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Cost Modeling in the Back End of the Nuclear Fuel Cycle: A Data-Driven DEMATEL and Shapley-Based Approach †

Francesco Ventura [1,*], JR James [1], Giuseppe Caristi [2], David Barilla [2] and Daniela Barba [3]

[1] CROWN Group Inc., 4730 S. Fort Apache Rd., Suite 300, Las Vegas, NV 89147, USA; jr.james@crownig.com
[2] Department of Economics, University of Messina, Via dei Verdi, 98122 Messina, Italy; gcaristi@unime.it (G.C.); david.barilla@unime.it (D.B.)
[3] QBM S.r.l., Via Faraldo 2/3, 84085 Mercato San Severino, Italy; daniela.barba.84@gmail.com
* Correspondence: f.ventura@crownig.com
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Abstract

Nuclear decommissioning is a key phase of the back end of the nuclear fuel cycle, influenced by both technical and institutional factors. This study develops an integrated framework combining DEMATEL analysis, a log-linear econometric model, and Shapley value decomposition to assess the determinants of decommissioning costs. The results show that high-level radioactive waste and plant capacity are the main cost drivers, while institutional complexity significantly affects cost outcomes. The proposed framework captures both technical and governance dimensions, providing a useful tool for cost estimation and policy planning in nuclear decommissioning.

Keywords: nuclear decommissioning; cost modeling; DEMATEL; Shapley value; institutional complexity

1. Introduction

Nuclear decommissioning is a critical and costly phase of the back end of the nuclear fuel cycle, requiring reliable cost estimation. While technical factors have traditionally received the most attention, institutional and regulatory interactions also generate significant complexity and uncertainty [1]. To capture these effects, this study combines DEMATEL analysis, a log-linear econometric model, and Shapley value decomposition [2]. The results show that high-level radioactive waste and plant scale remain the main cost drivers, but institutional complexity significantly influences costs through systemic interactions, highlighting the need to integrate engineering and governance perspectives in decommissioning cost assessment.

2. Materials and Methods

The framework combines DEMATEL-based complexity measurement, log-linear cost estimation, and Shapley decomposition [3].

2.1. DEMATEL-Based Construction of the Complexity Index

DEMATEL represents interdependencies among technical and institutional factors [3,4]. For standardized indicators $Z = \{z_1, z_2, \ldots, z_m\}$, matrix A yields

$$T = A(I - A)^{-1}, \quad (1)$$

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where I is the identity matrix; T provides normalized weights w_j ($\Sigma_j w_j = 1$) and the project complexity index

$$CI_i = \Sigma_{j=1}{}^{m}\, w_j\, z_{ij}, \tag{2}$$

where z_{ij} is indicator j for project i and w_j is its normalized DEMATEL weight [3].

2.2. Parametric Cost Model

Decommissioning cost is estimated through the following log-linear specification:

$$\begin{aligned} \ln C_i = \alpha + \beta_1 \ln P_i + \beta_2 \ln(1 + V_i,\mathrm{LLW}) + \beta_3 \ln(1 + V_i,\mathrm{ILW}) + \\ \beta_4 \ln(1 + V_i,\mathrm{HLW}) + \gamma \ln T_i + \delta\, CI_i + \theta\, D_i + \varepsilon_i. \end{aligned} \tag{3}$$

where C_i is total cost; P_i is installed capacity [5,6]; V_i,LLW, V_i,ILW, and V_i,HLW are waste volumes [7]; T_i is project duration [8]; CI_i is the DEMATEL complexity index [3,4]; D_i is the strategy dummy (1 = immediate; 0 = deferred dismantling) [8]; and ε_i is the error term.

In the log-linear specification, coefficients associated with logarithmic variables (β_k, γ) can be interpreted as elasticities. For example, β_4 measures the percentage change in total cost associated with a 1% increase in high-level waste volume, which is typically the dominant cost driver due to long-term management requirements [8]. Coefficients associated with non-logarithmic variables (δ, θ) represent semi-elasticities. In particular, θ captures the percentage difference in costs between immediate and deferred decommissioning strategies—an issue extensively debated in the recent policy-oriented literature [8].

