Bayesian Networks for Substation Schedule-Delay Risk: A Practitioner-Adaptable Theoretical Model Demonstrated on a Synthetic Case [1]

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Abstract

Electric substation projects frequently encounter schedule slippage driven by design nonconformities, supply chain setbacks, and environmental licensing uncertainty. We develop and evaluate a compact Bayesian Network that quantifies schedule-delay risk pathways from those drivers using a fictitious, yet plausible synthetic dataset created for clarity, replication, and teaching. The five-node model—Team Experience, Project Conformity, Supply Delay, Licensing Issue, and Schedule Delay—uses expert-elicited conditional probabilities under monotonic causal assumptions. We report a theoretical baseline delay probability of ≈ 0.372, decompose contributions by parent configurations, and examine mitigation portfolios (independent design review, supply expediting, licensing task force), yielding single-lever reductions of 3.9–6.2 percentage points and ≈ 15.7 points combined in the synthetic population. Crucially, the workflow is designed for practitioner adaptation: we provide a ready-to-use prompt enabling managers to ingest their own historical spreadsheets to estimate parameters, run scenarios, and prioritize actions—without coding. All values are synthetic; no confidential data are used.
Keywords: Bayesian networks; schedule-delay risk; delivery risk; project management; electric substations; causal inference; decision support; artificial intelligence.

1. Introduction

Substations intertwine civil works, high-voltage apparatus, protection and control systems, and multi-agency approvals. Two symptoms dominate managers' attention: schedule delays and rework from design nonconformities. Traditional critical-path schedules and checklists remain indispensable, yet they struggle with interdependencies and partial evidence that emerge during procurement, licensing, and commissioning

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(PMI, 2021). Bayesian Networks (BNs) address this gap by: (i) encoding causal structure; (ii) allowing probabilistic inference with missing data; and (iii) supporting what-if reasoning and mitigation planning (Pearl, 1988; Jensen and Nielsen, 2007; Koller and Friedman, 2009).

This paper makes three contributions. First, we specify a parsimonious BN tailored to substation schedule-delay risk, grounded in causal intuition engineers recognize. Second, we construct a synthetic dataset and use it to illustrate baseline risk, sensitivity to priors, and mitigation effects, with results presented in reusable tables. Third, we provide a practitioner-ready prompt that ingests a manager's historical spreadsheet to estimate BN parameters with simple regularization and monotonicity checks, enabling immediate adoption without coding. Throughout, we emphasize interpretability and auditability, aligning with good governance and lessons from reliability engineering (Billinton and Allan, 1996) and decision analysis (Fenton and Neil, 2019).

Positioning in recent literature. Since 2020, applications of AI/ML and causal models in project management have expanded markedly, with systematic reviews and empirical studies highlighting opportunities and pitfalls for prediction, decision support, and governance (Nenni et al., 2024; Adamantiadou et al., 2025; Felicetti et al., 2024; Salimimoghadam et al., 2025; Datta et al., 2024; Prasetyo et al., 2024). Within construction and infrastructure, BNs and dynamic BNs have been applied to schedule risk, multi-hazard interactions, and reliability-driven planning (Zhong and Zhang, 2025; Chen et al., 2023; Rezakhani, 2022; Arabi et al., 2022; Bakhtiari et al., 2025; Machado et al., 2023). In parallel, LLM-based assistants and cognitive agents are being piloted to operationalize workflows for non-programmers, echoing our practitioner prompt (Alliata et al., 2025; Cinkusz et al., 2025; Couder, 2024). We situate our theoretical construct against this body of work while focusing on an auditable BN that is readily adapted by practitioners to their own datasets.

2. Research Questions

RQ1. Can a five-variable BN provide interpretable and actionable estimates of schedule-delay risk for substation projects?
RQ2. Among design review, supply expediting, and licensing acceleration, which lever reduces population-level delay prevalence the most?
RQ3. How sensitive is the baseline delay probability to plausible changes in supply and licensing priors?
RQ4. Can natural-language workflows operationalize BN estimation and scenario analysis for nonprogrammers?

