

Implementation of the Just-in-Time Philosophy in Coal Production Processes as an Approach to Supporting Energy Transition and Reducing Carbon Emissions: An Extended Multi-Factor Demand Model

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Abstract

Under the European Green Deal, the Fit for 55 package, and the ban on hard-coal imports from Russia and Belarus, stabilizing Poland's energy-commodity market requires forecasting coal demand well in advance so production can follow a just-in-time (JIT) logic. The KOMAG Coal Platform integrates resource, production, and demand data and uses artificial intelligence for forecasting. The demand model developed for 2024-2030 uses 12 variables, and among the eight tested methods, ARX, IV4, and FLNN reproduce the historical decline almost perfectly (R² close to 1.000), projecting a fall to 33-36 Mt by 2030. This paper synthesizes that work and extends it. Starting from an inventory of thirty-eight candidate demand factors, a transparent multi-criteria screening is applied to the twenty-six drivers outside the current model; seven are recommended for inclusion (carbon price, renewable penetration, gas price and supply risk, weather anomalies, GDP growth, generation efficiency and energy storage), an extended model specification is proposed, and a set of additional analytical elements - collinearity mapping, interaction and lag structure, data-operationalisation, non-linearity and prioritisation - is defined for the factor analysis. Finally, demand-relevant elements absent from both the original article and the factor inventory are identified.

Keywords

EU climate policy; coal platform; just-in-time strategy; demand forecasting; multi-factor model; multi-criteria screening; energy transition.



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Introduction

In response to the European Union's climate goals—climate neutrality by 2050 and at least a 55% reduction in greenhouse-gas emissions by 2030 relative to 1990—Poland faces a profound energy transition. This process is shaped not only by decarbonization requirements but also by technological, economic, social, and political conditions, including the growing penetration of renewable energy sources, volatility in energy commodity markets, and the need to maintain system reliability throughout the transition (Węgrzyn et al., 2022). At the same time, the 2022 ban on hard-coal imports from Russia and Belarus (Journal of Laws, 2022) has increased the importance of maintaining a stable domestic coal market. Hard coal will nonetheless remain central to Poland's energy security for years, making accurate and up-to-date information on resources, production, and demand a strategic requirement (Barszczowska et al., 2025).

To address this, the KOMAG Institute of Mining Technology, together with the Mineral and Energy Economy Institute of the Polish Academy of Sciences and the Ministry of Industry, launched the DynGOSP project on dynamic management of demand, production, resource economy, and distribution logistics for hard coal in a decarbonizing energy mix. Its central instrument is the Coal Platform, an information system that balances long-term and dynamic demand with mine production capacity, following a just-in-time philosophy that minimizes stocks and waste (Marlega et al., 2024; Singhal et al., 2025).

A JIT strategy presupposes the ability to predict demand well in advance, which requires advanced analytical tools. The original study, therefore, built a multivariable demand model and compared forecasting methods. The present paper has two aims: first, to synthesize that model and its results; and second, its main contribution, to extend the model by systematically analyzing a broad inventory of demand-shaping factors, selecting those that should enter the mathematical model, and identifying the additional analytical elements and the missing dimensions that a robust demand model must address (Martin and Broughel, 2025).

Materials and Methods

The Coal Platform and the JIT framework

The Coal Platform integrates production data (resource potential, mining schedules, extraction, processing, sales, and distribution) with demand data (long-term contracts and dynamic seasonal and end-user demand), which are fed at different frequencies and compared analytically in near real time (Marlega et al., 2024). Conceptually, JIT is extended from intra-plant flow control to national resource coordination: inventories are minimized across nodes, production and dispatch follow validated, scenario-based demand signals, and uncertainty is handled through scenario design and adaptive replanning (Amiri et al., 2024; Mubarik et al., 2025). The platform is implemented on a cloud-native Azure architecture with staged data ingestion, validation, and analytical layers.

