Modeling and Analyzing Interactions Between Stakeholders for Train Decarbonization Decisions at a Regional Scale

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Abstract: This study addresses the complex network process regarding the technological swap of diesel-powered regional trains to reach the Paris Agreement's targets. Interviews with technical experts from Authorities for transport Organization on their Territory (AOT) allowed to build a stakeholder influence model, studying the interaction dynamics within this network. Thanks to a Design Structure Matrix (DSM) approach, we analyzed the complex stakeholder network influencing decarbonization strategies at the regional level. We investigate the workflows of various actors, including public authorities, industry experts, and technology providers, in selecting traction technologies. Our DSM analysis reveals the dominant roles of key public entities and strategic industrial stakeholders and highlights the challenges of integrating multicriteria considerations into the decision-making process. This research contributes to the DSM application for decision support with actor-actor workflows. The proposed methodology offers a structured framework for decision-making, reducing private sector bias and aligning with regional and environmental imperatives.

Keywords: stakeholder network, decision process clusters, topological analysis, railway decarbonization

1 Introduction

As ecological transition and the Paris Agreement call for a gradual decarbonization of transportation, the rail sector must contribute by replacing current fossil fuels-based traction. The Paris Agreement roadmap calls for a 55% reduction in Greenhouse Gas (GHG) emissions by 2030 compared to 1990 levels (European Climate Law, 2021). Currently, 0.3% of CO_2 emissions result from using fossil fuels in railways for 8% of the world's motorized passenger movements (Mandegari et al., 2023; Rungskunroch et al., 2021). Therefore, a global and ambitious decarbonization approach must be considered to improve this performance in low-emission transportation. The French railway network comprises 65% of electrified lines, mostly on high-density lines. 85% of the 9 137 km of low-density lines are powered by diesel trains (Ministère de la transition écologique et solidaire, 2020). French territory is divided into regions, each owning its Authority for transport Organization on their Territory (AOT) that possesses its own trains. Regional trains undergo major maintenance when they reach half-life to ensure their 40-year lifetime. This operation is a favorable context for replacing their energy storage system. AGC, a highly represented model of French trains, will reach its half-life between 2024 and 2031.
However, there are no proven cost-efficient solutions today to replace diesel-powered trains (European Commission, 2017). Electrification was a promising alternative. However, this solution’s infrastructural costs are too high to be acceptable in low-density lines. New alternatives are emerging, offering potentially more environmentally friendly and cost-efficient perspectives, such as:

- Battery-powered traction, heavily inspired by the automotive sector and recent developments in lithium batteries. The high cost of lithium-ion batteries is widely seen as the most significant barrier to mass adoption (European Commission, 2017).
- The use of various biofuel technologies to power a combustion engine (Bernard & Prieur, 2006).
- Using a hydrogen fuel cell with batteries to power an electric motor (Akhoundzadeh et al., 2021).
- These new technologies can also be hybridized (Meynerts et al., 2018).

Different technological maturities characterize these alternatives.

The problem is that, although promising, these technologies’ maturities are low and thus difficult to assess in terms of various parameters, such as their potential for reducing environmental footprint, their performance (energy efficiency, autonomy, maintainability, lifespan) and their impact on the rest of the lifecycle (the production, the infrastructure, and the maintenance for instance). The target of reducing greenhouse gas emissions during the use phase generally results in environmental impacts shifting towards equipment production phases, infrastructure construction, and end-of-life management. Additionally, consideration of development, deployment, and operational costs is necessary. Uncertainty varies with technology maturity, and a choice of technology implies tradeoffs in the decision criteria. Reaching a decision on this technological swap (referred to as train decarbonization in the paper) is thus a methodological and practical challenge due to the number and diversity of decision criteria, alternatives, and involved actors. It is a crucial issue since closing low-density lines when diesel trains cannot circulate anymore has societal and economic consequences for the territory. Keeping only diesel is impossible; however, closing the lines is not desired either.

A specific decision process assisting Authorities for transport Organization on their Territory (AOT) must be created to consider the technical, environmental, societal, and economic targets and constraints. This process must be constructed in collaboration with public and industrial actors at a local (territory) and global level (European Union). This process has not yet been formalized in the literature. Our research project aims to formalize this decision process, responding to the following question: "Which decision process for train decarbonization?"

This overall question is broken down into several sub-questions, one of which concerns the influence of stakeholders in the decision-making process and how to manage it. This article addresses the specific research question: "How do we quantify stakeholders' influence on the decision-making process and help decision-makers manage it?". This paper aims to contribute to this research question by formalizing the network of actors and their reciprocal influences at different stages of the decision-making process.

The structure of the paper is as follows. First, the data collection methodology is presented. It is followed by a literature review of the data treatment methods used in this paper to model and analyze the Design Structure Matrix (DSM). The data collection allowed us to understand and describe the decision-making process and the stakeholders' network. The data treatment methods were then applied to model the stakeholders' network and understand the influences on the decision. The last part will develop different results in the modeling and analysis of the DSM. Finally, some conclusions and perspectives will be drawn.

