

Bayesian network approach for electric vehicle integration: Tunisian case study

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Abstract: The rapid adoption of electric vehicles presents both opportunities and challenges for modern transportation systems. Integrating this kind of vehicles into existing networks requires careful consideration of charging infrastructure development and the potential impacts on electrical grids. This paper proposes a Bayesian network approach to model and analyze the complex interplay between electric vehicles adoption, infrastructure deployment, and grid stability. By leveraging probabilistic reasoning, the methodology provides a framework for decision-makers to evaluate strategies, optimize resource allocation, and mitigate risks. Our results suggest that a coordinated approach, balancing charging station placement and grid reinforcement, is essential for sustainable electric vehicles integration.

Keywords: Electric vehicle; Bayesian network; Charging infrastructure; Stability; Sustainable transportation.

JEL Codes: C11; Q42; R41; L94.

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I. Introduction:

Electric vehicles (EVs) represent an important element in global strategies aimed at mitigating greenhouse gas emissions and reducing reliance on fossil fuels within the transportation sector (IEA[†], 2022) (Zhan et al., 2024). While the environmental and economic benefits of EVs are widely acknowledged, their large-scale adoption demands substantial adaptations to both transportation and energy infrastructures (Salah et al., 2025). In Tunisia, the transition to EVs carries particular significance, as the country seeks to embed sustainable development into its national policy framework. However, integrating EVs into Tunisia's transportation and energy systems presents unique challenges and opportunities, given the country's economic constraints and evolving infrastructure. As of late 2020, Tunisia's EV landscape was modest, with only 34 electric vehicles registered and an equal number of charging stations available—one per vehicle[‡]. Yet, recent years have marked a turning point. By September 2024, sales of EVs reached 90 units, driven by growing availability of fully electric and hybrid models from dealerships. Experts project a significant leap forward, with estimates suggesting 5,000 EVs on Tunisian roads by 2025 and an ambitious target of 130,000 to 150,000 by 2030. This acceleration reflects a broader recognition that electric mobility is not just an environmental priority but a budgetary necessity, offering a pathway to cheaper, cleaner travel when paired with renewable energy development. Infrastructure, however, remains a critical bottleneck. With approximately 60 charging stations currently operational, the goal is to achieve a ratio of one station per ten

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[†] International Energy Agency (IEA). (2022). *Global EV Outlook 2022: Securing supplies for an electric future*. (iea.org)

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vehicles—necessitating 500 stations to support 5,000 EVs[§]. This rapid evolution raises a key question: How can Tunisia effectively integrate electric vehicles into its transportation and energy systems while ensuring grid stability and equitable access to charging infrastructure? Addressing this requires a nuanced understanding of the interplay between EV adoption, infrastructure deployment, and electrical grid capacity. It's essential that the municipalities, commercial entities, public infrastructure managers, and fuel distributors must collaborate to drive this transition. There are two critical challenges: the deployment of an adequate and accessible charging infrastructure and the effective management of the increased electricity demand imposed on power grids (Deb et al., 2017). These challenges are deeply interrelated, as decisions made regarding charging infrastructure can significantly influence the stability of the electrical grid and vice versa. Traditional deterministic models, which often rely on fixed inputs and outputs, tend to fall short in capturing the complex and uncertain nature of these interdependencies (Ul-Haq et al., 2017). In contrast, probabilistic approaches, such as Bayesian Networks (BN), offer a more adaptable analytical framework. BN enable the modeling of conditional dependencies among variables, providing a sophisticated understanding of how changes in one factor might propagate through the system (Pearl, 1988). For this reason, we utilize the strengths of BN to evaluate strategies for integrating EVs into existing systems. Our aim is to address these challenges through three key objectives: (1) Model the interdependencies between EV adoption and grid capacity, (2) Evaluate infrastructure deployment strategies, and (3) Propose policy recommendations for sustainable EV integration in Tunisia. Given the dynamic and uncertain nature of EV integration, a Bayesian network approach provides a robust framework to model the probabilistic relationships between adoption rates, infrastructure deployment, and grid stability.

