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DRIVERS OF PRICE VOLATILITY IN ROMANIA'S ELECTRICITY MARKETS

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Abstract. The paper examines the price volatility, key determinants, and autoregressive distributed lag (ARDL) framework of Romania's Intraday Continuous Market (IDC) during the summer months. The stability of the ARDL-ECM coefficients is assessed using the cumulative sum (CUSUM) test. We explore the interaction between IDC and Day-Ahead Market (DAM) prices, alongside the influence of economic and environmental variables, including traded volumes, consumption, export/import and the generation mix. Using hourly data and econometric techniques, we identify significant short- and long-run relationships between IDC prices and their drivers. DAM prices exhibit a strong positive impact on IDC prices, reflecting tight market integration. Higher shares of Renewable Energy Sources (RES) such as wind and solar are associated with increased IDC prices, highlighting challenges in integrating intermittent resources. Conventional sources, particularly coal and oil/gas, also elevate prices due to higher marginal costs. Conversely, electricity consumption is negatively related to IDC prices, suggesting that anticipated demand patterns may contribute to system stability. The findings carry implications for policymakers, indicating a need for enhanced forecasting, flexible resources and improved inter-market coordination to ensure price stability and efficient integration of RES.

Keywords: electricity markets, generation breakdown, renewables, total consumption, ARDL-ECM, CUSUM.

JEL Classification: O13, P18, Q42, D47, C01.

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1. Introduction

Electricity price volatility has become an increasingly important topic within the evolving power systems. Price fluctuations in wholesale electricity markets can have significant implications for consumers, market participants, regulators and policymakers, influencing decisions related to investment, risk management and market design (Haugom et al., 2024); (C. Wang et al., 2020). The transition towards Renewable Energy Sources (RES) and the integration of decentralized generation units (including storage) have amplified the complexity and dynamism of electricity markets, making the study of price behaviors essential for ensuring market efficiency and system reliability (Masoumzadeh et al., 2018; Cevik & Ninomiya, 2022; Mosquera-López & Nursimulu, 2019).

Among the European countries, Romania presents a particularly compelling case for examining electricity price dynamics (Dzhalladova et al., 2023). The Romanian power sector operates within a liberalized framework aligned with European Union directives yet maintains certain specificities that distinguish it from more mature markets. Romania's electricity market is structured around several key segments: the Day-Ahead Market (DAM), Intraday Continuous Market (IDC), Balancing Market (BM) and Ancillary Services Market (ASM) (Bâra et al., 2023a, 2024). The DAM plays a dominant role in energy scheduling, while the IDC provides critical flexibility for real-time system balancing and integration of intermittent RES, such as wind and solar.

Romania's generation mix is variate, encompassing significant shares of hydro, nuclear, coal, oil/gas and an expanding contribution from RES (Spiru, 2023; Burlăcioiu et al., 2023). However, the variability inherent to RES generation poses integration challenges that can exacerbate intraday price volatility. Moreover, Romania is characterized by a unique interplay between domestic production, consumption and cross-border exchanges, further influencing market dynamics (Zlateva et al., 2020; Bâra et al., 2023b).

By employing hourly data and econometric techniques, including the Autoregressive Distributed Lag (ARDL) framework and Error Correction Models (ECM), we investigate both the short- and long-run relationships between IDC prices and a set of economic and environmental drivers. The stability of these relationships is assessed through the cumulative sum (CUSUM) test, ensuring robustness of the findings. Particularly, we focus on the interaction between IDC and DAM prices, traded volumes, consumption patterns, export/import activities, and the influence of different generation sources.

During the summer months, the IDC Price[1] in Romania has demonstrated a high degree of volatility, with a mean of 625.61 RON/MWh and a substantial standard deviation of 545.15. The extreme fluctuations in prices, ranging from a low of –672.53 to a high of 1844.70, suggest that market conditions were dynamic and influenced by shifts in supply, demand and external factors such as weather and fuel prices. The negative price spikes occurred during periods of overproduction, linked to RES surges (like wind or solar), combined with low demand, or during times of market congestion

The DAM Price[2], a key determinant of IDC price, averaged slightly higher than IDC prices, at 636.26 RON/MWh, with a comparable level of volatility (standard deviation of 558.96). The correlation between the DAM and IDC prices is expected since the DAM establishes a baseline expectation for the market. However, deviations in the IDC could reflect intra-day adjustments to real-time consumption, generation or transmission constraints. The wide range in DAM price values (from –50 to 1640) shows that participants in the DAM also experienced considerable price volatility, driven by fluctuating demand profiles or RES forecasts that were not fully realized, necessitating balancing adjustments in the IDC.

DAM quantity averaged 2041.25 MWh, with a standard deviation of 558.10 MWh. The high variability in traded quantities suggests that market participants faced significant uncertainty regarding demand and supply conditions in advance of real-time operations.

Electricity consumption in the Romanian power system averaged 6069.84 MW with significant variability (standard deviation of 857.18 MW). The summer months introduced variability due to factors such as air conditioning loads during heatwaves, fluctuating industrial activity and public holidays.

The generation mix[3] (Coal, OilGas, Hydro, Nuclear, Wind, SolarPV) is an important factor in determining IDC prices, particularly the proportion of RES versus conventional sources. Overall, the summer months were marked by significant volatility in the Romanian IDC (IDC price),

[1] https://www.opcom.ro/rapoarte-pi-raport-cuplare-pi/ro

[2] https://www.opcom.ro/grafice-ip-raportPIP-si-volumTranzactionat/ro

[3] https://www.transelectrica.ro/widget/web/tel/sen-grafic/-/SENGrafic_WAR_SENGraficportlet

largely driven by fluctuations in demand, variability in RES generation and adjustments from the DAM (DAM price). Net export and import dynamics further compounded this volatility.

Thus, our research examines the volatility of prices in Romania's IDC and identifies its principal determinants. It explores the connection between IDC and DAM prices, alongside the influence of traded volumes, cross-border exchanges (import and export), consumption levels and the contribution of both RES and conventional energy sources to the generation mix. The findings contribute to the understanding of electricity price formation in emerging European markets and offer actionable insights for policymakers aiming to improve forecasting capabilities, promote system flexibility and enhance inter-market coordination to support RES integration and price stability.

The rest of the paper is organized as follows: Section 2 provides a comprehensive literature review of the key factors affecting intraday electricity prices. Section 3 outlines the methodology, including stationarity tests and the ARDL model. Section 4 presents the empirical results, focusing on price dynamics across different market conditions. Finally, Section 5 concludes the paper by highlighting key policy implications, limitations of the study and potential future research.

2. Literature review

The impact of hydropower on system electricity price and price volatility in the New England Independent System Operator (ISONE) region was investigated from 2014 to 2020 (Owolabi et al., 2022). It performed a robust analysis of mean, quantile and marginal effects of hydropower alongside solar and wind resources. After adjusting the price data for deterministic temporal trends, multiple linear and quantile regressions showed that hydropower contributed to reducing electricity price and volatility. Additionally Hu and Wang (2022) investigated how storage devices impact electricity price volatility. By analyzing the connection between an economic dispatch problem and its Lagrange dual, the authors revealed that the capacity and charge/discharge power of a storage device installed at a node had an aggregate effect on the range of price changes at that node. They proposed a model to calculate the sensitivity of price volatility to storage device parameters and developed a chance-constrained optimization model.