2 Methodology

To understand the decision-making process regarding train decarbonization and the interactions between actors involved, our approach was to interview the regions' technical departments responsible for the technological comparison of traction systems for regional trains. These interviews, lasting around 2 hours, were about the decision process in the context of train decarbonization in French regions. The objective was to interview members of the AOT on the decision process and criteria. The semi-structured approach was decided to avoid influencing the interviewee's answers with oriented questions. However, a list of questions was used as a reference to ensure the collection of the same minimum information from the different interviewees. This data collection process allowed us to formalize the decision process by identifying the different stakeholders and their workflows. We can note that the interviewees are within the AOT. They are part of the analysis process of train decarbonization solutions to help the decision-makers. Their precise role is detailed in part "AOT's organization and process." The final decision-makers, elected officials, were not interviewed. The data collection was realized through the interview of 6 regions agreeing to this interview process. 11 experts were interviewed:

- Eight directors and technical management experts responsible for comparing rail technologies,
- Two experts in ecological and energy transition in transportation collaborating with the technical department to provide complementary environmental expertise,
- One mobility expert was also interviewed to find synergies between regions' train decarbonization decisions.

3 Literature Review of Stakeholder Network

3.1 Stakeholder network modeling

In our context, stakeholders represent the key entities or groups involved in the system and contribute to or at least influence the decision. The workflows, or the interactions between these stakeholders, are depicted as edges linking the nodes in the network. These edges allow a clearer understanding of the system's information and task flow. Mapping these connections helps visualize and analyze the network structure and stakeholders' interactions. Tsvetkova and Ouarda analyzed workflow interdependence in and around a project that is embedded in a business. The authors' data came from interviews, observations, and the study of archival sources to develop a project analysis framework of workflows in a business ecosystem (Tsvetkova & Ouarda, 2019). This analysis uncovered four types of workflows, which are detailed in Table 1.

Alternative graphical representation approaches can be used to represent the interactions between the principal and other stakeholders, emphasizing stakeholders' interactions through edge sizes and color (Fassin, 2008). However, Yassine uses the complexity of a graphical representation to justify a Design Structure Matrix (DSM) approach when the spaghetti representation of a system is too complex (Yassine, 2004). A DSM uses a matrix structure to represent relations and dependencies among objects (Steward, 1981). Introduced for task-based system modeling, DSM has expanded its application beyond initial planning issues to model relationships among various entities such as product components (Eppinger & Browning, 2012), project organization (Worren et al., 2017), risks (Fang et al., 2010; Marle, 2010), and deliverables (Jaber et al., 2018). DSMs can be binary, identifying the presence of dependencies, or numerical, quantifying the strength of these dependencies. DSMs can also be oriented, from rows to columns or vice-versa, or symmetrical by their diagonal axis.

Table 1: Workflow interdependencies and mechanisms for their coordination and governance (Tsvetkova & Ouarda, 2019)

<table>
<tr><th>Name</th><th colspan="2">Description</th></tr>
<tr><td>Pooled Interdependence</td><td colspan="2">The simplest type of workflow involves "pooled" interdependence, in which workers accomplish a set of activities, all needed to achieve the desired system-level outcome. However, there are no technical or timing interdependencies between tasks.</td></tr>
<tr><td>Sequential Interdependence</td><td colspan="2">If a given task that already has pooled interdependence with all other tasks in the project faces the additional constraint that it cannot be initiated until one or more prerequisite tasks have been partially or fully completed, the two or more involved tasks exhibit “sequential” interdependence as well as pooled interdependence.</td></tr>
<tr><td rowspan="3">Reciprocal Interdependence</td><td colspan="2">The third type of workflow involves “reciprocal” interdependence between two or more subtasks.</td></tr>
<tr><td>Compatible-reciprocal</td><td>“Compatible-reciprocal” interdependence requires mutual adjustment to achieve a spatial or functional fit between the task outputs of the interdependent workers; however, achieving mutual adjustment to obtain the fit does not invoke conflicting sets of subgoals for the involved actors.</td></tr>
<tr><td>Contentious-reciprocal</td><td>In contrast, “Contentious-reciprocal” interdependence also requires mutual adjustment to achieve a spatial or functional fit between the outputs of the interdependent workers’ tasks; however, achieving alignment now invokes conflict between one or more of the subgoals held by each worker—i.e., a given choice of the output that is more desirable to one is less desirable to the other and vice versa.</td></tr>
</table>

3.2 Stakeholders’ network analysis

Network theory-based analysis of workflows between stakeholders. It is based on various indicators attached to graph nodes, links, or sub-parts (like loops and cliques). We have drawn on elements used in other contexts, such as centrality (Borgatti, 2005), reachability (Sinha & Weck, 2009), betweenness (Perera et al., 2018), and closeness (Wang & Wang, 2014). A network is a graph, represented by its adjacency matrix g ∈ $\mathbb{N}^{n\times n}$. We consider a weighted network on n nodes indexed by i ∈ {1, 2,…n}. $g_{ij} \neq 0$ indicates the existence of an edge between nodes i and j with g_{ij} the edge’s weight. The distance between nodes i and j, g_{ij} is the number of edges involved in a geodesic between i and j. We consider here several widespread indicators:

