896,57	7.070,23	1.248,07	216,47	32,40	1.312,91	194,30	589,75	735,62	0,00	0,00	316,00	101,90
01.01.2022	10:00	29.068,38	8.460,00	1.528,05	5.576,69	934,76	7.598,76	1.259,67	414,83	32,50	1.305,69	192,09	597,81	745,57	0,00	0,00	317,00	104,96
01.01.2022	11:00	30.251,12	8.919,38	2.174,75	5.655,46	812,08	7.726,02	1.124,32	552,80	33,70	1.293,46	189,88	595,42	766,96	0,00	0,00	305,00	101,89
01.01.2022	12:00	30.838,37	9.089,87	3.033,60	5.721,17	750,22	7.616,92	1.044,52	528,45	23,10	1.288,39	194,30	588,54	764,28	0,00	0,00	92,00	103,01
01.01.2022	13:00	31.364,83	9.321,69	3.376,75	5.701,19	807,07	7.561,98	1.023,55	529,18	33,50	1.289,87	189,88	585,70	767,07	0,00	0,00	76,41	100,99
01.01.2022	14:00	31.616,24	9.580,57	3.384,05	5.689,25	837,32	7.635,17	938,01	399,17	32,70	1.281,67	189,88	576,63	761,59	0,00	0,00	207,63	102,60
01.01.2022	15:00	31.926,46	9.774,59	3.282,59	5.692,85	855,78	7.747,93	1.024,38	332,06	32,60	1.280,31	194,30	583,68	754,55	0,00	0,00	268,40	102,44
01.01.2022	16:00	33.035,10	10.617,91	3.451,20	5.739,68	1.034,63	7.849,70	1.068,22	179,36	33,60	1.281,01	189,88	585,53	768,05	0,00	0,00	134,55	101,78
01.01.2022	17:00	35.026,48	11.039,35	5.047,59	5.779,34	1.272,60	7.870,41	1.055,43	14,94	26,70	1.285,71	189,88	581,92	764,54	0,00	0,00	-6,00	104,07
01.01.2022	18:00	36.649,19	11.436,39	5.931,95	5.767,93	1.400,29	7.881,43	1.283,08	0,25	26,80	1.297,18	189,88	573,52	763,69	0,00	0,00	-8,31	105,11
01.01.2022	19:00	36.170,95	11.162,26	5.522,31	5.722,08	1.425,42	7.867,78	1.496,68	0,00	26,20	1.301,42	189,88	588,46	765,98	0,00	0,00	2,46	100,02
01.01.2022	20:00	35.247,11	10.645,02	4.989,08	5.696,76	1.394,35	7.864,52	1.700,04	0,00	26,70	1.299,00	189,88	578,61	776,86	0,00	0,00	-14,15	100,44
01.01.2022	21:00	34.318,44	10.254,75	4.403,39	5.713,21	1.221,40	7.881,94	1.897,77	0,00	26,60	1.305,21	192,09	583,78	780,33	0,00	0,00	-41,63	99,60
01.01.2022	22:00	33.469,09	8.772,93	5.406,60	5.658,43	986,00	7.728,53	2.114,75	0,00	26,10	1.306,89	187,67	455,50	777,90	0,00	0,00	-51,12	98,91
01.01.2022	23:00	31.692,57	8.302,90	5.232,19	5.153,04	890,53	7.002,08	2.263,56	0,00	26,10	1.305,96	189,88	441,07	783,99	0,00	0,00	0,00	101,27
02.01.2022	00:00	30.578,26	6.545,94	5.261,14	5.676,05	776,25	7.058,29	2.450,21	0,00	25,20	1.299,62	189,88	445,47	772,86	0,00	0,00	-21,00	98,35
02.01.2022	01:00	29.114,41	6.223,20	3.760,53	5.604,42	722,75	7.220,40	2.675,47	0,00	23,40	1.307,30	189,88	439,98	743,65	0,00	0,00	104,00	99,43
02.01.2022	02:00	27.808,78	6.016,57	2.368,60	5.564,50	777,44	7.216,32	3.008,29	0,00	23,30	1.307,66	194,30	429,36	765,24	0,00	0,00	37,00	100,20
02.01.2022	03:00	27.205,46	5.629,17	1.839,29	5.605,60	629,76	7.137,53	3.161,56	0,00	22,90	1.312,21	189,88	422,40	769,56	0,00	0,00	385,00	100,60
02.01.2022	04:00	26.862,67	5.337,78	1.759,75	5.616,85	630,18	6.939,23	3.329,67	0,00	23,10	1.312,09	194,30	426,02	777,19	0,00	0,00	416,00	100,51
02.01.2022	05:00	26.853,37	5.328,44	1.423,56	5.613,31	632,10	7.032,29	3.399,65	0,00	23,10	1.311,43	192,09	432,21	779,75	0,00	0,00	586,00	99,44
02.01.2022	06:00	27.121,00	6.016,97	1.083,94	5.454,98	663,66	7.047,72	3.339,31	0,63	23,30	1.313,37	192,09	426,01	789,26	0,00	0,00	673,00	96,76

Please visit the link for all data: https://seffaflik.epias.com.tr/transparency/uretim/gerceklesen-uretim/gercek-zamanli-uretim.xhtm