Furthermore, Rintamäki et al. (2017) examined how the penetration of variable RES (VRES) affects electricity price volatility by building distributed lag models using Danish and German data. The study found that in Denmark, wind power decreased daily price volatility by flattening the hourly price profile, while in Germany, it increased volatility due to a stronger impact on off-peak prices. Solar power, however, decreased price volatility in Germany. Weekly price volatility increased in both regions because of VRES intermittency. The impact of wind and solar power generation on the level and volatility of wholesale electricity prices in the Greek electricity market from August 2012 to December 2018 was further investigated using a GARCH-in-Mean model (Maniatis & Milonas, 2022). The findings confirmed the merit-order effect, stronger for wind power. Controlling for regulatory mechanisms, the research showed that while RES overall decreased price volatility, wind power tended to increase it and solar power tended to decrease it. During peak hours, both wind and solar generation reduced price volatility, supporting the idea that RES lower volatility when correlated with electricity load. Also, Ciarreta et al. (2020) analyzed structural changes in Spanish electricity spot price volatility from January 2002 to December 2017, focusing on the role of regulatory developments alongside RES expansion. The research identified two major structural breaks linked to the abolishment of the feed-in tariff scheme and the introduction of a more market-oriented regulation based on investment and operating costs. The findings concluded that stable regulatory policies reduced price volatility despite the growing presence of RES, and that market-based measures effectively achieved lower volatility while supporting the integration of intermittent renewable electricity.

Another research investigated the impact of variable RES (VRES) supply on electricity price volatility in the Iberian Market of Electricity (MIBEL) from 2010 to 2015 (Pereira da Silva & Horta, 2019). Using regression analysis and EGARCH models, the research concluded that VRES, particularly wind power, increased price volatility. It also found that greater intraday variability of VRES further heightened volatility. Additionally, the analysis showed that market coupling with the French market could help mitigate the sensitivity of price volatility to wind power variability. Moreover, Lin et al. (2021) examined the impact of product price risk on firms' liquidity management in the electricity industry. It found that higher electricity price volatility led to an increase in cash holdings, with the result remaining robust when instrumenting price risk with weather volatility.

Also, Segnon et al. (2022) analyzed Australian electricity price returns and found evidence of volatility clustering, long memory, structural breaks and multifractality. To model return dynamics, the authors employed smooth transition ARFIMA (STARFIMA) and Markov-switching ARFIMA (MSARFIMA) processes, while volatility was modeled using short- and long-memory GARCH processes, Markov-switching GARCH processes, and a Markov-switching multifractal (MSM) process. Out-of-sample forecasting performance, assessed using MSE and MAE loss functions, showed that the MSM model performed competitively with conventional GARCH- and MSGARCH-type models and outperformed them when daily squared returns were used as a proxy for latent volatility. The short- and long-term impacts of hydroelectric power generation, economic growth, energy demand and exchange rates on electricity price volatility in Cameroon from 2000 to 2019 was further investigated using an autoregressive distributed lag model (Akono & Kemezang, 2024). It found that while increased hydropower generation raised short-term electricity price variation, it significantly reduced prices in the long term. The research suggested that promoting SME engagement in RES could reduce price volatility and emphasized the importance of expanding power generation to support economic growth and attract private investment.

Another research analyzed the impact of RES penetration on electricity price volatility using a non-parametric model and historical spot price data from Danish and Swedish price areas of the Nord Pool and the PJM market (Dong et al., 2019). It found that electricity prices were most stable in Swedish areas, where hydropower dominated, followed by the PJM market, where fossil fuels were the primary energy source. In contrast, Danish price areas exhibited greater volatility, largely due to the intermittency of wind power. The research highlighted how different RES influence electricity price stability. Mwampashi et al. (2021) examined the impact of wind power generation on electricity price dynamics in Australia's National Electricity Market (NEM) using an eGARCH model. It found that a 1 GWh increase in wind generation decreased daily prices by up to 1.3 AUD/MWh and increased price volatility by up to 2%. Beyond consumption and gas prices, hydro generation also contributed to rising electricity prices and volatility. The study highlighted the critical role of cross-border interconnectors in influencing price levels and volatility and emphasized the need for strategic investments in connectivity. Also, da Silva Leite and Andrade de Lima (2023) modeled the realized volatility of electricity spot prices in Brazil using a GARCH model based on 862 weekly observations across four different markets. It concluded that Brazil's spot electricity prices exhibited high volatility, posing risks to market participants. The research attributed this volatility to institutional factors and the growing share of RES in the country's electricity mix.

Furthermore, D. Wang et al. (2022) explored electricity price fluctuations in the DE-LU bidding zone from October 2018 to March 2022 using time series analysis. It categorized the determinants into exogenous prices (gas, coal, CO_2), internal factors (consumption and generation) and external electricity flows (net imports). The SARIMAX model, incorporating all these factors, was identified as the best fit based on AIC and MAPE values. The study found that anonymous trading and unpredictable bidding strategies contributed to persistent price volatility. Additionally, Baule and Naumann (2021) analyzed volatility and dispersion in individual hourly contracts on the continuous intraday market of EPEX SPOT, adapting volatility measures to account for market-specific characteristics. Five price fluctuation measures were tested and found similarly suitable, with minor differences. The analysis identified that a higher share of wind energy increased price dispersion, and dispersion was positively correlated with traded volume and the absolute difference between day-ahead and intraday prices. The research also found that trading-related variables were more important than fundamental factors in forecasting a contract's peak trading hour fluctuations, achieving an adjusted R^2 of 0.479 for volatility and around 0.3 for dispersion measures. Sikorska-Pastuszka and Papież (2023) investigated volatility connectedness among 26 European electricity markets from August 2007 to February 2022 using a time-varying parameter vector autoregressive (TVP-VAR) model based on the extended joint connectedness method. It found that volatility connectedness, reflecting market integration, generally increased over time. Initially, stronger connectedness was observed among geographically closer markets, but since 2016, both regional and interregional connectedness rose, especially during periods of high energy price volatility. However, when adjusting for the volatility of electricity price determinants, the connectedness appeared lower, particularly from 2021 onward, indicating that volatility connectedness mainly remained within the same regions. Gudkov and Ignatieva (2021) analyzed continuous-time stochastic volatility jump-diffusion processes for modeling electricity spot prices and pricing futures contracts. It proposed models that captured key features of the electricity market, such as mean reversion, seasonality, extreme volatility and price spikes, extending existing approaches by allowing jumps and stochastic volatility in both the spot price and its volatility. Parameters were estimated using the Markov Chain Monte Carlo (MCMC) method for the Australian electricity market. The study found that incorporating stochastic volatility and jumps was essential for accurately fitting observed spot prices and derived semi-closed form futures prices. Further, Krečar and Gubina (2020) discussed the growing importance of the risk premium (RP) as an indicator of supply and demand uncertainty in electricity markets, particularly in the context of rising RES penetration. It highlighted that traditional RP models, based on daily electricity prices, had become inadequate due to the increased sub-hourly variability introduced by RES. To address this, the research proposed a stochastic method for RP calculation driven by intraday dynamics. Using historical data from the German electricity market, it illustrated how RP signals evolved with increasing market uncertainty.

The objectives across these studies varied but converged on several key themes. A major goal was to assess electricity price volatility and identify its key determinants, including the roles played by RES integration, storage systems, consumption patterns, and regulatory changes. Several studies focused on detecting structural breaks and evaluating the impact of regulatory reforms, such as Spain's transition from feed-in tariffs to market-based mechanisms. Other research investigated the growing integration and volatility connectedness among European electricity markets, especially during periods of high energy price volatility.