- The in(out)-degree: Nodes with high in(out)-degree centrality, Ω_i^+ (Ω_i^-), receive (send) many direct connections from (to) other nodes in the network. Without considering their weights, the number of edges gives information about the number of connections that this node will have to manage.
- The weighted in- or out-degree: Counting the total weights of in- or out-relationships, φ_i^+ & φ_i^-, gives another information about the amount of information or strength of influence (Opsahl et al., 2010).
- $\varphi_i^+ = \sum_{j=1}^{n} g_{ij}$ (1)
- $\varphi_i^- = \sum_{j=1}^{n} g_{ji}$ (2)
- The total node weight is the weighted in- and out-degree sum. In social networks, individuals with a high degree of centrality may have many friends or followers, indicating high social influence. In transportation networks, nodes with a high degree of centrality may represent major intersections or transportation hubs (Barabási, 2017).
- The total node normalized weight φ_i is similar but weighted in- and out-degree sum are normalized. Cameron used this approach to evaluate NASA's societal impact (Cameron et al., 2011). Cameron first identified NASA's surrogate economic stakeholders. Then, he identified their workflows and regrouped them into categories. A notation system was developed to associate a weight on the decision process to each category. Once weighted, he could sum up each stakeholder's workflow notations to evaluate impacted stakeholders by NASA. We note that the author arbitrarily decides the relationship's weight.
- $\varphi_i = \frac{\varphi_i^+ + \varphi_i^-}{2\sum_{i=1}^{n} \varphi_i^+}$ (3)
- The Normalized degree centrality of a node i Ω_i is the degree sum divided by the maximum possible degree expressed as a percentage.
- $\Omega_i = \frac{\Omega_i^+}{\max(\Omega_i^+)} + \frac{\Omega_i^-}{\max(\Omega_i^-)}$ (4)
- Normalized between centrality of a node i measures the importance of a node in connecting other nodes in the network. It considers all geodesics between two nodes j, k (different from i, with all possible combinations), which pass through i (Bloch et al., 2023; Freeman, 1978).
- Normalized Closeness centrality $C_c(i)$ measures a node's i distance ρ(i) from all other nodes j. This measure has been inverted to grow with the node’s centrality and normalized to facilitate its interpretation (Bloch et al., 2023; Sabidussi, 1966).
- $C_c(i) = \frac{n-1}{\sum_{j\neq i}^{n} \rho(i)}$ (5)
- Harmonic Centrality: The sum of the reciprocals of the shortest path distances from a node to all other nodes in the network. Nodes with high harmonic centrality can reach many other nodes in the network quickly, either

directly or indirectly. Individuals with high harmonic centrality may be more likely to contract or spread disease in disease transmission networks. In social networks, individuals with high harmonic centrality may have diverse social ties, which can influence the flow of information or resources in the network (Rochat, 2009).

Interaction-based clustering of stakeholders' network. In complex networks where numerous links can complicate representation and management, clustering helps group similar or closely related elements to simplify analysis and understanding of the network. This approach not only clarifies the structure and dynamics of the network but also aids in identifying strategic points for intervention or further analysis. In former works, clustering has been used to organize and group interdependent elements into groups with strong interactions (Ventroux et al., 2018). It has been developed in different contexts forming clusters of elements of different objects such as activities, actors, complexity-induced project failure factors (Rodríguez Montequín et al., 2018), deliverables (Jaber et al., 2018), components of a product (Thebeau, 2001), project scheduling problem-related behaviors and decisions (Rudeli et al., 2018), project risks (Marle & Vidal, 2014), and project decisions (Campagna et al., 2020). This method offers several advantages in decision-making and management. For instance, a clustering approach to building a group of stakeholders engaged in numerous collaborative decisions can lead to coordinated and potentially more collective decisions. Among the prominent algorithms, the Newman-Girvan and Leiden algorithms have gained significant attention for their ability to identify community structures in networks and graphs. The Newman-Girvan algorithm is a hierarchical clustering method that aims to maximize the modularity of a network (Bolla, 2011). It iteratively removes edges with the highest betweenness centrality, effectively separating communities within the network. The Leiden algorithm offers an efficient and scalable approach to community detection, moving nodes between communities to optimize the modularity metric (Li et al., 2023; Riva et al., 2023).

4 The key decision characteristics

The intervewees of this research are experts from the Region's technical department for regional trains. They are responsible for comparing regional train technologies and recommending the best decarbonization tradeoff within the allocated budget. From the technical department interview data, we expressed a global decision-making process and formalized the decision criteria of the elected officials.