Mathematical model

Demand for hard coal $Z(t)$ (million tonnes) is modeled by a multivariable regression with linear, non-linear, interaction, and lagged terms:

$$Z(t) = b_0 + b_1E(t) + b_2C(t) + b_3G(t) + b_4O(t) + b_5I(t) + b_6R(t) + b_7S(t) + b_8E(t)C(t) + b_9G(t)^2 + b_{10}O(t-1) + b_{11}Z(t-1) + e(t) \quad (1)$$

where $E(t)$ is electricity production from coal (TWh), $C(t)$ heat production from coal (PJ), $G(t)$ the coal price (PLN/t), $O(t)$ the alternative-energy price (PLN/MWh), $I(t)$ industrial demand, $R(t)$ the intensity of climate regulation (ordinal 1-10), $S(t)$ a seasonality index, and $e(t)$ a random term; the model also contains the energy-heat interaction, a quadratic coal-price term, a lagged alternative price and the demand autoregression. The twelve components were retained from a wider candidate set after screening on Pearson correlation with demand ($|r| \geq 0.3$) and significance ($p < 0.05$). Data for 2010-2023 were taken from GUS, the Ministry of Climate and Environment, Eurostat, ARE, and the IEA.

Forecasting methods

Eight approaches were compared: ARX, ARMA, NARX, ARXNL, IV4, GARCH, FLNN, and RKHS, evaluated with MSE, RMSE, MAE, MAPE, and the coefficient of determination R^2 (Dong et al., 2023; Pillonetto et al., 2025). A simple OLS time-trend and a time-trend with AR(1) inertia served as parsimonious baselines.

Results

ARX, IV4, FLNN, and RKHS tracked the historical series most closely, with ARX and IV4 reaching $R^2 = 1.000$ (RMSE = 0.14 and 0.13), and FLNN achieving $R^2 = 0.999$; GARCH and ARMA performed poorly. The

four best methods project a decline from about 42 Mt in 2024 to 33-36 Mt in 2030 (with a mean of about 33.5 Mt), with ARX, IV4, and FLNN showing the smallest dispersion. Over 2010-2030 demand falls by roughly 54%, and by a further about 25% between 2023 and 2030; long-term projections reach about 26 Mt in 2030 (a 63.7% reduction versus 2010) and about 17.7 Mt by 2049.

Against the baselines, the multivariable models materially reduce error (R^2 about 1.000 versus about 0.89 for the linear trend) and, crucially, explain deviations from the trend around 2014-2016 and 2021-2022 through the price, regulation, and alternative-energy channels. This confirms that, although the long-run decline is nearly linear and structurally driven, the operational value of the model lies in explaining and anticipating deviations, which motivates the factor extension developed next.

Tab. 1. Performance of the four best forecasting methods and the demand forecast for 2030. Source: authors' own work.

Method	RMSE	MAE	R^2	Forecast 2030 (Mt)
ARX	0.142	0.105	1.000	33.1
IV4	0.135	0.100	1.000	33.1
FLNN	0.319	0.242	0.999	33.0
RKHS	0.730	0.564	0.993	33.6

Extension of the Model with Additional Demand-Shaping Factors

The DynGOSP inventory lists thirty-eight candidate demand factors; twelve form the current model, and twenty-six lie outside it. This section describes those candidates, adopts a transparent methodology to decide which of them should enter the mathematical model and to what degree, defines the additional analytical elements the factor analysis must incorporate, and proposes an extended specification.

Screening methodology and its justification

A purely data-driven feature selection method (LASSO, elastic-net, random-forest permutation importance, or SHAP) is preferable when all candidates are available as clean, aligned time series (Huang et al., 2016). That precondition fails here: many of the twenty-six factors lack consistent national series aligned with the demand data; several act only through variables already in the model (extraction cost feeds into the coal price; social acceptance acts through regulation); and several are strongly collinear with existing regressors. A structured multi-criteria qualitative screening was therefore adopted as a pre-selection stage that precedes, rather than replaces, later econometric estimation. Multi-criteria decision analysis is a well-established, well-documented method for ranking options in sustainable-energy decisions when evidence is partly qualitative (Wang et al., 2009); it is transparent, reproducible, and consistent with the two-stage logic already used in the original screening.