Some studies also aimed to develop new, more precise modeling approaches that account for the sub-hourly variability introduced by RES, improving forecasts of spot and futures market behaviors. Finally, a number of papers sought to guide risk management strategies by linking electricity price risks to liquidity management practices and by identifying optimal storage placement to help mitigate price volatility.

While the literature review offers a comprehensive overview of electricity price volatility in various global markets, it did not cover Eastern European energy markets, including Romania, largely due to the limited number of publications available for these regions.

3. Methodology

3.1. Theoretical framework

Stationarity tests are performed first to assess whether the time series are stationary. We use two stationarity tests: Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) and the Phillips-Perron (PP) test (Phillips & Perron, 1988). The ADF unit root test works under the following hypotheses:

The null hypothesis, denoted by H_0 asserts that the time series has a unit root. The alternative hypothesis denoted by H_1 asserts that the time series is stationary.

The Equation of the ADF test is:

$$\Delta Y_t = a + bt + cY_{t-1} + \sum_{i=1}^{p} d_i \Delta Y_{t-i} + \varepsilon_t. \quad (1)$$

ΔY_t represents the first difference of the series at time t, Y_{t-1} is the lagged value of Y, a is the intercept, bt denotes a deterministic trend, d_i is the lagged difference term, ε_t is the error term.

Lagged differences explain the serial correlation in the residuals. $c = 0$ points to non-stationarity.

The PP test adjusts for serial correlation and heteroskedasticity in the error terms, using the same hypotheses and regression equation as the basic Dickey-Fuller test.

$$Y_t = a + bt + cY_{t-1} + \varepsilon_t. \quad (2)$$

Both unit root tests help avoid spurious regressions in non-stationary data.

The ARDL model, initially developed by (Pesaran & Shin, 1999; Maddala & Wu, 1999), is a flexible econometric approach used to examine both short-run dynamics and long-run relationships between a dependent variable and its regressors. It is particularly suitable for time series data that may contain variables integrated of order zero, I (0), and/or order one, I (1), but not higher.

In contrast to traditional cointegration techniques, the ARDL model does not require all variables to be integrated of the same order, making it an attractive choice for empirical analyses involving mixed integration orders. The model estimates a dynamic relationship by including lags of both the dependent variable and the independent variables. The basic form of an ARDL (p, q_1, q_2, ..., q_k) model is:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{k} \sum_{l=0}^{q_j} \beta_{jl} x_{jt-l} + u_t. \quad (3)$$

In Eq. (3), y_t is the dependent variable, x_{jt} are explanatory variables, α_i and β_{jl} are parameters to be estimated, u_t is the error term.

A major advantage of the ARDL approach is its use of the bounds testing procedure for cointegration, which enables testing for the existence of a long-run relationship regardless of whether variables are I (0) or I (1). The null hypothesis of no cointegration is tested by computing an F-statistic on the joint significance of lagged level variables. If the test statistic exceeds the critical value bounds, cointegration is confirmed.

Once cointegration is established, the model can be reformulated into an error correction model (ECM), which separates the short-run effects from the long-run equilibrium relationship:

$$\Delta y_t = \lambda\left(y_{t-1} - \theta_0 - \sum_{j=1}^{k}\theta_j x_{jt-1}\right) + \sum_{i=1}^{p-1}\phi_i \Delta y_{t-i} + \sum_{j=1}^{k}\sum_{l=0}^{q_j-1}\gamma_{jl}\Delta x_{jt-l} + u_t. \quad (4)$$

In Eq. (4), λ is the error correction coefficient and should be negative and significant to confirm convergence toward long-run equilibrium, θ_j represent the long-run coefficients, ϕ_i and γ_{jl} capture the short-run dynamics.

This structure allows for the separation of immediate effects from long-term relationships, a main feature for policy analysis and market response studies. The ARDL model is particularly useful in energy market studies where structural changes, market reforms, and seasonal demand variations may affect the time series properties of data.

3.2. Justification of variable selection

The selection of variables in this research is grounded in both theoretical considerations and empirical evidence from the literature on electricity markets and price formation. The core aim is to identify the short-run and long-run determinants of IDC prices in Romania, with a focus on market integration, generation variability and real-time demand factors.

We include the DAM price due to its role as a forward-looking benchmark that strongly influences intraday pricing behavior. DAM prices reflect anticipated system conditions and are typically the most informative variable for setting price expectations in the IDC (Heijden et al., 2021).

The traded quantity in the DAM (DAM quantity) is included to account for the volume of pre-committed trades. A high traded volume may imply lower flexibility for adjustments during intraday trading, potentially influencing price volatility or spikes. While not always significant in other contexts, its inclusion helps capture potential capacity constraints or arbitrage effects (Shah & Chatterjee, 2020).

Electricity consumption is an essential demand-side driver. We use system-wide consumption as a proxy for real-time demand pressure, consistent with market microstructure studies. High consumption typically leads to tighter market conditions, and its inclusion allows us to observe how anticipated or unanticipated load patterns affect IDC prices.

The generation mix, including Coal, Oil&Gas, Hydro, Nuclear, Wind and SolarPV, is important for understanding cost variability and market flexibility. Conventional sources (Coal, Oil&Gas) often serve as marginal units with higher marginal costs and slower ramping capabilities, likely contributing to price spikes. Nuclear and Hydro are typically baseload or flexible sources, but their impact can vary depending on seasonal and system constraints. Wind and SolarPV are volatile and intermittent, and their influence on prices may be twofold: while they reduce marginal costs, they also impose balancing and forecasting challenges.

The Export/import variable captures immediate supply-demand balance on the IDC and reflects real-time bidding behavior. It also indicates the extent of net exports or imports, which can significantly affect local prices due to transmission constraints or regional market coupling. Other potentially relevant variables, such as weather conditions, cross-border flows in MWh, reserve market prices or generation forecast errors, were not included due to data unavailability at the desired hourly frequency or multicollinearity with existing generation variables. However, our model design already incorporates proxies for these effects through the actual output of RES and consumption.

3.3. Data collection and treatment

The dataset used in this research comprises hourly observations collected from the official platform of the Romanian electricity market operator (OPCOM) and Transelectrica, covering the period from June 4 to September 9, 2024. This timeframe corresponds to the summer months, which are characterized by higher demand volatility and increased RES generation due to seasonal effects.

All variables, including prices, consumption, generation by source and traded volumes, were collected or derived at hourly resolution, without aggregation into daily averages. This approach ensures a more precise modelling of the real-time dynamics in the IDC, especially relevant for the ARDL framework that relies on high-frequency data to capture short-run dynamics and long-run equilibria.

IDC price and DAM price were recorded at the hourly level as published by OPCOM. For DAM, we used the hourly clearing price of the corresponding delivery hour. Hence, no daily averaging was applied; the DAM price was mapped to each hour of delivery.

DAM quantity represents the traded volume in the DAM for each delivery hour. Consumption data reflects the hourly system load, sourced from Transelectrica. Generation data (Coal, Oil&Gas, Hydro, Nuclear, Wind and SolarPV) are based on the actual generation for each source, provided by Transelectrica's operational reports. Export/import represents the net export or import with the Romanian neighboring countries. To ensure consistency and comparability across variables, timestamps were harmonized to Central European Summer Time (CEST), and any missing values were handled via linear interpolation.

This granularity enables us to accurately estimate the intraday price response to real-time fluctuations in demand and generation. Unlike studies using daily averages, which smooth out volatility and obscure within-day patterns, our approach preserves the sharp dynamics and volatility typical of the IDC, yielding more relevant insights for both traders and policymakers.

4. Results

4.1. Input data

Tables 1–2 presents summary statistics of the input dataset that contains hourly observations for three summer months (from 4th of June to 9th of September).