4.1 AOT's organization and process

The technical department for regional trains issues technical documents intended to assist the elected officials in their decision-making process and provide them with justificatory support for regional council advice. These outputs are not directly provided to the decision-makers but are arbitrated by the elected officials' advisors and the president's office for summary and validation before being provided to the officials (Figure 1). The technical department documents and the elected officials' decisions are influenced by different actors represented at the origins of the "influence" arrows figure 1. To reach a decision, elected officials are influenced by the information flow from the technical department, local stakeholders, and political objectives, such as their electoral proposals. The direct influence of private parties is limited as they interact with the technical department.

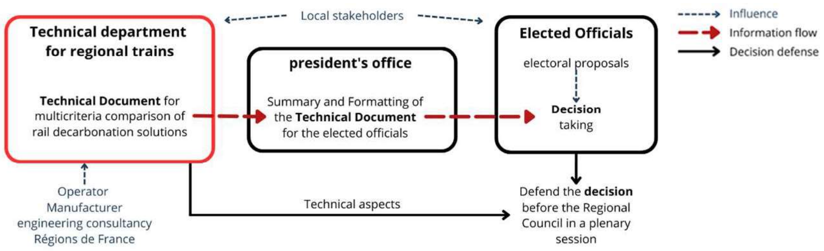

Figure 1: Decision-making process for trains decarbonization through technological substitution

Once a decision has been reached, it must be defended by the elected officials in front of the Regional Council in a plenary session to become validated. The technical department for regional trains is also present during these sessions to defend the technical aspects of the decision. The decisions are presented in assembly by the vice-president in charge of mobility, with information from the office and various reports. The difficulty lies in understanding how the elected officials and the president's office interpret data in their decisions. Election-related promises for developing a line or a technology can drive rail decarbonization. They can also redirect funds to projects where decarbonization interest is not the highest priority. For example, Inter-region trains are less the focus of regions' political projects as they involve non-voters inhabitants of surrounding regions. The regions also influence the national government strategically and vice-versa. Local investments can be blocked if no national plan is put in place. That was the case during the launching of the French national development plan "France Hydrogen" for hydrogen production and usage in France. Regions encouraged its creation by blocking national projects. Created by French regions, "Régions de France" is an association responsible for finding synergies to optimize investments and promote information sharing among regions and other private and public actors. It comprises experts in different fields without any hierarchical position for the regions but a facilitating position. They were interviewed as part of the decision process.

4.2 Decision criteria formalization

As a result of this first series of interviews, the AOT's criteria for train decarbonization decisions were identified. Decision-makers use elimination and preference criteria to choose a technology adapted to the technical and cost constraints and the environmental impact reduction objectives.

Elimination criteria. An elimination criterion is a criterion that must be respected to allow the technology in the comparison process. The **first elimination criterion** is the technology's capacity to satisfy the Paris Agreement's requirements in terms of **reducing GHG emissions** by 90% in 2050 compared to the 1990 level. The **second elimination criterion** for the technologies considered is to be **mature** enough to replace the existing traction technologies once they arrive at their mid-life or end-of-life stages. The considered technologies must reach a Technological Readiness Level (TRL) of 9 (Department of Defense, 2010), i.e., the actual system proven in an operational environment, before the Paris Agreement deadlines and the existing rolling stock end-of-life (defined by the elimination criteria 1 & 2). The technological maturity of the technologies considered is not publicly known; however, some interviewees have provided an estimation. Trains using a hybrid technology of hydrogen and batteries are announced to reach a TRL 8, system complete and qualified, for 2026 after two years of delay. According to interviewees, IP100, biofuel sourced from colza considered by regions for train decarbonization, is also supposed to reach a TRL 8 for 2027. Finally, batterie trains have already reached a TRL 8 and are expected to reach a TRL 9 during 2024. That is a constraint given that AOTs do not want to support the additional engineering costs of developing those technologies that fall under the industrials' responsibility. The **third elimination criterion** for the technology considered is to **comply with the trains' current exploitation schedule**. That is a technical constraint on the autonomy and power provided by the energy storage system. The objective here is to avoid disturbances for regular passengers that could impact the attendance rate.

Preference criteria. A preference criterion is a criterion that is evaluated while comparing the competing solutions. The **first preference criterion** the AOT considers is the **cost of the technological substitution**. Significant emphasis is placed on the costs associated with acquiring new trains or retrofitting existing ones with new technologies. However, it also considers infrastructure costs, including energy providing and sometimes producing infrastructures. AOT chose not to finance the technological development of the technological alternatives considered for train decarbonization. The train's constructors, therefore, support the development costs and the risk associated with them. The **second preference criterion** is the **reduction of GHG emissions**. This criterion requires an evaluation of the GHG emissions associated with a technological swap. This evaluation also estimates the emission of embedded technology that supplies energy to the train as a replacement for diesel. Apart from GHG emissions and their contribution to global warming, other environmental impact sources are not considered in the existing decision process. The following section will introduce the stakeholder network modeling once the global decision process and criteria are established.