Each factor is scored 1-5 on five criteria: C1, causal strength of the link to coal demand; C2, data availability and quality for Poland; C3, expected magnitude of effect; C4, incremental information (non-redundancy with the twelve existing variables); and C5, forecast-horizon relevance. Weights prioritize causal validity and non-redundant, well-measured signal over raw effect size: $w = [0.25, 0.20, 0.20, 0.20, 0.15]$. The weighted score (max 5.0) determines the decision: inclusion at ≥ 3.6 , secondary candidate at 3.3-3.5, and conceptual inventory below 3.3.

Catalog and description of the twenty-six candidate factors

Each candidate is described by its mechanism of action on hard-coal demand and its relation to the existing model, grouped by the nine thematic categories of the DynGOSP inventory.

Macroeconomic and political (B):

Tab. 2. List of factors in macroeconomic and political categories

Factor	Description of factor
PKB(t)	GDP growth: economic activity raises energy use economy-wide, an effect broader than the industrial term $I(t)$
POL(t)	regulatory-political uncertainty: volatility of climate and support policy that delays or accelerates fuel-switching investment
TAX(t)	taxation and subsidies: direct and indirect fiscal burdens on coal and support for alternatives, altering relative costs

Technological (C):

Tab. 3. List of factors in technological category

Factor	Description of factor
EFF(t)	generation efficiency: higher net efficiency lowers the tonnes of coal per unit of electricity, acting as a physical multiplier on $E(t)$
STOR(t)	energy storage: storage deployment enables higher renewable shares and reduces the need for dispatchable coal capacity
DISP(t)	dispatch capability: the availability and flexibility of coal units determines how much coal capacity is actually called

Geopolitical and financial (D):*Tab. 4. List of factors in geopolitical and financial categories*

Factor	Description of factor
GAS_RISK(t)	gas price and supply risk: governs coal-to-gas switching at the generation margin and the 2021-2022 shock
CARBON_FIN(t)	availability of financing: ESG-driven risk premia constrain coal-sector investment and capacity
IMPORT(t)	import competitiveness: competition from imported coal reallocates demand between domestic and foreign supply

Social and environmental (E):*Tab. 5. List of factors in the social and environmental category*

Factor	Description of factor
SOC_AW(t)	social acceptance of coal: public pressure shaping the political feasibility of continued coal use
WATER(t)	water stress: droughts constrain cooling and can force capacity reductions at coal plants
HEALTH(t)	external health costs: air-pollution externalities raising the social cost of coal, acting indirectly through policy

Infrastructural (F):*Tab. 6. List of factors in the infrastructural category*

Factor	Description of factor
INFRA(t)	transport infrastructure: rail and logistics capacity governing timely coal delivery
STOCK(t)	operational coal stocks: buffer inventories that smooth short-term supply-demand mismatches
GRID(t)	transmission grid and RES integration: grid capacity determines how much renewable generation can be integrated and therefore how much coal is displaced

Geological and extractive (G):*Tab. 7. List of factors in the geological and extractive category*

Factor	Description of factor
GEOL(t)	geological conditions: deteriorating mining conditions raise costs and thus act on demand only through the coal price $G(t)$
CAPEX(t)	capital expenditure: investment in mine maintenance and development, constrained by financing and sector uncertainty
PROD_COST(t)	production cost: rising extraction costs feed the coal price already present in the model

Demographic and urban (H):*Tab. 8. List of factors in demographic and urban category*

Factor	Description of factor
DEMOG(t)	demographic trends: population change and internal migration affecting energy demand and settlement structure
THERM_MOD(t)	building thermo-modernization: efficiency retrofits reduce heat-related coal demand, overlapping with $C(t)$
URBAN(t)	urban low-emission policy: clean-transport zones and district-heat expansion, limiting individual coal heating