There is a positive correlation between total electricity consumption and IDC price. As consumption increases beyond 6000 MW, IDC price rises, with some significant price spikes seen at consumption levels exceeding 7000 MW, suggesting that high demand leads to price surges in the intraday market (Figure 1). There is a positive relationship between Sold (Export/import – negative values for export and positive values for import) (MW) and IDC price. As the Export/import increases, so does the IDC price. However, there is considerable dispersion, especially at higher Export/import values, with some extreme price spikes. Prices can exceed 5000 RON/MWh at high Export/import values, reflecting volatility during periods of high-power export or import requirements (as in Figure 2).

Table 1. Summary statistics

	DAM price	DAM quantity	IDC price	Consump-tion	Coal	Oil&Gas
count	2400	2400	2400	2400	2400	2400
mean	636.26	2041.25	625.61	6069.84	874.49	1092.64
Std	558.96	558.10	545.15	857.18	140.39	207.46
min	–50	994	–672.53	3791.83	521.33	209.67
25%	419	1606.75	396.50	5389.92	766.29	1045.83
50%	516	1942.50	509.07	6046.00	868.25	1147.75
75%	666	2395	688.42	6670.83	951.00	1227.54
max	5084	4247	5210.49	8549.50	1329.83	1403.67

Table 2. Summary statistics (cont.)

	Hydro	Nuclear	Wind	SolarPV	Export/import
count	2400	2400	2400	2400	2400
mean	1451.43	1095.40	476.77	357.52	670.16
Std	495.46	303.52	392.06	420.02	620.95
min	273.83	614.00	–14.17	–4.00	–1385.17
25%	1078.13	685.17	172.63	–1.67	259.45
50%	1359.75	1304.50	372.92	116.00	676.92
75%	1742.87	1326.17	684.58	735.62	1058.79
max	3545.50	1350.43	2314.17	1248.00	2453.67

The seasonal decomposition of the IDC price (RON/MWh) provides insight into the underlying patterns and structure of the IDC price data over the summer months (Figure 3). The top panel displays the observed series, which represents the raw IDC price over time. It captures the overall movement of prices from 4th June to 9th September, revealing considerable fluctuations throughout the summer. Noticeable price spikes occur in mid-July and late August. The second panel shows the trend component, which smooths out short-term fluctuations and captures the long-term progression of the IDC price. The trend exhibits a gradual increase starting in late June, peaking around mid-July. After this peak, the price trend declines in early August and stabilizes by early September. The third panel presents the seasonal component, revealing periodic fluctuations that repeat in a consistent pattern. These fluctuations likely correspond to recurring factors such as daily or weekly demand cycles. The seasonal pattern repeats roughly every 7 to 10 days, with a moderate magnitude of around ±200 RON/MWh. This consistency indicates that prices are influenced by regular factors, potentially related to daily consumption peaks or RES generation cycles. Finally, the bottom panel shows the residual component, which captures the noise or irregular variation in the data after accounting for the trend and seasonal components. The residuals are scattered, with some points showing deviations of up to ±500 RON/MWh. These represent unpredictable price movements that are not explained by the trend or seasonal patterns, likely resulting from market shocks, unexpected supply-demand imbalances or external factors such as weather conditions. Both the IDC price and DAM price distributions are centered around a similar range (approximately 0 to 1000 RON/MWh), with most prices clustered in this interval. IDC price tends to have more extreme outliers on the higher end, reaching above 5000 RON/MWh, whereas DAM price stays relatively lower. This suggests that the IDC experiences greater volatility than the DAM (Figure 4).

Wind and solar generation show peaks that correspond with periods of lower IDC price values, indicating that high RES output is likely associated with reduced prices. There are noticeable dips in IDC price during high wind and solar generation spikes, particularly around mid-July, which could be a result of oversupply and reduced demand for other, more expensive energy sources (Figure 5). Both markets show periods of simultaneous price spikes, with IDC price consistently showing more extreme variability than DAM price. Between mid-July and early August, IDC price frequently surpasses DAM price, likely reflecting short-term imbalances in supply and demand not covered by the DAM, driving intraday prices higher (Figure 6).

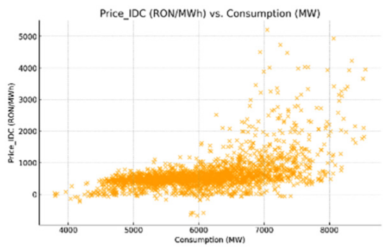

Figure 1. Scatter plots. IDC price & Consumption

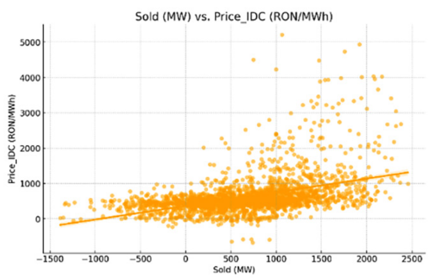

Figure 2. Scatter plots. Export/import & IDC price

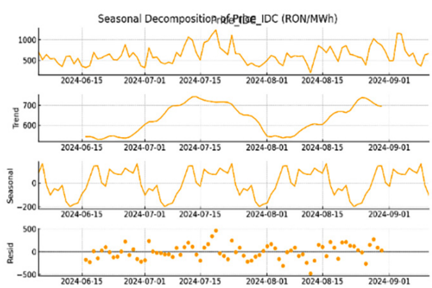

Figure 3. Seasonal decomposition of IDC price

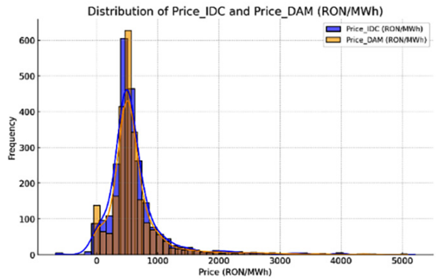

Figure 4. Prices distributions on IDM and DAM

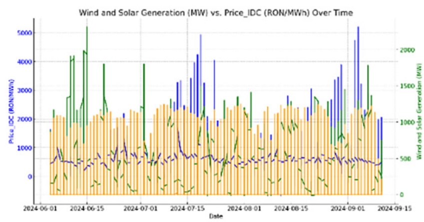

Figure 5. Trend plots for Wind and solar generation vs. IDC price

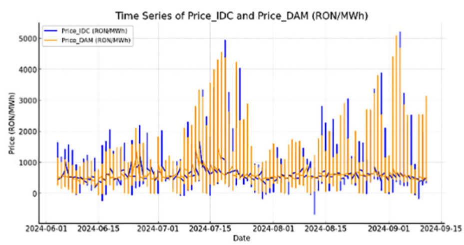

Figure 6. Trend plots for Prices on IDC and DAM

There is a clear upward trend in IDC price during the late afternoon and evening hours (between 16:00 and 21:00), with prices peaking just before 20:00 (Figure 7). The IDC experiences much lower prices during the early morning and midday hours, reflecting lower demand or higher RES generation during these periods. Solar power generation follows a typical daily cycle, peaking around midday (11:00 to 14:00) and reaching up to 1200 MW during its maximum hours. This consistent solar generation could contribute to lower IDC price during midday hours due to the abundance of supply from solar energy (Figure 8).