5 Modeling the Stakeholder Network

5.1 Stakeholders' identification

Public institutions. French **Regions** (A1) are AOT for their territory. However, the Ministry of Transportation gives authority for low-speed trains going through multiple regions (called TET for *Trains d'Equilibre du Territoire*) to another actor, the Directorate-General for Infrastructure, Transport and Mobility (**DGITM)** (A13). The DGITM is attached to the **Ministry of Transportation** (A2) and is an equivalent of an AOT for inter-regional trains. This Ministry itself is part of the **French government** (A3). These entities have different objectives and constraints, and we represent them separately. The **European Union** (A4) is the highest authority considered in this analysis. Under the regions, different local authorities exist, such as departments and municipalities. The other local stakeholders, such as associations, have been accounted as **other territory stakeholders** (A17). The public railway safety establishment **(EPSF** for *Etablissement Public de Sécurité Ferroviaire* in French**)** (A16) delivers security certifications for trains and railway tracks.

Consultancy. **"Régions de France"** (A15) is an association created by French regions to identify synergies and optimize inter-regions investments. It has a consultancy value for AOT. The regions can also contract **engineering consultancy** (A14) to verify their information or provide new ones.

Industrials. **"SNCF Réseau"** (A11) builds and maintains the railway network. It is responsible for the construction of railway infrastructure, including energy-providing infrastructures. It is also financially responsible for it by charging a toll on exploitation companies such as **railway network operators** (A12) (like SNCF, Trenitalia, or Deutsche Bahn, for instance). Indeed, the network operating market is open to competition thanks to European market laws (Pernice & Debyser, 2023). **Rolling stock manufacturers** (A5) are manufacturers of the medium-speed trains used in our context. They also manufacture and provide maintenance and retrofit parts for the existing trains. **Infrastructure constructors**

(A8) are responsible for constructing and maintaining infrastructures outside **SNCF réseau**'s scope (A11). **Electricity producers and distributors** (A6) produce and provide electricity to the stakeholders. **Hydrogen** (A7) and **diesel producers** (A10) represent the industrials responsible for producing, transporting, and storing hydrogen and diesel. Finally, we include in a last category, "**industry actors**" (A9), actors that are cited in interviews (like, for instance, battery manufacturers) but do not deserve, according to the interviewees, to appear as first-level stakeholders.

5.2 Stakeholders' interactions

The binary network. The second part of the data gathered through interviews enabled the development of a representation of the stakeholders and their relationships with the decision process. This diagram is represented in Figure 2. We adopt Fassin's approach of centering our diagram around the final decision-makers (Fassin, 2008). The relationships between the stakeholders implicated in the decision-making process, directly or indirectly, are also represented, including the interviewees' feedback. This data-gathering method ensures we represent every stakeholder thanks to the interviewees' feedback. In addition, the interview process allows us to identify further and more detailed workflows that do not appear in this first representation.

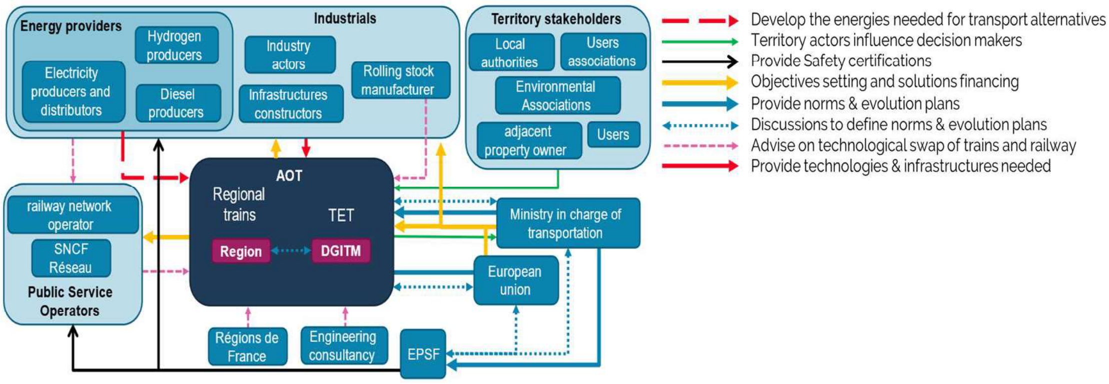

Figure 2: Stakeholder's relationships graphical representation

This representation was complex and unfit to represent every interaction between the stakeholders mentioned during the interviews. We used a DSM approach to ensure we got all the workflow and to analyze them. Multiple workflows can exist between 2 actors.

The weighted network. The objective is now to evaluate the impact of these workflows on the decision-making process. We regrouped our workflows under Tsvetkova and Ouarda's types introduced in Table 1. As illustrated in Table 2, we associated weight with each workflow type following a similar approach to Cameron's (Cameron et al., 2011). Reciprocal contentious interdependence puts a high constraint on the system as these actors mainly develop different or opposite ways to impact the decision. The weight is established as three times more impacting than pooled interdependence. Sequential interdependence has an intermediary impact, and its weight is 2. As compatible reciprocal interdependence encourages workflow resolution, its weight is at -1.