Behavioral (I):*Tab. 9. List of factors in behavioral category*

Factor	Description of factor
EXPECT(t)	market expectations: participants' price, regulation, and technology expectations shaping contracting and investment timing
CRED(t)	government credibility: perceived consistency of decarbonization policy, affecting investment certainty in alternatives

Global (J):*Tab. 10. List of factors in global category*

Factor	Description of factor
GLOB_TECH(t)	global technological progress: falling costs of renewables, storage, and nuclear, lowering the cost of alternatives
CLIMATE_EV(t)	extreme weather: degree-day anomalies drive interannual deviations in heating demand distinct from the smoothed index $S(t)$
EU_ETS_GLOBAL(t)	global carbon-price trends: a market-priced, high-frequency measure of decarbonization pressure, more granular than the ordinal index $R(t)$

Additional analytical elements to be included in the factor analysis

Beyond describing and scoring the factors, a robust extension of the model requires several analytical dimensions that were only implicit in the original study. These are the elements that the factor analysis should explicitly incorporate.

(a) Redundancy and collinearity mapping. Each candidate must be mapped against the twelve existing variables to isolate genuinely new signals: the carbon price is correlated with the ordinal regulation index $R(t)$, the gas price with the alternative-energy price $O(t)$, heating-degree-days with the seasonality index $S(t)$, and extraction cost with the coal price $G(t)$. Only the residual, non-redundant component of each factor should enter the model, obtained by orthogonalization or by regularised estimation (ridge or elastic-net).

(b) Interaction effects. Some drivers act jointly rather than additively. Priority interactions are carbon price $\times$ coal price (cost stacking at the switching margin), renewable penetration $\times$ gas price (joint displacement of coal), and weather anomaly $\times$ heat production. Interaction terms should be explicitly tested, extending the single $E(t)C(t)$ term in Eq. (1).

(c) Lag and dynamic structure. Financing conditions, investment, thermo-modernization, and policy credibility affect demand with delays of 6 to 18 months; each selected factor should be screened for its optimal lag, complementing the existing $O(t-1)$ and $Z(t-1)$ terms.

(d) Non-linearity and thresholds. Several effects are non-linear: coal-to-alternative switching accelerates above coal- or carbon-price thresholds, and renewable displacement saturates at high shares. Quadratic or piecewise/threshold specifications should be evaluated, generalizing the existing $G(t)^2$ term.

(e) Data operationalization. For each selected factor, the analysis must specify the variable, unit, source, update frequency, and any proxy or transformation, so that the qualitative screening can be converted into an estimable model. Tab. 4 provides this mapping for the selected factors.

(f) Uncertainty and scenario dependence. Because several factors are policy and price-contingent, their contribution should be assessed across baseline, optimistic, and restrictive scenarios and reported as probabilistic rather than point effects.

(g) Prioritization and staging. Factors should be grouped into tiers - immediate inclusion, secondary (data permitting), and monitoring only - so that scarce data-collection and modeling effort is directed first at the highest-value drivers.

Screening results and ranking

Tab. 11. Multi-criteria screening of the 26 additional candidate factors (scores 1-5; weighted score, maximum 5.0). Source: authors' own work.