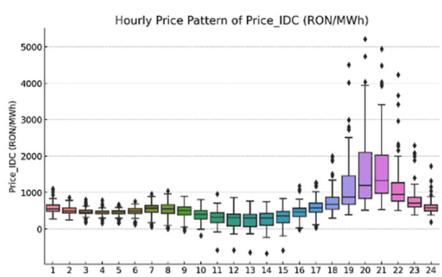

Figure 7. Hourly pattern of (1) IDC price

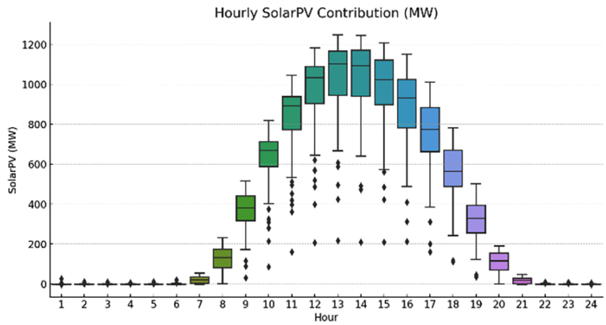

Figure 8. Hourly pattern of SolarPV

The generation mix is relatively stable over time, with nuclear, hydro and fossil fuel sources (coal and oil/gas) contributing significantly to the energy supply. Periods of high wind and solar generation are visible and seem to correspond with lower IDC price values, as RES reduce the reliance on more expensive generation forms (Figure 9). Wind power shows more variability compared to solar, with its generation spread throughout the day but with significant fluctuations. Maximum wind generation reaches above 2000 MW, and the highest wind generation occurs during the night and early morning hours, contributing to price stability in those periods (Figure 10).

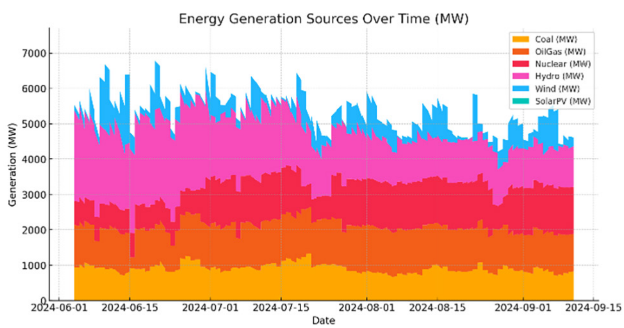

Figure 9. Generation mix over time

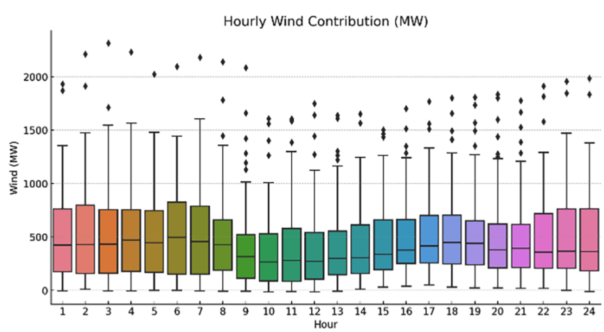

Figure 10. Hourly pattern of Wind

IDC price has a strong positive correlation with DAM price (0.8), showing that both markets influence each other. There are moderate correlations between IDC price and DAM quantity (0.5), Consumption (0.51) and Export/import (0.44), indicating that higher traded volumes, consumption and Export/import are associated with higher IDC prices. SolarPV and Wind show slight negative correlations with IDC price (–0.34 and –0.04 respectively), implying that RES helps suppress intraday prices (Figure 11). The 3D surface plot in Figure 12 illustrates the relationship between IDC price (RON/MWh), electricity consumption (MW) and time (days). One can observe that low consumption, ranging from around 4000 to 6000 MW, is associated with lower electricity prices, as seen by the blue to light-blue regions. This suggests that lower demand tends to correlate with lower IDC prices, which is a typical market behavior. However, as consumption rises above 7000 MW, we see significant price volatility. Price spikes are prominent, with the color transitioning from blue to red, indicating that high consumption levels, particularly when approaching 8000 MW, are linked to much higher prices, some reaching over 3500 RON/MWh.

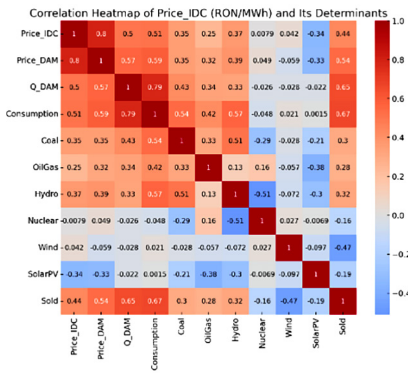

Figure 11. Correlation heatmap

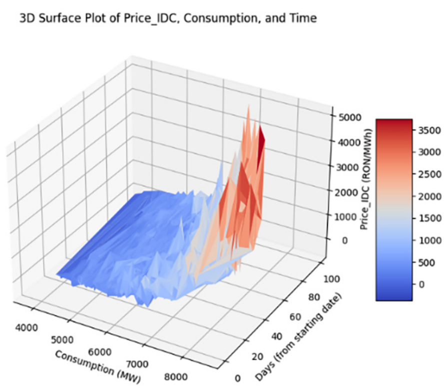

Figure 12. 3D plot of IDC price and Consumption over time

In June, Hydro is a significant contributor to electricity generation, likely due to increased water availability, while Wind and Nuclear also play important roles. By July, Hydro generation declines slightly, and Coal and OilGas generation increase, to meet higher electricity demand during the summer. Wind shows a slight increase compared to June. In August, Coal and OilGas remain high to meet peak demand, while Hydro generation continues to decline. Wind generation increases further, due to stronger seasonal wind patterns and SolarPV shows a small rise, likely due to longer daylight hours (Figure 13).

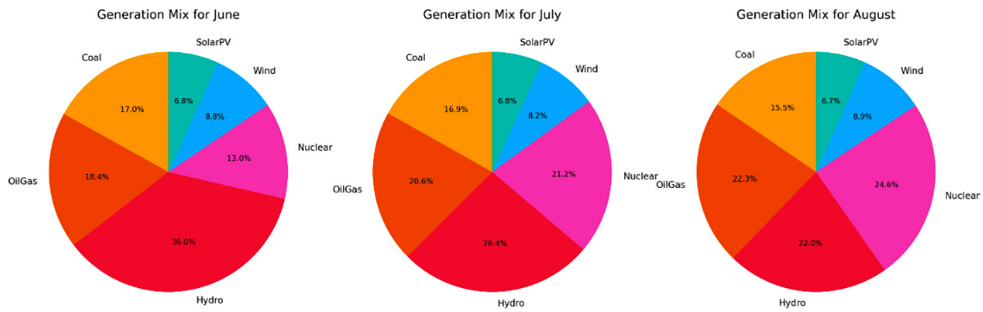

Figure 13. Generation shares by month

4.2. Empirical results

Table 3 reports the data stationarity by applying ADF and PP unit root tests.

Table 3. Unit root tests

Variables	ADF		PP	
	Level	First difference	Level	First difference
	T-statistics	T-statistics	T-statistics	T-statistics
IDC price	–4.63***(0.000)	–17.35*** (0.000)	–14.00***(0.000)	–117.16***(0.000)
DAM quantity	–14.26*** (0.000)	–13.14*** (0.000)	–11.64*** (0.000)	–35.15***(0.000)
Nuclear	–2.69* (0.075)	–40.43*** (0.000)	–4.19*(0.100)	–40.83***(0.000)
Hydro	–18.34*** (0.000)	–14.47***(0.000)	–19.38***(0.000)	–58.29***(0.000)
SolarPV	–3.71***(0.004)	–14.61***(0.000)	–7.86***(0.000)	–6.41***(0.000)
Oil&Gas	–6.44***(0.000)	–10.70***(0.000)	–6.89***(0.000)	–37.33***(0.000)
Wind	–11.00***(0.000)	–21.56***(0.000)	–7.00***(0.000)	–23.95***(0.000)
Export/import	–6.40***(0.000)	–10.88***(0.000)	–3.85***(0.002)	–42.27***(0.000)
Consumption	–6.25***(0.000)	–8.76***(0.000)	–6.48***(0.000)	–12.05***(0.000)
Coal	–3.43**(0.010)	–12.02***(0.000)	–6.59***(0.000)	–51.53***(0.000)
DAM price	–4.30***(0.000)	–16.91***(0.000)	–14.16***(0.000)	–111.54***(0.000)

Note: *, **, *** significant at 10 %, 5% and 1% level.