2.3. Estimation Strategy

The model is estimated using Ordinary Least Squares (OLS) with heteroskedasticity-robust standard errors [9]. All monetary values are expressed in constant euros to control for inflation effects. Given the limited sample size typical of nuclear decommissioning datasets, model parsimony is prioritized. Multicollinearity is assessed using Variance Inflation Factors (VIFs), and alternative specifications are tested for robustness [10]. These practices are consistent with recent empirical analyses in the energy economics literature [8].

To assess the relative importance of each cost driver, Shapley value decomposition is applied to the estimated model. Originally developed in cooperative game theory [11], this approach has been increasingly adopted in econometrics and machine learning to interpret model predictions [12,13].

Let $\hat{C}_i$ denote the predicted cost, and let K be the set of all predictors. For predictor $k \in K$, the Shapley value is defined as

$$\varphi_k = \Sigma_\{S \subseteq K \setminus \{k\}\} \left[\, |S|!\, (|K| - |S| - 1)! \;/\; |K|! \, \right] \left[\, f(S \cup \{k\}) - f(S) \, \right], \tag{4}$$

where S is any subset of predictors that excludes k, $|S|$ is the number of predictors in S, $|K|$ is the total number of predictors, and f(S) denotes the model output obtained using the predictor subset S. Thus, φ_k represents the average marginal contribution of predictor k over all possible predictor orderings.

This decomposition attributes to each variable its average marginal contribution across all possible combinations of predictors, ensuring a fair and consistent allocation. In the context of nuclear decommissioning, it enables the identification of the most influential cost drivers, such as high-level waste management or institutional complexity.

2.4. Integration of Methods

The integrated use of DEMATEL, econometric modeling, and Shapley decomposition provides a comprehensive framework for analyzing decommissioning costs. DEMATEL captures interdependencies among drivers, the econometric model estimates their effects

on costs, and Shapley values assess their relative contributions. This hybrid approach is particularly suitable for complex systems involving both quantitative and qualitative interactions [3].

2.5. Limitations

The framework may be affected by DEMATEL assessment subjectivity, small-sample and measurement-error issues in the econometric model, and sensitivity of Shapley results to model specification. These limitations motivate validation with real-world data.

3. Results

The analysis uses 150 illustrative nuclear decommissioning projects including technical, operational, and institutional variables. DEMATEL identifies regulatory stringency as the main causal institutional factor and supports construction of the complexity index. The log-linear model confirms HLW volumes and plant capacity as the main cost drivers, while project duration and institutional complexity also have significant effects. Shapley decomposition further shows that HLW, plant scale, and institutional complexity explain most of the modeled cost variability, supporting the integrated interpretation of technical and governance-related drivers.

4. Discussion

DEMATEL reveals strong interdependencies among institutional variables: regulatory, licensing, and socio-political factors operate as an interconnected system rather than as independent drivers. The prominence–relation map indicates that institutional complexity arises from mutual reinforcement among these factors rather than from a single dominant factor (Figures 1 and 2).