#	Factor (symbol)	C1	C2	C3	C4	C5	Score	Decision
1	Carbon price (EU ETS / EUA) - EU_ETS_GLOBAL(t)	5	5	4	3	5	4.40	Include
2	Renewable penetration & grid integration - GRID(t)/RES	5	4	4	4	5	4.40	Include
3	Gas price & supply risk - GAS_RISK(t)	4	4	4	4	4	4.00	Include
4	Weather anomaly (heating-degree-days) - CLIMATE_EV(t)	4	5	3	4	4	4.00	Include
5	GDP growth rate - PKB(t)	4	5	3	3	4	3.80	Include
6	Average generation efficiency - EFF(t)	4	4	3	4	4	3.80	Include
7	Energy-storage deployment - STOR(t)	4	3	3	4	4	3.60	Include
8	Import competitiveness - IMPORT(t)	3	4	3	4	3	3.40	Secondary
9	Building thermo-modernisation - THERM_MOD(t)	4	3	3	3	4	3.40	Secondary
10	Global technological progress - GLOB_TECH(t)	4	3	3	3	4	3.40	Secondary
11	Regulatory-political uncertainty - POL(t)	3	4	3	3	3	3.20	Inventory
12	Taxation & subsidy systems - TAX(t)	3	3	3	3	3	3.00	Inventory
13	Extraction cost - PROD_COST(t)	3	3	3	3	3	3.00	Inventory
14	Availability of financing - CARBON_FIN(t)	3	3	3	3	3	3.00	Inventory
15	Coal-unit dispatch capability - DISP(t)	3	3	3	3	3	3.00	Inventory
16	Transport infrastructure - INFRA(t)	3	3	3	3	2	2.85	Inventory
17	Operational coal stocks - STOCK(t)	3	3	2	4	2	2.85	Inventory
18	Social acceptance of coal - SOC_AW(t)	3	3	2	3	3	2.80	Inventory
19	Pressure on water resources - WATER(t)	3	3	2	3	3	2.80	Inventory
20	Urban low-emission policy - URBAN(t)	3	3	2	3	3	2.80	Inventory
21	Government credibility - CRED(t)	3	2	3	3	3	2.80	Inventory
22	Demographic trends - DEMOG(t)	2	4	2	3	3	2.75	Inventory
23	External health costs - HEALTH(t)	2	3	2	3	3	2.55	Inventory
24	Geological conditions - GEOL(t)	2	3	2	3	3	2.55	Inventory
25	Mining capital expenditure - CAPEX(t)	2	3	2	3	3	2.55	Inventory
26	Market expectations - EXPECT(t)	2	2	2	2	3	2.15	Inventory

Seven factors reach the inclusion threshold; four fall in the secondary band, and the remainder are retained only in the conceptual inventory. The included factors target precisely the deviations from the structural decline:

carbon and gas prices and renewable penetration govern the switching margin, weather anomalies drive interannual heat demand, and GDP, efficiency, and storage shape the slope of the structural path.

Selected factors, degree of impact, and extended specification

Tab. 12. Selected factors: expected direction, degree of impact and evidence base. Source: authors' own work.

Factor (symbol)	Sign	Degree	Indicative sensitivity	Evidence base
Carbon price EUA - CO ₂ (t)	-	High	Near-full pass-through to generation cost; step cuts above switching thresholds	European Commission, 2025
Renewable penetration - RES(t)	-	High	Merit-order displacement of coal output and price	European Commission JRC, 2023
Gas price/supply risk - GAS(t)	+/-	Medium-High	Coal-gas substitution close to 1:1 in output at the margin	Linn and Muehlenbachs, 2018
Weather anomaly (HDD) - HDD(t)	+	Medium	Heat-related coal demand scales with degree-day deviations	Eurostat, 2024
GDP growth - PKB(t)	+	Medium	Output elasticity of energy demand is about 0.3-0.5; partial decoupling	Gurgul and Lach, 2012
Generation efficiency - EFF(t)	-	Medium	About 0.5-1% p.a. fall in tonnes per TWh	IEA / authors' data
Energy storage - STOR(t)	-	Low-Medium	Reduces dispatchable coal need; effect emerging	IRENA, 2019

Tab. 13. Operationalization of the selected factors for estimation. Source: authors' own work.

Factor	Variable / proxy	Unit	Source	Frequency
CO ₂ (t)	EU ETS EUA settlement price	EUR/tCO ₂	EEX / ICE	daily->monthly
RES(t)	Installed RES capacity/generation share	MW / %	PSE, URE, ENTSO-E	monthly
GAS(t)	TTF gas price / supply-risk index	EUR/MWh	TGE, EEX, ENTSOG	daily->monthly
HDD(t)	Heating-degree-day anomaly vs normal	degree-days	IMGW, Eurostat	monthly
PKB(t)	Quarterly GDP growth	%	GUS, Eurostat	quarterly
EFF(t)	Average net generation efficiency	%	ARE, URE, IEA	annual
STOR(t)	Installed storage power	MW	URE, PSE, EASE	annual