All the time series are stationary in level, I (0). It means that all stationarity conditions are fulfilled in order to further apply the ARDL model.

In ARDL modelling, determining the optimal lag length is important for accurate estimation. The proper lag selection avoids overfitting and underfitting, ensuring that the model is neither too complex nor too simplistic. Table 4 reports that the optimal lag number is 4, according to four out of five criteria.

Table 4. VAR Lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	–180105.1	NA	5.47e+51	150.34	150.37	150.35
1	–151886.6	56154.27	3.56e+41	126.89	127.21	127.00
2	–146781.4	10112.36	5.56e+39	122.73	123.34*	123.34
3	–146318.8	912..06	4.18e+39	122.44	123.35	123.35
4	–146027.9	570.04*	3.63e+39*	122.3	123.5*	123.50*

Notes: *indicates the lag order selected by the criterion, LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion.

According to the Akaike criterion, the best model is ARDL (4,4,3,2,3,0,0,1,3,4,2), as shown in Figure 14.

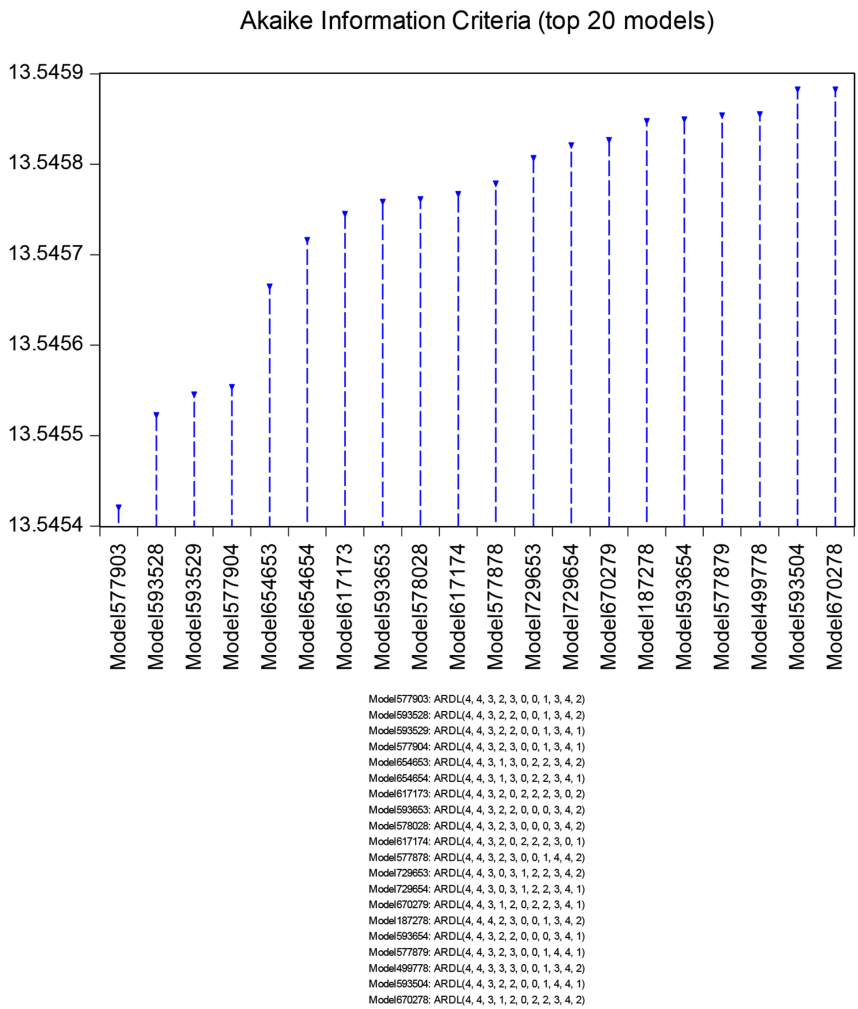

Figure 14. The choice of the best ARDL model according to AIC

Table 5 presents the results of the ARDL bounds cointegration test, indicating a statistically significant long-run relationship between Romania's IDC price and its determinants, including generation mix components, consumption, traded quantities and DAM prices. The computed F-statistic exceeds the upper critical value at the 1% significance level, confirming the rejection of the null hypothesis of no cointegration. This result proves the existence of a stable long-term equilibrium among the variables.

Table 5. Results of ARDL cointegration bounds test

Test statistic	Value	K (number of regressors)
F-statistic	24.04	10
Critical value bounds		
Significance	I (0)	I (1)
10%	1.76	2.77
5%	1.98	3.04
1%	2.41	3.61

The long-run ARDL estimates presented in Table 6 offer both statistical and economic insights into the determinants of IDC price in Romania. Several variables prove to be significant predictors at conventional confidence levels.

A 1% increase in DAM price leads to an estimated 0.55% increase in IDC price, holding other variables constant. This relationship is statistically significant at the 1% level, reflecting strong coupling between DAM and IDC. Economically, this finding confirms the strong market integration between the DAM and IDC in Romania. The DAM serves as a primary price signal for electricity traders, utilities and other market participants, setting expectations about supply-demand conditions for the following day. When DAM prices rise, due to factors like expected high demand, limited generation availability or weather uncertainties, these signals are quickly incorporated into IDC pricing, even in real-time or near-real-time trading. This spillover effect suggests that the IDC is highly responsive to the forward-looking information embedded in the DAM, making it a reactive rather than independent market segment. The relatively elastic relationship implies that changes in the DAM price do not transmit fully to the IDC but still represent a substantial pass-through. The consistent direction and strength of this relationship highlight the importance of efficient DAM price discovery, accurate forecasting and informed bidding strategies, not just for the DAM itself but for mitigating volatility and optimizing trades in the IDC (Oprea & Bâra, 2025).

A 1% increase in Nuclear generation results in a 3.89% increase in IDC price. This means that there is a positive long-run association between nuclear generation and IDC price in Romania. The nuclear power is inflexible in the short term, once scheduled, it cannot easily be ramped up or down to respond to sudden shifts in demand or supply conditions. Thus, during periods of elevated nuclear output, there may be reduced flexibility in the overall generation mix, potentially creating stress in the system if demand unexpectedly rises or if intermittent RES generation fluctuates. In such cases, reliance on nuclear necessitates additional balancing efforts from other, often more expensive, generation sources during real-time trading, pushing up IDC prices.

A 1% increase in Hydro generation is associated with a 3.78% increase in IDC price. This may reflect seasonal or operational constraints that limit hydro's price-lowering potential in the Romanian context. This result may seem counterintuitive, as hydroelectric power is generally considered a low-cost, RES and price-stabilizing energy source, often used to meet peak loads and reduce system costs. In the Romanian context, several underlying factors could explain this unexpected positive association. The presence of seasonal constraints and variability in water availability, which limits the ability of hydro plants to operate consistently at high capacity. During dry periods or drought conditions, especially common in the summer months analyzed in this study, hydro output may be strategically allocated to specific hours when electricity prices are already high, effectively aligning increased hydro generation with periods of elevated market prices. In this case, hydro does not reduce prices; rather, it follows price signals, acting more as a price taker than a price setter.