3. Objectives

1. Formalize a causal BN linking experience, conformity, supply, and licensing to schedule outcomes.
2. Create a fictitious dataset to demonstrate the workflow end-to-end without confidentiality constraints.
3. Quantify baseline risk, contributions by parent configurations, and mitigation effects; present results in clear tables.
4. Deliver a natural-language practitioner prompt for managers to estimate parameters from their own historical data.

4. Hypotheses to be Tested

H1. Holding supply and licensing constant, Nonconformant designs increase delay risk relative to Conformant designs (e.g., 0.70 vs. 0.45 when Supply=Yes, Licensing=No). **H2.** Reducing the prior probability of Supply Delay from 0.35 to 0.15 decreases population-level delay probability by ≥ 5 percentage points in this BN. **H3.** A combined mitigation portfolio (design review + supply expediting + licensing acceleration) reduces baseline delay probability by ≥ 15 percentage points.

5. Approach/Methodology (including use of AI)

5.1 Model Structure and Factorization

We define a BN with nodes Team Experience (High/Medium/Low), Project Conformity (Conformant/Non-conformant), Supply Delay (Yes/No), Licensing Issue (Yes/No), and Schedule Delay (Yes/No). Directed arcs encode the causal structure:

$$\text{Team Experience} \rightarrow \text{Project Conformity} \rightarrow \text{Schedule Delay}$$
$$\text{Supply Delay} \rightarrow \text{Schedule Delay}$$
$$\text{Licensing Issue} \rightarrow \text{Schedule Delay}$$

The joint distribution factors as

$$P(T,C,S,L,D) = P(T)\,P(C|T)\,P(S)\,P(L)\,P(D|C,S,L),$$

enabling inference and scenario analysis by marginalizing/conditioning on parent nodes (Pearl, 1988; Koller and Friedman, 2009).

> **Assumption (independence):** Supply Delay and Licensing Issue are modeled as a priori independent in this synthetic study. For real datasets, we recommend testing dependence (e.g., mutual information) and, if needed, revising the structure (e.g., adding an arc or a latent parent) (Fenton and Neil, 2019; Zhong and Zhang, 2025).

5.2 Synthetic Data (Demonstration Only)

We construct *SE_Alto_Vale_Synthetic*, a fictitious dataset with N = 300 records representing an urban 138/13.8 kV substation planned over 14 months. Priors:

$P(Team) = \{0.30, 0.45, 0.25\}$ (High/Medium/Low),
$P(Supply{=}Yes) = 0.35,$
$P(Licensing{=}Yes) = 0.30.$

The CPT *P(Conformant |Team) = {0.92, 0.78, 0.55}* encodes the monotone effect of experience on design quality. The outcome CPT *P(Delay=Yes|Conformity, Supply, Licensing)* spans 0.15 (all favorable) to 0.88 (triple adversity with non-conformity). Values are illustrative and consistent with engineering judgment and BN parameterization practices (Fenton and Neil, 2019; Jensen and Nielsen, 2007).

> **Data provenance.** The dataset is entirely synthetic; numbers are pedagogical and not tied to any organization. Generation used i.i.d. sampling from the stated distributions with seed = 2025 to ensure reproducibility.

5.3 Natural-Language Execution and AI Use

All computations (marginalization, scenario analysis, sensitivity) were performed in a natural-language environment. The LLM was used to: (i) restate and verify the BN; (ii) execute arithmetic marginalization; (iii) format tables; and (iv) craft a practitioner prompt. No internet access or external datasets were used. To guard against spurious patterns, we applied a gentle monotonicity check (isotonic-regression "nudge" if needed) to ensure that, holding Supply and Licensing fixed, Nonconformant ≥ Conformant for *P(Delay = Yes)*. The design emphasizes transparency and reproducibility (PMI, 2021; Pearl, 2009). In parallel, we align with recent guidance on AI adoption in project settings, including governance, validation, and human-in-the-loop review (Nenni et al., 2024; Adamantiadou et al., 2025; Salimimoghadam et al., 2025).