Table 2: Workflow groups weight

Workflow type	Pooled interdependence	Sequential interdependence	Compatible-reciprocal	Contentious-reciprocal
Weight	**1**	**2**	**-1**	**3**

Let us note that each cell in the DSM aggregates the different relationships going from one actor to another and thus adds the weights that represent each relationship. Once the DSM workflows have been converted to a weight, we obtain a non-binary DSM (visible in Figure 4b) as a basis for further network analysis.

6 Analyzing the stakeholder network to help choose a traction technology

The weighted DSM representation in Figure 4b highlights the multitude of interdependencies between stakeholders. The first analysis is the high percentage of high-weight links going to the regions. Moreover, on a total of 306 potential values, there is only one "6" (corresponding to two relationships of value 3), one "5", and ten "4" (corresponding to 3+1). Most values correspond to "3" (contentious reciprocal), with 124 times or 41% of total cells, followed by "0", with 102 occurrences and 33% of cells. Low values are once again with lower percentages, with respectively 6 "-1" (2%), 34 "1" (11%), and 28 "2" (9%). After this initial basic analysis, three alternative types of analysis are performed to catch information from the raw DSM: the relative influence regarding edge weights, a network theory-based topological analysis, and an interdependency-based clustering.

6.1 The network theory-based topological analysis

The DSM also allows us to compare each actor on network-based indicators to understand their influence on the actor network better and, thus, on the decision process. This comparison is available in Table 3, with several relevant network theory indicators.

Table 3: Illustration of the most significant contributors to network behavior according to a selection of topological indicators

Actor's ID	Actor's Name	Number of Outputs Ω+	Number of Inputs Ω-	Weighted Out-Degree ϕ+	Weighted In-Degree ϕ-	Normalized weight ϕ	Normalized Degree Centrality Ω	Normalized Betweenness Centrality	Normalized Closeness Centrality Cc	Harmonic Centrality
A1	Region	16	17	45	56	0,100	1,94	0,101	0,944	16,5
A2	Ministry in charge of transportation	14	14	36	40	0,075	1,65	0,028	0,850	15,5
A5	Rolling stock manufacturer	13	16	33	42	0,074	1,71	0,023	0,810	15
A11	SNCF Réseau	14	14	29	38	0,066	1,65	0,018	0,850	15,5
A3	French government	13	14	36	31	0,066	1,59	0,023	0,810	15
A6	Electricity producers and distributors	12	12	34	31	0,064	1,41	0,031	0,773	14,5
	[..]									
A14	Engineering consultancy	9	10	22	20	0,041	1,12	0,006	0,680	13
A16	EPSF	7	8	15	23	0,037	0,88	0,014	0,630	12
A18	Local authorities under regions (departments, EPCI, cities…)	11	11	6	29	0,035	1,29	0,012	0,739	14
A17	Other territory stakeholders Associations (users, environmental…)	5	3	15	9	0,024	0,47	0,001	0,586	11
A15	Régions de France	10	1	20	2	0,022	0,65	0,000	0,708	13,5

The number of outputs and inputs represents the number of edges going in and out of a node. In our case, many actors have non-null relationships with others, meaning we are in a very connected network. Weighted out-degree and in-degree (and their sum called the total node weight) show that ten actors on 18 have strong values, superior to 30. That represents, on average, ten links of value 3, which is significant. Once the edge weight has been set, we can sum each node's weight on rows and columns to obtain a global weight and divide it by the total weight of all actors to obtain P_i, the weight of a stakeholder on the decision, reflecting their relative influence on the decision process. The stakeholders' proportional weight in the decision-making is represented in Figure 3. The high-level public actors (**Region, Ministry, government, and European Union**) are strongly connected, which is unsurprising. However, the **Rolling Stock manufacturer** has relatively more influence than could have been expected before the analysis. It is the second most influential (in terms of topological indicators) actor, with the highest number of inputs, right after the **Region**, which is, of course, the central node of the network. Initially, so-called secondary stakeholders, the **industry actors**, were involved in multiple strong interactions.

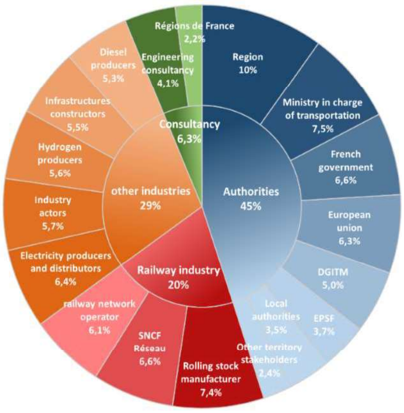

Figure 3: Graphical representation of stakeholders' weight on the decision-making

They are slightly more influential than other industrial actors, such as **energy providers** and, more surprisingly, **railway network operators**. **Local stakeholders** and **consultancy actors** are secondary influencers in this network. Finally, applying topological indicators reveals that certain actors hold critical roles within the network, inducing a need for cluster analysis.

6.2 Managing dense networks through interdependency-based clustering

We applied two algorithms introduced in the "Stakeholders' network analysis" sub-section of the Literature Review (p. 4). That enabled us to separate stakeholders into clusters effectively. The clusters are represented in Figure 4a, and the raw matrix format is shown in Figure 4b. Clustering highlighted three elements.