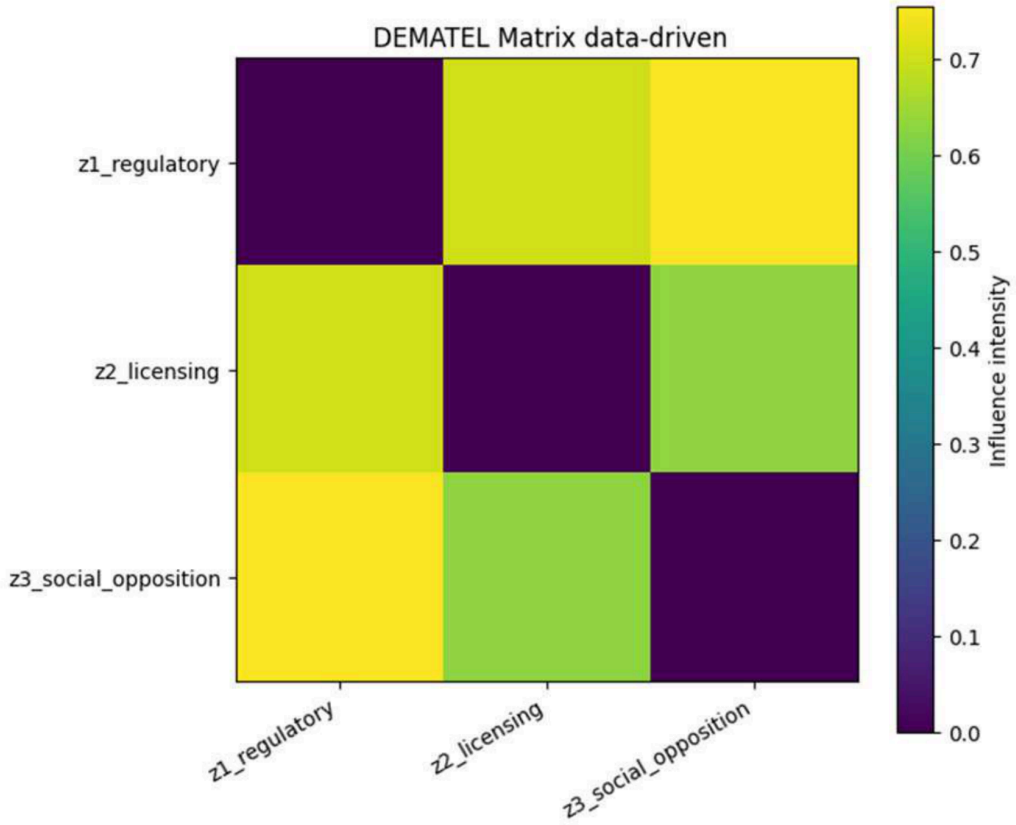


Figure 1. DEMATEL direct-relation matrix (data-driven).