A 1% increase in SolarPV generation increases IDC price by 3.77%, with marginal statistical significance at the 10% level. The result suggests that under certain market conditions, solar power may not consistently lower prices in the long run. This finding stands in contrast to the widely held assumption that solar photovoltaic power, due to its zero marginal cost, typically helps to reduce electricity prices, especially during daytime hours when solar output is at its peak. The result from the Romanian intraday market suggests a more complex reality, where solar generation does not consistently act as a price suppressant in the long run. Several structural and operational explanations may account for this counterintuitive relationship. First, solar generation is inherently intermittent and concentrated in specific hours of the day, particularly between 10:00 and 16:00. While this generation reduces prices during those periods, it may not align with peak demand times, which in Romania often occur in the late afternoon and evening, after solar output begins to decline. As a result, increased solar capacity during daylight may not alleviate price pressure during high-demand hours, and the system may need to rely on more expensive, flexible resources to meet demand later in the day, thus contributing to overall higher intraday prices. Second, a high share of solar generation without adequate energy storage or demand-side flexibility can lead to issues of overgeneration and ramping requirements. If solar output surges in the middle of the day, followed by a sharp drop, the grid must quickly ramp up alternative generation sources, often gas or coal-fired units, which are more expensive to operate. This phenomenon, known as the "duck curve" effect, can result in price volatility and higher average prices over the day, even if solar reduces prices during specific hours.

A 1% increase in Oil&Gas generation leads to a 3.77% rise in IDC price, also marginally significant at the 10% level. Though flexible in the short term, these sources may contribute to higher long-run costs. Oil and gas power plants are often considered essential for maintaining grid reliability, especially during periods of high demand or when RES generation is insufficient. Their ability to start up quickly and respond dynamically to fluctuations in load or intermittent RES output makes them valuable balancing resources in the real-time market. In the short term, their dispatch stabilizes prices and prevent more severe spikes, particularly when the system is under stress. This long-run relationship suggests that a sustained increase in oil and gas usage is associated with persistently higher IDC price. From an economic policy perspective, the findings suggest that while oil and gas generation provides critical operational flexibility, its long-run use should be strategically minimized to avoid price inflation. Investments in grid modernization, forecasting tools and storage technologies can reduce the need for frequent oil and gas dispatch. Reforms that incentivize real-time demand response and better integration of RES can lower systemic reliance on fossil-based generation in the intraday market.

A 1% increase in Wind generation corresponds to a 3.98% increase in IDC price. This finding may be due to the intermittency of wind power, which could impose balancing costs on the market. In the Romanian IDC, the finding suggests that the operational characteristics of wind power, and the system's ability to manage them, play a critical role in price dynamics. Wind power output is highly variable and often deviates from forecasts, especially in markets without advanced short-term forecasting tools or sufficient reserve capacity. When actual wind generation falls short of expectations, system operators must quickly procure balancing energy, often from more expensive and fast-ramping sources such as oil and gas or imported electricity, to avoid shortfalls. These sudden adjustments can lead to spikes in intraday prices, even when wind capacity is technically abundant.

In Romania, wind generation tends to peak during nighttime or early morning hours, while electricity demand, and hence price pressure, peaks in the late afternoon and early evening. If the system is not equipped to store or shift wind-generated electricity to these high-demand periods, the benefits of wind generation in reducing prices are lost, and the market may experience higher average prices due to reliance on more expensive, dispatchable resources during peak hours. In markets like Romania's, limited demand-side participation and low storage capacity can exacerbate the price impact of wind variability. Without flexible demand response or energy storage systems to absorb excess generation or bridge shortfalls, the system becomes more vulnerable to fluctuations in supply, with prices adjusting accordingly in the IDC.

A 1% increase in Export/import increases IDC price by 3.89. This suggests that greater exports reduce local supply, pushing up domestic prices. From an economic perspective, this result reflects a fundamental supply-demand mechanism: when Romania exports more electricity, the available domestic supply decreases, tightening the internal market. This reduced supply, if not offset by corresponding reductions in demand or increases in local generation, creates upward pressure on prices, especially in the IDC where trading occurs closer to real-time and flexibility is limited.

A 1% increase in Consumption leads to a 3.90% decrease in IDC price. This counterintuitive result might reflect that higher consumption occurs during periods of well-anticipated and well-supplied demand, thus stabilizing IDC price. However, the negative relationship observed here suggests that the context and timing of consumption increases matter greatly, particularly in the Romanian IDC. Higher consumption may coincide with well-forecasted and well-supplied conditions. In modern electricity systems, particularly in summer months when air-conditioning and industrial loads are predictable, system operators and market participants are often able to anticipate and prepare for increases in demand. This advanced preparation can lead to efficient resource scheduling, reduced need for costly last-minute balancing and ultimately more stable or even lower prices in the IDC. Thus, consumption increases during these periods may stability in the system's operation. On the other hand, large consumers, such as industrial users, often enter into forward contracts or participate directly in day-ahead and intraday markets. Their demand may be both flexible and strategically scheduled, aligning with lower-priced hours or times when supply is abundant. In such cases, increased consumption can actually flatten price volatility, reduce peak demand pressure and contribute to efficient load balancing, resulting in lower IDC price.

A 1% increase in Coal generation results in a 4.38% increase in IDC price. This finding aligns with the broader economic understanding that coal-based electricity tends to carry higher marginal and environmental costs compared to RES or even gas-fired generation. One factor contributing to IDC price increase is the inflexibility and cost structure of coal plants. Unlike gas turbines or hydropower, coal units are less responsive to short-term market signals. They operate more efficiently when run continuously and are typically dispatched as baseload or mid-merit options. However, in IDC, where price volatility and rapid supply adjustments are common, the operational rigidity of coal makes it less capable of responding to real-time changes in demand or RES generation. As a result, increased coal output may coincide with times of system stress or reduced flexibility, leading to higher IDC price.

Moreover, Coal generation incurs substantial environmental compliance costs, including carbon emissions penalties under the EU ETS. These costs are passed through to market prices, especially in tight markets where lower-cost alternatives are unavailable. When coal output rises, it often reflects a lack of cheaper or cleaner generation options (e.g., low wind or solar availability), pushing up average generation costs and thus IDC prices. This finding highlights the long-term inefficiency of coal in a dynamic, decarbonizing power system. While coal can still provide dispatchable power, its use is increasingly associated with higher costs and price instability. The result also reinforces the importance of accelerating the energy transition toward more flexible and cleaner sources. In Romania's context, reducing reliance on coal could contribute directly to lowering IDC price pressures and enhancing market efficiency. Further, a 1% increase in DAM quantity is associated with a 1.08% increase in IDC price, though this effect is not statistically significant (as in Table 6), indicating an uncertain long-run relationship.

Table 6. Long-run estimated results (ARDL (4,4,3,2,3,0,0,1,3,4,2))

Variables	Coefficient	T-Statistics	Prob.
DAM quantity	1.08	1.29	0.194
Nuclear	3.89	2.01	0.043**
Hydro	3.78	1.98	0.047**
SolarPV	3.77	1.95	0.050**
Oil&Gas	3.77	1.94	0.051*
Wind	3.98	2.06	0.039**
Export/import	3.89	2.01	0.043**
Consumption	–3.90	–2.03	0.042***
Coal	4.38	2.27	0.022**
DAM price	0.55	10.02	0.000***
C	240.94	1.20	0.228

Note: *, **, *** indicate the significance of variables at 10%, 5%, and 1% levels, respectively.