Adding the seven drivers to Eq. (1) - with the seasonality-orthogonalized weather term and the multiplicative efficiency term written explicitly - yields the extended specification:

$$Z(t) = [Eq. (1)] + b_{12}CO_2(t) + b_{13}CO_2(t)G(t) + b_{14}RES(t) + b_{15}GAS(t) + b_{16}HDD^*(t) + b_{17}PKB(t) + b_{18}[E(t)/EFF(t)] + b_{19}STOR(t) + e'(t) \quad (2)$$

where $HDD^*(t)$ is the degree-day anomaly net of normal seasonality. Because $CO_2(t)$, $GAS(t)$, and $HDD^*(t)$ are correlated with $R(t)$, $O(t)$, and $S(t)$ respectively, Eq. (2) should be estimated with regularisation or after orthogonalization, and variable importance re-checked with permutation importance and SHAP once the aligned series of Tab. 4 are assembled. Each selected factor is justified below.

Carbon price CO₂(t)

High impact, negative. The EU ETS allowance price directly alters the short-run marginal cost of coal generation; the 2024 carbon-market assessment records that hard-coal combustion in the ETS reached a historical low as carbon and gas costs reshaped dispatch (European Commission, 2025). Unlike the ordinal index $R(t)$, $CO_2(t)$ is a continuous, market-observed, high-frequency signal and should enter both linearly and through the interaction $CO_2(t)G(t)$.

Renewable penetration RES(t)

High impact, negative. Zero-marginal-cost wind and solar are dispatched first and push coal down the merit order, cutting coal output and wholesale prices (European Commission JRC, 2023). $RES(t)$ captures a structural substitution that the current model only proxies through the alternative-energy price $O(t)$.

Gas price and supply risk GAS(t)

Medium-high impact, ambiguous sign. At the generation margin, cheaper gas displaces coal roughly one-for-one in output (Linn and Muehlenbachs, 2018). $GAS(t)$ refines the aggregate alternative-price term $O(t)$ and explains the 2021-2022 shock that the base model only partially absorbs.

Weather anomaly HDD(t)

Medium impact, positive. Heating-degree-day deviations drive interannual fluctuations in heat-related coal use that the smoothed seasonality index $S(t)$ cannot capture; Eurostat provides a consistent, long, publicly available series (Eurostat, 2024). To avoid collinearity with $S(t)$, it should enter as an anomaly net of normal seasonality.

GDP growth PKB(t)

Medium impact, positive. Activity raises energy demand economy-wide; for Poland, a significant causal relation from energy use to output is documented, with an activity elasticity typically 0.3-0.5 and evidence of partial decoupling (Gurgul and Lach, 2012). $PKB(t)$ broadens the activity signal beyond the industrial term $I(t)$.

Generation efficiency EFF(t)

Medium impact, negative. Because demand is measured in tonnes while $E(t)$ is in TWh, average net efficiency is the physical converter between them; a 0.5-1% annual efficiency gain lowers tonnes per unit of electricity and should enter multiplicatively as $E(t)/EFF(t)$ rather than additively.

Energy storage STOR(t)

Low-to-medium impact, negative. Storage widens the operating range of the system and reduces the reliance on dispatchable coal (IRENA, 2019). Because the Polish series is still short (about 0.1-1 GW in 2024), the factor is included provisionally and flagged for reassessment as data accumulate.

Elements absent from both the original article and the factor inventory

Comparing the original manuscript with the DynGOSP factor inventory reveals that neither document contains demand-relevant elements; their omission constitutes a substantive gap rather than a modeling choice. Nine such elements are identified.