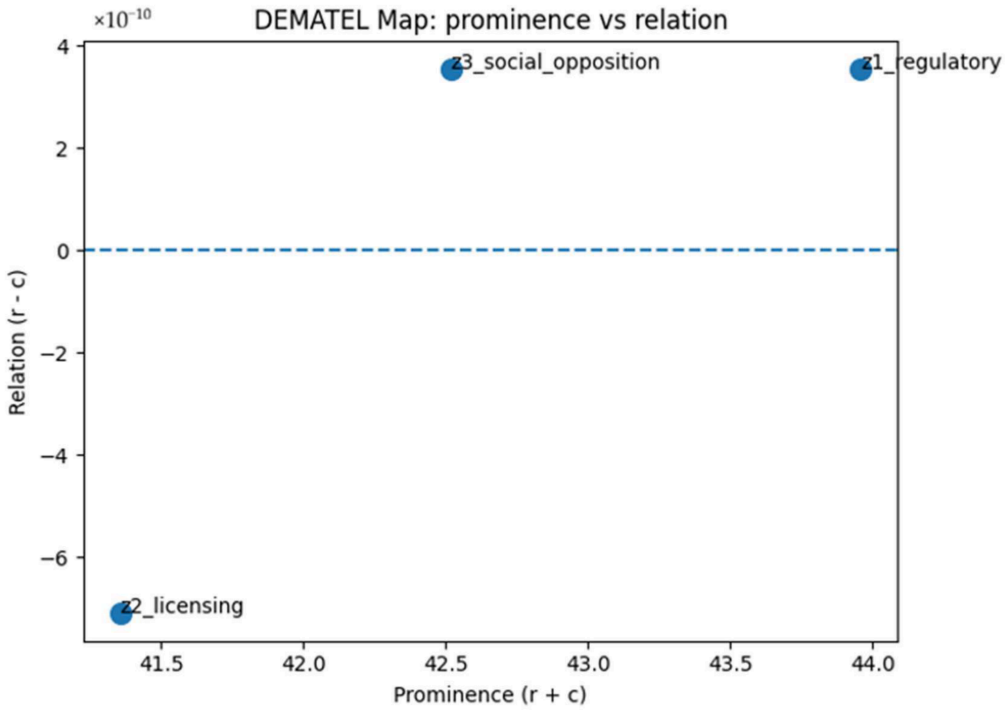


Figure 2. DEMATEL prominence–relation map.

The econometric results identify HLW and plant capacity as the main technical cost drivers. Plant capacity exhibits economies of scale, while project duration and institutional complexity have a positive and significant impact, showing that non-technical factors also contribute to cost variability (Figure 3).

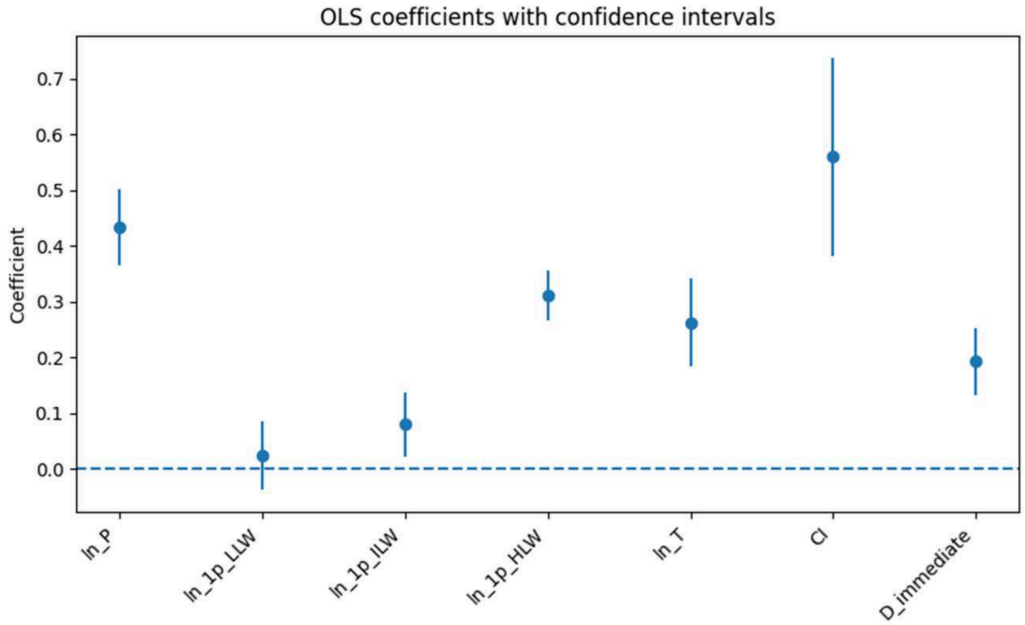


Figure 3. Estimated coefficients with confidence intervals.

Predicted and observed costs are closely aligned, indicating satisfactory explanatory power and internal consistency of the model (Figure 4).