6. Results — Baseline, Contributions, and Mitigations

6.1 Variables and Priors

Table 1 — Variables and roles (synthetic)

Variable	Type	Values	Role in BN
Team Experience	Categorical	High / Medium / Low	Parent of Project Conformity
Project Conformity	Binary	Conformant / Non-conformant	Parent of Schedule Delay
Supply Delay	Binary	Yes / No	Parent of Schedule Delay
Licensing Issue	Binary	Yes / No	Parent of Schedule Delay
Schedule Delay	Binary	Yes / No	Outcome

Source: Author's synthetic BN (this paper).

Table 2 — Generating priors and expected marginals (N = 300)

Quantity	Value	Expected count
P(Team=High)	0.30	90
P(Team=Medium)	0.45	135
P(Team=Low)	0.25	75
P(Supply Delay=Yes)	0.35	105
P(Licensing Issue=Yes)	0.30	90
P(Conformant	High)	0.92
P(Conformant	Medium)	0.78

Table 2 — Generating priors and expected marginals (N = 300)

Quantity	Value	Expected count
P(Conformant	Low)	0.55
P(Conformant) (marginal)	0.7645	≈ 229
P(Non-conformant)	0.2355	≈ 71

Source: Author's synthetic BN (this paper).

6.2 Conditional Probabilities

Table 3 — CPT: Project Conformity | Team (synthetic)

Team Experience	P(Conformant)	P(Non-conformant)
High	0.92	0.08
Medium	0.78	0.22
Low	0.55	0.45

Source: Author's synthetic BN (this paper).

Table 4 — CPT: Schedule Delay (Delay=Yes) | (Conformity, Supply, Licensing)

Project Conformity	Supply Delay	Licensing Issue	P(Delay=Yes)
Conformant	No	No	0.15
Non-conformant	No	No	0.40
Conformant	Yes	No	0.45
Conformant	No	Yes	0.35
Non-conformant	Yes	No	0.70
Non-conformant	No	Yes	0.65
Conformant	Yes	Yes	0.60
Non-conformant	Yes	Yes	0.88

Source: Author's synthetic BN (this paper).

6.3 Baseline Prevalence and Contributions

Marginalizing over parents yields *P(Delay=Yes) ≈ 0.3717*. The decomposition clarifies where delays originate in the synthetic population.

Table 5 — Parent configurations: weights and expected delayed cases (N = 300)

Conformity	Supply	Licensing	Combination weight	Expected cases	P(Delay=Yes)	Expected delayed
Conformant	Yes	Yes	0.08027	24.08	0.60	14.45
Conformant	Yes	No	0.18730	56.19	0.45	25.29
Conformant	No	Yes	0.14908	44.72	0.35	15.65
Conformant	No	No	0.34785	104.35	0.15	15.65
Non-conformant	Yes	Yes	0.02473	7.42	0.88	6.53
Non-conformant	Yes	No	0.05770	17.31	0.70	12.12
Non-conformant	No	Yes	0.04592	13.78	0.65	8.95
Non-conformant	No	No	0.10715	32.15	0.40	12.86
Totals			1.00000	300.00	—	≈ 111.50

Source: Author's synthetic BN (this paper).

The highest per-case risk sits at the triple-adversity corner with nonconformity (0.88), while the largest block of expected delays arises from conformant projects experiencing procurement or licensing adversity—highlighting why governance must address gatekeepers beyond design quality (Fenton and Neil, 2019; PMI, 2021).

6.4 Mitigation Scenarios (Population Level)

We analyze four scenarios conceptualized as interventions on parents (Pearl, 2009): enforce Conformity (independent design review, IDR), reduce Supply Delay prior (expediting/substitution), reduce Licensing Issue prior (task force), and the combination.