- (1) Coal quality and grade heterogeneity. Demand is treated as aggregate tonnage, yet it is grade-specific (calorific value, sulfur, ash content). The Platform records grades operationally, but quality-differentiated demand is modeled nowhere.
- (2) The Polish nuclear program. Planned reactors from the early-to-mid 2030s would displace baseload coal directly, yet nuclear appears only inside a generic global-technology item, never as a domestic, dated capacity driver.
- (3) Cross-border electricity trade. Interconnector flows and electricity imports and exports affect how much domestic coal generation is dispatched, but only coal imports - not electricity imports - are considered.
- (4) Demand-side response and load flexibility. Explicit demand response is central to a just-in-time logic, yet it is neither a model variable nor an inventory factor.
- (5) Hydrogen, power-to-X, and CCS/CCUS. These long-run structural disruptors of coal use in power and industry are absent from both documents.
- (6) Energy poverty and household affordability of substitutes. The micro-level affordability constraint that keeps some households on coal - distinct from aggregate social acceptance - is not represented.
- (7) Spatial disaggregation. Regional demand distribution, distance-to-mine, and corridor-level transport costs are combined into a single infrastructure index, with no spatial or GIS dimensions.
- (8) Endogenous just-transition feedback. Employment and regional-GDP effects of mine closures feed back into the political pace of phase-out; this policy-endogeneity loop is absent from both documents.
- (9) Input-data uncertainty as a modeled quantity. The project's own premise is data scarcity, yet neither document parameterizes measurement error or reporting lags as stochastic inputs to the forecast.

Discussion

The near-perfect in-sample fit of the twelve-variable model is itself a caution: on a short, strongly trending series, almost any smooth specification tracks the structural decline, so a high R^2 is weak evidence of external validity. The scientific and operational value lies in explaining and anticipating deviations from the decline, which is exactly what the seven selected factors target. The screening also clarifies what should not be added: supply-side geological and cost factors affect demand only through the coal price, and several behavioral and social factors are hard to measure and are largely mediated by prices and regulation, so adding them as separate regressors would raise multicollinearity without adding an independent signal. The multi-criteria screening, therefore, performs a genuine parsimony function rather than merely enlarging the variable list.

Conclusions and Recommendations for Further Research

The original study produced a stable twelve-variable demand model and identified ARX, IV4, and FLNN as the most accurate methods, projecting 33-36 Mt of hard-coal demand in Poland by 2030. This paper extended that

work by screening twenty-six additional candidate factors, selecting seven for inclusion, proposing an extended specification, defining the additional analytical elements the factor analysis must incorporate, and identifying elements missing from both prior documents.

The following research is required to validate the proposal. First, assemble aligned 2010-2025 series for the seven selected factors from the sources in Tab. 3. Second, estimate the extended model using regularised regression and confirm importance using permutation importance and SHAP, explicitly diagnosing collinearities in carbon regulation, gas alternatives, and weather-seasonality. Third, validate out-of-sample against the now-available realized 2024-2025 demand, replacing the previously used ARX proxy. Fourth, apply regime-switching or structural-break models to capture policy and price shocks. Fifth, couple the statistical model with a power-system dispatch (merit-order) model to endogenously represent the carbon, gas, and renewable channels. Sixth, quantify forecast uncertainty with Bayesian or ensemble methods to yield probabilistic scenarios. Seventh, extend the model to the missing dimensions of Section 4.6 - coal quality, nuclear, electricity trade, demand response, hydrogen and CCS, energy poverty, spatial disaggregation, and data uncertainty - so that the Coal Platform can anticipate the deviations that matter for just-in-time coal management.