First, both algorithms propose the same two clusters. A1, the Region, is the common element between these two clusters (by allowing non-disjunct clusters). The first cluster, C1, is composed of industrials with informative workflow toward the core private to public cluster. This **informative private-to-public cluster** comprises public actors such as Regions & DGITM, the railway industries and consultants (see Figure 4a), and industrials such as diesel producers, hydrogen producers, and industry actors. A second **local strategies cluster**, C2, is composed of more local industrials and public entities.

Second, a post-treatment analysis of cluster C1 shows a sub-cluster of higher density, including the Region, the Ministry, the DGITM (strongly connected to the Region), two entities related to the infrastructure and operation of the network (SNCF Réseau and the Railway network operator), and, more surprisingly, a private actor, the Rolling Stock manufacturer. However, as seen in the previous topological analysis, this specific private actor has a particular role in the network. Its inclusion into a higher-density sub-cluster of C1 confirms its specific influence. That means that communication frequency should be higher, probably with a higher consideration of its constraints.

Third, a dense kernel of public institutions at different levels, including the **Region, the Ministry, the government, and the European Union**, has been identified post-treatment. It is expected to have strong relationships, even if it does not mean that some specific way of organizing and communicating should be relevant in that case. There are already formal and recurrent circuits of communication between these actors. To minimize the influence of private actors on the decision-making process, we configured this cluster to isolate the most significant public actors to train decarbonization into a central cluster. This configuration ensures focused discussions among **national strategies cluster** stakeholders such as regions, the Ministry in charge of transportation, the French government, and the European Union. That setup facilitates a structured interaction where the core public cluster can maintain initial deliberations insulated from private interests.

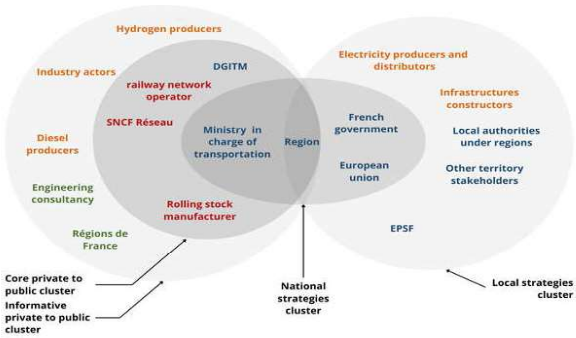

Figure 4a: clusters representatio

	A7	A9	A10	A14	A15	A11	A12	A5	A13	A2	A1	A3	A4	A18	A6	A16	A17	A8
A7				3	2	1	1	3	3	3	3	3	3	-1				
A9	1		1	2	2	1		3	3	3	3	3	3	-1	1			1
A10				3	2	1	1	3	3	3	3	3	3	-1				
A14	2	2	2		2	2	2	2		2	2							2
A15											2							
A11	3	3	3	2	2		2	3		3	3	3	3	2	3			3
A12	3	3	3	2	2	3		3	3		3				3	3		3
A5	3	3	3	2	2	3	3		3	3	3	3	3	-1	3	3		3
A13	3	3	3			4	4	1		1	-1	1	1		3			3
A2	3	3	3			4	5	1			4	3	3	1	3	1	3	3
A1	3	3	3	2	2	4	4	6	3	4		4	3	3	3	3	3	3
A3	3	3	3			1	1	1		1	4		3	1	3	1	3	3
A4	3	3	3			1	1	1		1	4	1		1	3	1	3	3
A18	3	3	3						1	3	3	3	1		3		3	3
A6	3			3	2	1	1	3	3	3	3	3	3	3				
A16		3				2		3		3	3	3	3					3
A17							3								3	3		
A8				3	2	1			3	3	3	3	3	-1	3			