Table 6 — Delay prevalence under mitigations (synthetic)

Scenario	Assumptions	P(Delay=Yes)	Δ vs. baseline (pp)	Delays avoided / 100 projects
Baseline	P(Conformant)=0.7645; P(Supply=Yes)=0.35; P(Licensing=Yes)=0.30	0.3717	—	—
Independent Design Review	Conformity fixed to Conformant	0.3098	−6.19	6.19

Table 6 — Delay prevalence under mitigations (synthetic)

Scenario	Assumptions	P(Delay=Yes)	Δ vs. baseline (pp)	Delays avoided / 100 projects
Supply expediting	P(Supply=Yes) → 0.15	0.3149	−5.68	5.68
Licensing task force	P(Licensing=Yes) → 0.10	0.3331	−3.86	3.86
Combined (A+B+C)	Conformity fixed; Supply 0.15; Licensing 0.10	0.2143	−15.74	15.74

Source: Author's synthetic BN (this paper).

6.5 Sensitivity (Textual Tornado)

Varying the Supply Delay prior by ±10 percentage points around 0.35 changes the baseline delay by approximately ±2.8 pp; varying the Licensing Issue prior by ±10 points around 0.30 shifts the baseline by ≈ ±1.9 pp (holding other quantities fixed). Sensitivities were computed by re-marginalizing with priors set to 0.25/0.45 (Supply) and 0.20/0.40 (Licensing). This ranking supports prioritizing supply interventions, closely followed by licensing, with design conformity acting as a high-leverage structural lever because it modifies the outcome CPT directly (Fenton and Neil, 2019; Chen et al., 2023; Zhong and Zhang, 2025).

6.6 Illustrative Synthetic Sample (Subset)

A 20-row fictitious draw consistent with the generator appears in Table A1 (Appendix). Some conformant cases still delay under supply/licensing adversity, while some nonconformant cases finish on time when gatekeepers are favorable—exactly as encoded in Table 4.

7. Discussion — Interpretation and Relation to the Literature

Interpretability and governance. The BN's causal structure makes explanations auditable: posterior changes can be traced to specific parents, matching risk–response planning in PMBOK (PMI, 2021). This transparency contrasts with black-box predictors and aligns with causal-inference guidance (Pearl, 2009; Koller and Friedman, 2009; Fenton and Neil, 2019). Recent reviews emphasize the need for explainable, data-governed AI in PM settings, reinforcing our design choices (Nenni et al., 2024; Adamantiadou et al., 2025; Felicetti et al., 2024; Salimimoghadam et al., 2025).

Mitigation prioritization. In the synthetic portfolio, IDR and supply expediting provide the largest single-lever benefits (−6.19 and −5.68 pp). The combined portfolio halves expected delays (−15.74 pp), illustrating compounding effects when multiple parents are de-risked. Comparable magnitudes and rankings appear in BN-based or hybrid BN-MCS studies in construction schedule risk (Chen et al., 2023; Rezakhani, 2022; Arabi et al., 2022) and in sectoral reviews focused on energy projects (Machado et al., 2023).

Alignment with reliability and decision analysis. The emphasis on gating components (e.g., long-lead items) echoes reliability notions of weak links and series systems (Billinton and Allan, 1996). Extending the BN with utilities enables expected-value decisions and value-of-information analyses—standard in decision analysis but underused in project management (Fenton and Neil, 2019; PMI, 2021).

Generalization. While the numbers here are synthetic, the practitioner prompt operationalizes the same steps with historical data: field mapping, Laplace smoothing, monotonicity checks, baseline/marginalization, and scenario evaluation—entirely in natural language. This responds to calls for AI that is deployable by non-programmers in real project environments (Alliata et al., 2025; Cinkusz et al., 2025; Couder, 2024; Prasetyo et al., 2024).