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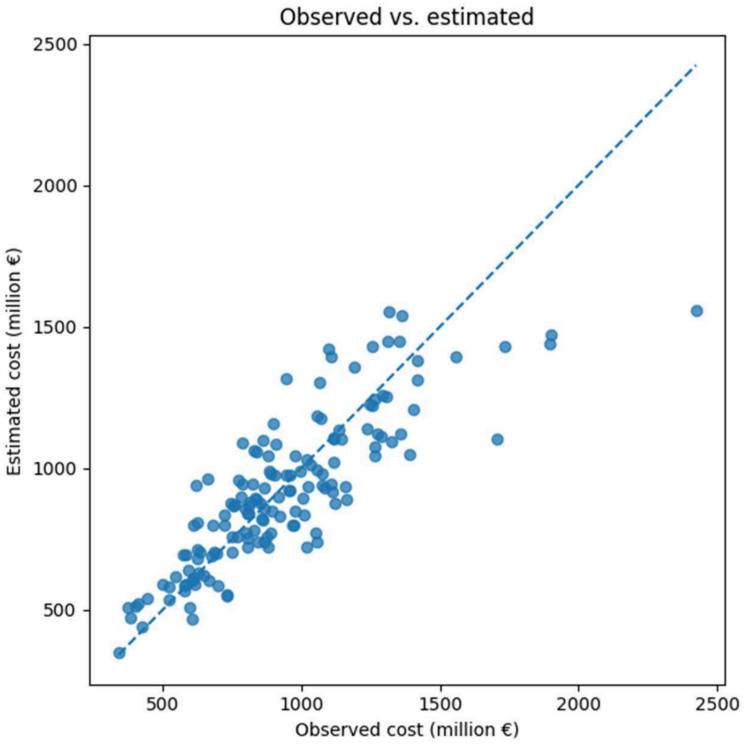


Figure 4. Observed vs. predicted costs.

Shapley decomposition confirms the dominance of technical drivers while showing a non-negligible contribution from institutional complexity and strategic choices, particularly in higher-cost scenarios (Figure 5).

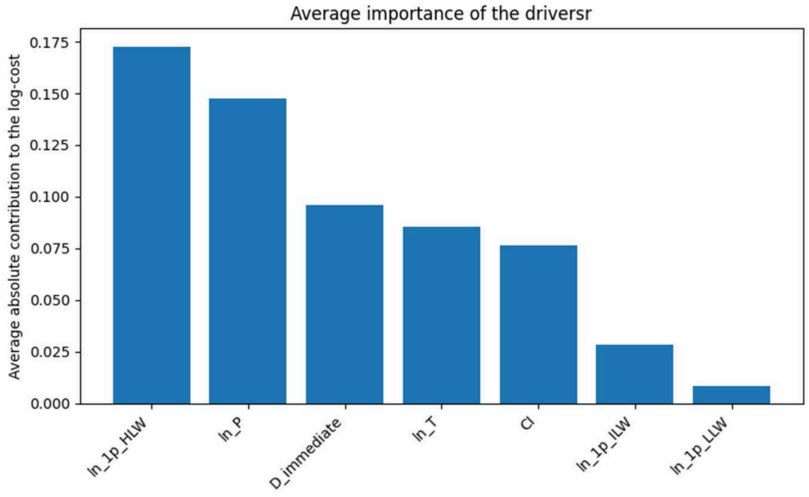


Figure 5. Average contribution of cost drivers.

These findings suggest that cost models excluding institutional interactions may underrepresent decommissioning complexity. The integrated framework improves interpretation by explicitly accounting for interdependencies among drivers. The illustrative dataset and log-linear specification limit generalizability; future work should validate the approach with real-world data and consider nonlinear and uncertainty-based extensions.

5. Conclusions

This study proposes an integrated framework for analyzing cost dynamics in the back end of the nuclear fuel cycle by combining a log-linear econometric model, DEMATEL

analysis, and Shapley value decomposition. The results confirm that technical factors, particularly high-level radioactive waste and plant scale, are the main determinants of decommissioning costs, while institutional complexity also exerts a significant influence through regulatory, licensing, and stakeholder-related factors. By capturing interdependencies among institutional drivers and quantifying their contribution to cost variability, the framework provides a more comprehensive and data-driven approach to cost estimation. These findings highlight the need to jointly consider technical and institutional dimensions in decommissioning planning and policy design. Although based on synthetic data, the methodology offers a solid foundation for future applications using real-world datasets and more advanced approaches to uncertainty and nonlinear dynamics.

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