References

- Amiri, M.M., Ameli, M.T., Strbac, G., Pudjianto, D. and Ameli, H. (2024). The Role of Flexibility in the Integrated Operation of Low-Carbon Gas and Electricity Systems: A Review. *Energies*, 17(9), 2187. Available at: <https://doi.org/10.3390/en17092187>
- Barszczowska, B., Czerwinski, S., Chmiela, A. and Smolinski, A. (2025). Change in the state of hard coal reserves in Poland in the years 2007-2023. *Mining Machines*, 43, 121-130. Available at: <https://doi.org/10.32056/KOMAG2025.11>
- Dong, A., Starr, A. and Zhao, Y. (2023). Neural network-based parametric system identification: A review. *International Journal of Systems Science*, 54, 2676-2688. Available at: <https://doi.org/10.1080/00207721.2023.2241957>
- European Commission (2025). Report on the Functioning of the European Carbon Market in 2024 (2025 Carbon Market Report). Brussels. Available at: https://climate.ec.europa.eu/news-other-reads/news/2025-carbon-market-report-eu-ets-lowers-power-sector-emissions-and-expands-maritime-transport-2025-12-03_en
- Eurostat (2024). Heating and cooling degree days - statistics. *Statistics Explained*. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Heating_and_cooling_degree_days_-_statistics
- Gurgul, H. and Lach, L. (2012). The electricity consumption versus economic growth of the Polish economy. *Energy Economics*, 34(2), 500-510. Available at: <https://www.sciencedirect.com/science/article/abs/pii/S0140988311002672>
- Huang, N., Lu, G. and Xu, D. (2016). A Permutation Importance-Based Feature Selection Method for Short-Term Electricity Load Forecasting Using Random Forest. *Energies*, 9(10), 767. Available at: <https://www.mdpi.com/1996-1073/9/10/767>
- IRENA (2019). Innovation landscape brief: Utility-scale batteries. International Renewable Energy Agency, Abu Dhabi. Available at: <https://www.irena.org/publications/2019/Sep/Utility-scale-batteries>
- Journal of Laws (2022). Act of 13 April 2022 on special measures to counteract support for aggression against Ukraine and to protect national security, item 835. Available at: <https://isap.sejm.gov.pl/isap.nsf/DocDetails.xsp?id=WDU20220000835>
- European Commission, Joint Research Centre (2023). The Merit Order and Price-Setting Dynamics in European Electricity Markets. JRC134300. Available at: https://publications.jrc.ec.europa.eu/repository/bitstream/JRC134300/JRC134300_01.pdf
- Linn, J. and Muehlenbachs, L. (2018). The heterogeneous impacts of low natural gas prices on consumers and the environment. *Journal of Environmental Economics and Management*, 89, 1-28. Available at: <https://www.sciencedirect.com/science/article/abs/pii/S0095069616303904>
- Marlega, R., Dragic, S. and Dydo, M. (2024). The implementation of information technology (IT) in the dynamic management of coal demand and supply processes. *Gospodarka Surowcami Mineralnymi*, 40(1), 161-182. Available at: <https://doi.org/10.24425/gsm.2024.152717>
- Martin, M. and Broughel, A. (2025). Just energy transition: Navigating Poland's transition away from coal mining. *Progress in Energy*, 7, 023001. Available at: <https://doi.org/10.1088/2516-1083/adba38>
- Mubarik, M.S., Gunasekaran, A., Khan, S.A. and Mubarak, M.F. (2025). Decarbonization through supply chain innovation: Role of supply chain collaboration and mapping. *Journal of Cleaner Production*, 507, 145492. Available at: <https://doi.org/10.1016/j.jclepro.2025.145492>

- Pillonetto, G., Aravkin, A., Gedon, D., Ljung, L., Ribeiro, A.H. and Schon, T.B. (2025). Deep networks for system identification: A survey. *Automatica*, 171, 111907. Available at: <https://doi.org/10.1016/j.automatica.2024.111907>
- Singhal, V., Maiyar, L.M. and Roy, I. (2025). Environmental sustainability consideration with just-in-time practices in industry 4.0 era - A state of the art. *Operations Management Research*, 18, 437-460. Available at: <https://doi.org/10.1007/s12063-024-00478-0>
- Wang, J.-J., Jing, Y.-Y., Zhang, C.-F. and Zhao, J.-H. (2009). Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renewable and Sustainable Energy Reviews*, 13(9), 2263-2278. Available at: <https://doi.org/10.1016/j.rser.2009.06.021>
- Węgrzyn, A., Spirydowicz, A., & Grebski, W. (2022). Dilemmas of the energy transformation in Poland 2021/2022. *Mining Machines*, 40(1), 32–42. <https://doi.org/10.32056/KOMAG2022.1.4>