8. Conclusions — Significance and Recommendations

A compact BN offers a rigorous yet accessible lens for managing substation schedule-delay risk. The synthetic study demonstrates how design conformity, supply performance, and licensing progress jointly shape outcomes and how targeted mitigations can materially lower portfolio-level delay prevalence. We recommend that organizations: (i) institutionalize independent design reviews at key interfaces; (ii) maintain expediting/substitution playbooks for long-lead procurement; and (iii) stand up licensing task forces early in the lifecycle. The provided practitioner prompt allows teams to calibrate the BN with their own histories, improving forecasts and enabling auditable, cross-disciplinary decisions (Weber and Jouffe, 2006; PMI, 2021; Fenton and Neil, 2019). In line with recent literature, this theoretical model is explicitly engineered for practitioner adaptation (Nenni et al., 2024; Adamantiadou et al., 2025; Salimimoghadam et al., 2025; Zhong and Zhang, 2025).

9. Acknowledgments, Declarations, Disclaimers, Disclosures, Use of AI

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Declarations. No human subjects, personal data, or proprietary datasets were used.

Disclaimers. All numerical values, tables, and examples are synthetic and created solely for research training and illustration; they do not represent any real organization, supplier, or authority.

Disclosures. The author declares no conflicts of interest.

Use of AI: Large language models (OpenAI ChatGPT-5) assisted with drafting, textual style editing, arithmetic marginalization, table formatting, and the practitioner prompt. All content was reviewed and verified by the author; no confidential or proprietary data were provided to the models; all third-party ideas are cited; and the models are not listed as authors nor bear responsibility for the claims.

10. Notes

None.

11. Appendix — Practitioner Prompt for Project Managers (Data-Driven with Your Historical Portfolio)

Goal: use your project history to estimate BN parameters (priors and CPTs), compute the baseline delay risk, run mitigations, and prioritize levers. Keep your data private in this chat; do not access the internet. Use Harvard-style citations in text (PMI, 2021; Pearl, 2009; Fenton and Neil, 2019; Jensen and Nielsen, 2007; Koller and Friedman, 2009).

> You are a project risk analyst for electric substation projects. I want to assess schedule-delay risk with a Bayesian Network (BN) using MY historical data. Follow the instructions below exactly.

1) SCOPE AND GRAPH (fixed)
• Variables:
– Team Experience ∈ {High, Medium, Low}
– Project Conformity ∈ {Conformant, Nonconformant}
– Supply Delay ∈ {Yes, No}
– Licensing Issue ∈ {Yes, No}
– Schedule Delay ∈ {Yes, No}
• Arcs:
Team Experience → Project Conformity → Schedule Delay
Supply Delay → Schedule Delay
Licensing Issue → Schedule Delay
• Do not change the graph structure. Focus on ESTIMATING parameters from my data.

2) DATA INPUT (my historical base)
• I will paste a table/CSV (hundreds to thousands of rows) with real columns.
• If my column names differ, perform a "field mapping" step.
• Target fields (synonyms allowed):
- team experience (High/Medium/Low; synonyms: Senior/Mid/Junior)
- project conformity (Conformant/Nonconformant; synonyms: Conforme/Não conforme; OK/NOK)
- supply delay (Yes/No; synonyms: Delay/No Delay; Yes/No; 1/0)
- licensing issue (Yes/No; synonyms: Pending/Not pending; Yes/No; 1/0)
- schedule delay (Yes/No; synonyms: Late/OnTime; Yes/No; 1/0)
- [optional] planned_duration_months, actual_duration_months, start_date, energization_date
• Standardize categories (case-insensitive), treat missing as “unknown,” and report % missing.

3) QUALITY AND NORMALIZATION
• Produce a "Data Quality Report": counts per category, % missing, ambiguous labels.
• Show the MAPPING table: {original_value → standardized_value} for each variable.

• If any critical variable has >10% missing, flag it and propose treatment (listwise deletion or conservative imputation).

4) PARAMETER ESTIMATION FROM THE DATA
• Estimate priors: P(Team), P(Supply Delay=Yes), P(Licensing Issue=Yes).
• Estimate P(Project Conformity | Team) with Laplace smoothing (α=1).
• Estimate P(Schedule Delay=Yes | Conformity, Supply, Licensing) with Laplace (α=1) for all 8 combinations.
• If any cell count < 10, keep the smoothed estimate and mark it ⚠ "low sample".
• Apply a gentle MONOTONICITY check; if inversions occur (e.g., Non-conformant risk < Conformant under same parents),
nudge minimally toward expected order and document the adjustment.