Table 7 presents the ECM results which capture the short-run dynamics between Romania's IDC price and its determinants. The ECT is statistically significant and negative, indicating that any short-term deviation from the long-run equilibrium is corrected over time, with approximately 27% of the disequilibrium adjusted each period. This confirms the existence of a stable long-run relationship among the variables.

In the short run, DAM price continues to exert a strong and positive influence on IDC price. This suggests that IDC price responds quickly to signals from the DAM, underlining the integration between these two segments. Hydro and SolarPV generation are also positively associated with IDC price in the short term. Despite their RES nature, their intermittent behavior may contribute to IDC price volatility due to the unpredictability of supply.

Table 7. ECM regression

Variable	Coefficient	T-statistics	Prob.
D (IDC price (–1))	0.07	3.39	0.000***
D (IDC price (–2))	–0.01	–0.80	0.422
D (IDC price (–3))	–0.05	–3.19	0.001***
D (DAM quantity)	0.08	3.04	0.002***
D (DAM quantity (–1))	0.001	0.05	0.953
D (DAM quantity (–2))	0.04	1.53	0.125
D (DAM quantity (–3))	–0.07	–2.40	0.016**
D (Nuclear)	0.55	2.48	0.013**
D (Nuclear (–1))	0.01	0.09	0.926
D (Nuclear (–2))	–0.63	–2.99	0.002***
D (Hydro)	1.18	15.14	0.000***
D (Hydro (–1))	0.08	2.48	0.013**
D (SolarPV)	0.89	8.27	0.000***
D (SolarPV (–1))	–0.31	–2.34	0.019**
D (SolarPV (–2))	0.15	1.75	0.079*
D (Export/import)	1.13	14.98	0.000***
D (Consumption)	–1.24	–14.48	0.000***
D (Consumption (–1))	0.02	0.43	0.665
D (Consumption (–2))	0.12	3.46	0.005***
D (Coal)	1.13	7.86	0.000***
D (Coal (–1))	–0.34	–2.80	0.005***
D (Coal (–2))	0.17	1.40	0.160
D (Coal (–3))	–0.23	–1.96	0.050***
D (DAM price)	0.55	32.89	0.000***
D (DAM price (–1))	0.03	1.61	0.106
CointEq (–1)	–0.27	–17.02	0.000***
R-squared	0.57		
Adjusted R-squared	0.57		

Note: *, **, *** indicate the significance of variables at 10%, 5%, and 1% levels, respectively.

Coal generation and Export/import also have significant positive effects on IDC price. Higher coal output may be associated with periods of market stress or limited RES generation, leading to increased IDC price. Nuclear generation shows mixed effects, with both positive and negative short-run impacts depending on the lag, suggesting that while it provides baseload stability, its rigidity may limit responsiveness during price fluctuations.

Electricity consumption has a significant negative impact on IDC price in the short run. This counterintuitive result may indicate that higher demand tends to occur during well-anticipated and adequately supplied periods, contributing to system stability and preventing price spikes.

Diagnostic tests in Table 8 are performed to verify the models' stability. The stability of the ARDL-ECM coefficients is assessed using the CUSUM test. The results, shown in Figure 15, prove that the CUSUM statistics remain within the 5% critical bounds, confirming the stability of the estimated coefficients.

Table 8. Results of diagnostic and stability tests

Diagnostic test	H_0	Decision Statistics [p-value]
χ^2 SERIAL	There is no serial correlation in the residuals	Accept H_0 0.04[0.956]
Durbin Watson statistics	There is no first-order autocorrelation.	Accept H_0 2.00[–]

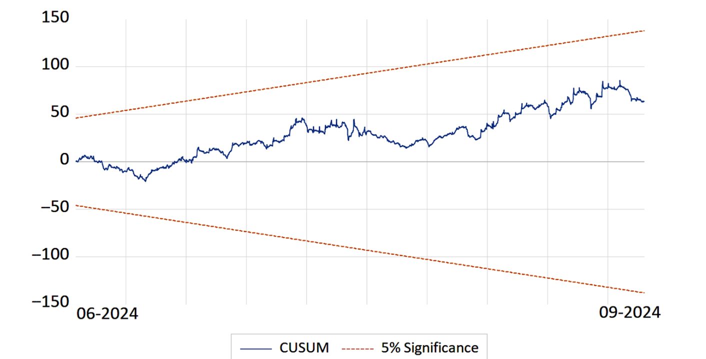

Figure 15. CUSUM for coefficients' stability of ARDL model at 5% level of significance

5. Conclusions and policy implications

Our research offers a detailed econometric assessment of the drivers of price volatility in Romania's IDC, focusing on the summer period. Through the application of ARDL modeling, the analysis provides evidence of both structural and temporal influences on intraday price dynamics.

The results indicate that DAM price is the most significant and consistent determinant of IDC price, proving the close relationship between these two market segments. This strong linkage suggests that optimizing DAM can have positive spillover effects on intraday price stability. The research also finds that both conventional and RES energy sources influence IDC price, although their effects vary in magnitude and direction. Notably, certain RES sources such as wind and solar exhibit a positive long-run impact on IDC price, which may reflect integration challenges or imbalances that arise from variability in their output. On the demand side, consumption appears to exert a negative effect on IDC price, indicating that predictable or efficient demand patterns may help reduce volatility.

These findings have several important policy implications. First, increasing the flexibility of Romania's electricity system is essential. Given the observed impact of various generation sources on IDC price, investments in flexible resources such as battery storage, demand-side response mechanisms and grid enhancements would help manage volatility and support a more stable integration of RES.

Second, improving the integration between the IDC and DAM is important. Since DAM prices strongly influence intraday pricing, enhancing forecasting accuracy, data transparency and market liquidity in the day-ahead segment can improve IDC performance. Measures that strengthen market participant confidence and reduce uncertainty will be particularly valuable.

Third, the positive relationship between solar, wind generation and IDC price highlights the need for better integration of RES. Improved scheduling, forecasting tools and infrastructure that can accommodate intermittent generation without causing instability should be prioritized.

Fourth, the research also reinforces the inefficiency of continued reliance on fossil fuels such as coal and oil/gas, which are associated with higher IDC price in the long run. Policymakers may accelerate their efforts to phase out these generation sources and support a just transition toward cleaner, more flexible technologies.

The finding that higher electricity consumption is associated with lower IDC price may point to an opportunity to promote demand-side measures. Policies that encourage load shifting, real-time price responsiveness or the adoption of time-of-use tariffs could enhance overall system efficiency and reduce volatility. Thus, Romania's IDC is responsive but faces significant challenges, particularly with regard to RES energy integration and price stability. One of the limitations is that the analysis focuses on summer months and may not fully capture seasonal variations throughout the year. The model primarily relies on Romanian data, and results may not be generalizable to other markets without further validation. Future research could expand the scope by including data from other seasons and countries to assess the robustness of the findings.

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Author contributions

S-V. O.: conceptualization, formal analysis, investigation, writing – original draft, writing – review and editing, visualization, project administration. I. A. G.: methodology, formal analysis, investigation, validation, writing – original draft, writing – review and editing. A. B. conceptualization, formal analysis, investigation, resources, writing – original draft, writing – review and editing, visualization, supervision.

Disclosure statement

The authors have no relevant financial or non-financial interests to disclose.

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