Figure 4b: The clustered DSM

7 Discussion

The DSM analysis yielded insightful findings regarding the interconnectedness of stakeholders. Notably, the analysis affirmed the centrality of the national strategies cluster, aligning with expectations but with a nuanced highlight on "**SNCF Réseau**" and "**Rolling stock manufacturer**" from the core private-to-public cluster that deserves special attention for their potential influence. Meanwhile, **Industry Actors** placed in the national strategies cluster demand vigilance. Their position indicates a level of influence that, while not paramount, is significant enough to affect the network dynamics. These two industrial actors within the top seven punctuate the importance of industry influence in the decarbonization narrative. It contrasts with low influence entities (regarding topological indicators, see the last actors in Table 3 ranking), primarily local actors (**local authorities, Régions de France, and other territorial stakeholders**. It underscores the disparity in the network values and accentuates the relative peripherality — indicative of a lower influence. The weighted relative influence of actors on the decision-making process, visible in Figure 3 shows unsurprisingly that the most influential stakeholder in the decision-making process is the **Region**. **AOTs** decide which technologies to implement in their territory, with 10% of the weight. The lowest influence on the decision-making process comes from **Régions de France** with 2,2%. This distribution of decisional power among stakeholders is relatively balanced. The other stakeholders weighing over 6% are the **electricity producers and distributors, Railway network operators, SNCF Réseau, the rolling stock manufacturers, the European Union, the French government, and the Ministry in charge of transportation**. We notice they are all Railway industries or public authorities except for the electricity producers and distributors. We also grouped some actors by similarity. Private stakeholders in the railway sector were grouped under "Railway industry." "Other industries" groups the more specialized industry stakeholders. These two groups combined represent the private sector's influence on the decision-making process with 49%. The consultancy actors for regions are regrouped under "consultancy," while the public authorities are grouped under the "Authorities" label. They have a combined influence of 51% on the decision-making process. We observe that the 6,3% of weight brought by consultancy is essential to stay over 50% of the weight on the decision-making process. That enlightens the openness of AOT to outside help in the decision process. Regarding clustering, we have analyzed the influence of negative values on the algorithm's results. There are only a few "-1" values, so removing these values does not affect clustering. However, from a practical point of view, we have analyzed what the presence of a "-1" represents in a cluster and, therefore, in a communication circuit between cluster players. From a practical point of view, we can keep both actors in the cluster or remove one of them. We have a first cluster, which includes a denser sub-cluster. A "-1" exists in this sub-cluster between A13 and A1, who is our decision-maker. Moving one of the two actors involved in the "-1" relationship is possible. That would correspond here to moving A13 out, as A1 is the network's central node. The second "-1" is between A18 and A8 in the bottom right-hand cluster. It takes work to choose which actor to move, as they interact almost the same amount with the other actors in the cluster.

Removing one of the two seems problematic, as there is no other larger cluster as in the previous case. One possible solution is to do the opposite, i.e., move one of the players to the center of the network rather than to the periphery. In this case, actor A18 could be proposed in the central cluster, the core. Indeed, it is a public player, like the other components of this core. However, from a purely mathematical point of view, actor A8, a private actor, has the most interactions with the core actors. We thus find ourselves in an interesting case of divergence between mathematical logic and the logic of considering the nature of things, i.e., public or private actors. We cannot formulate a proposal at this stage, as these refinements would have to be proposed to decision-makers, who might also adopt a different strategy depending on the region and its local context. That is a conceptual proposal for treating -1 in the matrix. This work evaluates the weight of private actors in the decision process. Compared to elected officials and independent actors, 49% of the weight on the decision process is from private actors with a vested financial interest in the outcomes of these decisions. Also, in the clustering analysis, the current close circle of decision-making is composed of deciders and the same private entities. This situation is further exacerbated by the reliance on information about technologies predominantly sourced from industrial stakeholders. Currently, there is an absence of mechanisms for independent third-party or public organizations to gather and verify such critical data systematically. The predominance of private parties with financial interests in decision-making circles introduces a bias that could skew decisions in favor of specific technologies or solutions, irrespective of their overall correspondence to decision-makers' criteria. This situation raises concerns regarding the integrity and transparency of the decision-making process. To mitigate the risks associated with lobbying and ensure a more objective and transparent decision-making process, implementing actions regarding how actors organize their communication, coordination, and decision-related actions will aid in the strategic planning and decision-making for the decarbonization of regional trains.

8 Conclusions and Perspectives

This paper focused on analyzing the stakeholders' network involved in the complex choice of train decarbonization for low-density lines. Our primary aim was to explore the decision process and the stakeholders influencing or contributing to the decision. Data were collected through interviews with the deciders' technical departments. We applied a methodology based on the Design Structure Matrix (DSM) combined with a wide range of indicators to map and analyze the workflows of various stakeholders in the decision process. This study allowed us to decompose and quantify the complex dynamics and interactions between diverse public and private actors. Our findings confirm the central influence of a core group of public actors while highlighting the strategic positions of certain industrial players. The clustering approach offers the possibility to analyze and possibly limit the influence of private parties' participation in public parties' exchanges. These results emphasize the complexity of reconciling technological potential, economic viability, environmental impact, and stakeholder interests in the decision-making process. Our work lays the foundation for a decision-support process that aligns with regional operational needs and environmental goals while mitigating the risk of undue private sector influence.

The AOTs face a complex challenge: selecting the most appropriate technology for train decarbonization that aligns with multi-objectives and constraints. Multicriteria decision-making (MCDM) methods have emerged as vital tools in such settings, providing a structured approach that facilitates transparent and informed choices. We aim to develop a methodology for a configurable multicriteria tool to assist AOTs' train decarbonization decision-making process following their strategies and constraints. This methodology is recommended for comparing technologies following AOT's decision criteria. Adopting a rigorous and methodical approach can limit the influence of vested interests and enhance the reliability of data and their usage in the decision-making process. Furthermore, this methodology should facilitate the choice of precise and context-specific solutions for decarbonization. The involvement of independent third parties or public organizations in data collection, treatment, and verification processes is also advocated to ensure the integrity and accuracy of the information upon which decisions are based.

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