5) BASELINE RESULTS
• Compute baseline P(Schedule Delay=Yes) by marginalizing over (Conformity, Supply, Licensing).
• Provide a table with: (Conformity, Supply, Licensing) | Combination weight | P(Delay=Yes) | Contribution to expected delays.
• Provide a textual sensitivity ("tornado"): ±10 percentage-point changes in Supply and Licensing priors and the impact on baseline.

6) SCENARIOS AND MITIGATIONS (population level)
• Report P(Delay=Yes) under:
a) Independent Design Review (force Conformity=Conformant).
b) Supply expediting (target P(Supply Delay=Yes)=0.15 — ask me to confirm).
c) Licensing task force (target P(Licensing Issue=Yes)=0.10 — ask me to confirm).
d) Combined (a+b+c).
• For each, include: New P(Delay=Yes) | Δ vs. baseline (pp) | "Delays avoided per 100 projects".

7) POINT QUERIES (what-if)
• Allow me to specify Team/Conformity/Supply/Licensing and return P(Delay=Yes) with a short causal explanation.

8) MANAGERIAL PRIORITIZATION
• In 4–6 sentences, rank levers by "delays avoided / 100 projects" and provide an ordered recommendation.
• Offer a qualitative EVPI proxy: which variable, if known perfectly, would most reduce delay uncertainty?

9) PRESENTATION
• Tables in markdown (4 decimals).
• Use Harvard-style citations in text: (PMI, 2021), (Pearl, 2009), (Fenton and Neil, 2019), (Jensen and Nielsen, 2007), (Koller and Friedman, 2009).
• Add a "References" list with these canonical works only.

10) RESTRICTIONS
• Do NOT access the internet or external data.
• Keep my data within this chat.
• If my data are insufficient, request samples or confirm provisional synthetic values (clearly labeled).

Informational note — Uncertainty (applicable when CPTs are calibrated from data). When conditional probability tables (CPTs) are calibrated from data, the uncertainty of each cell can be summarized with a 95% Bayesian credible interval under a Beta posterior obtained via Laplace smoothing (α = 1). Let y be the number of delayed cases in that parent configuration and n the total number of cases in the cell; then

$$p|data \sim Beta(y+1, n-y+1), \text{ and}$$
$$CI95\% = [BetaInv(0.025, y+1, n-y+1), BetaInv(0.975, y+1, n-y+1)],$$

where *BetaInv* denotes the quantile function of the Beta distribution. The practitioner prompt in this appendix estimates CPT parameters using the same Laplace smoothing (α = 1), so these intervals follow directly from that posterior. For purely elicited/synthetic CPTs, reporting intervals is optional and may be omitted or labeled illustrative.

Appendix — Illustrative Synthetic Records (subset)

Table A1 — Sample of 20 synthetic records (fictitious)

ID	Team Experience	Project Conformity	Supply Delay	Licensing Issue	Schedule Delay
001	High	Conformant	No	No	No
002	Medium	Conformant	Yes	No	Yes
003	Low	Non-conformant	Yes	Yes	Yes
004	Medium	Conformant	No	Yes	No
005	High	Conformant	Yes	Yes	Yes
006	Low	Conformant	No	No	No
007	Medium	Non-conformant	No	No	Yes
008	High	Conformant	No	Yes	No
009	Low	Non-conformant	Yes	No	Yes
010	Medium	Conformant	No	No	No
011	High	Conformant	Yes	No	Yes
012	Medium	Conformant	No	Yes	No
013	Low	Non-conformant	No	Yes	Yes
014	Medium	Conformant	Yes	Yes	Yes
015	High	Conformant	No	No	No
016	Low	Conformant	Yes	No	Yes
017	Medium	Conformant	No	No	No
018	High	Conformant	No	Yes	No
019	Medium	Non-conformant	Yes	No	Yes
020	Low	Non-conformant	No	No	Yes

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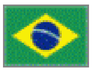

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