Literature Review

The integration of EVs into existing transportation systems has attracted significant attention in recent years as governments and industries aim to meet sustainability goals. In this section, we examine key studies related to EV adoption, charging infrastructure development, and grid impact, with a particular emphasis on analytical approaches such as BN that address the complexity and uncertainty of these interrelated challenges. Indeed, Wang and Shi (2024) highlight that EV market penetration has accelerated in urban areas, with adoption rates exceeding 20% in some regions by 2023. However, integrating these vehicles into transportation networks presents logistical challenges. Li et al. (2024) argues that existing road systems, designed for internal combustion engines, require reevaluation to accommodate EV-specific needs, such as range-related concerns range limitations and charging access. Their analysis suggests that without strategic planning, traffic congestion and range-related concerns could undermine EV adoption. Other studies consistently emphasize the need for a robust network of charging stations to support large-scale adoption. For example, Ren and Sun et al. (2025) conducted a spatial analysis of charging station placement, finding that urban centers and highway corridors are priority zones due to high traffic volumes. However, they note a trade-off between coverage and cost, with rural areas often underserved. Expanding on this, Mojlish et al. (2025) explore fast charging technologies, demonstrating their potential to reduce

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charging times but highlighting the increased pressure on local electricity networks. These works underscore the necessity of balancing accessibility with infrastructural feasibility, a challenge that probabilistic models can help address. In the other context, the electrification of transportation significantly affects electricity demand profiles, raising concerns about grid stability. According to Nijenhuis et al. (2025), EV charging during peak hours can increase demand by up to 25%, placing pressure on outdated grid infrastructure in many regions. Mitigation strategies, such as demand-response programs and renewable energy integration, have been proposed. For instance, Nwagu et al. (2025) and Hul et al. (2024) investigate the role of solar and wind power in offsetting EV-related loads, finding that a 15% increase in renewable capacity could stabilize grids in high-adoption scenarios. However, the variability of renewable sources and charging behavior introduces uncertainty, complicating deterministic forecasting methods. If we examine the applied methods, we discover that traditional modeling techniques, such as linear programming and simulation, have been commonly applied to study EV integration. However, these approaches often are limited in capturing the dynamic and uncertain nature of the problem, indeed, traditional linear programming models often fail to account for the stochastic nature of EV user behavior, leading to suboptimal infrastructure placement (Ye et al., 2024). Probabilistic frameworks, particularly BN, have emerged as a preferred more flexible alternative. Borunda et al. (2016) were among the first to prove BN to energy systems. Also, Li. (2025) extended this approach to EV charging, constructing a network to assess the interplay between station availability and user behavior. Their findings suggest that probabilistic reasoning can identify critical variables—such as charging demand and grid capacity—under fluctuating conditions. Despite these advances, gaps remain in the literature. Few studies integrate transportation and energy perspectives into a unified framework, often addressing charging infrastructure and grid impact as separate issues. Moreover, while BN have been used in related fields, their application to EV integration remains underexplored. Although significant progress has been made, notable gaps persist in the existing research. Current models often focus on isolated aspects, such as demand forecasting or infrastructure optimization, rather than adopting the holistic system proposed in this study.

Methodology

This study employs a BN approach to assess the integration of EVs into Tunisia's transportation systems, focusing on the interdependencies between EV adoption, charging infrastructure, and grid stability. The methodological process follows a systematic and sequential approach, outlined in the following steps:

- Step 1: Problem identification. The primary objective of this study is to develop a comprehensive strategy for integrating EVs into existing transportation systems while addressing critical challenges related to charging infrastructure and grid stability. Given Tunisia's ambitious EV adoption targets and current infrastructural constraints, a probabilistic approach is required to capture the complexity and uncertainty of these dynamics.

- Step 2: Variable selection and conceptual framework development. Building on insights from the literature review and expert consultations, our study identified five key variables critical to EV integration:
 - ✓ EV adoption rate (EAR): Measures the growth of EV ownership over time.
 - ✓ Charging station density (CSD): Represents the availability and distribution of charging facilities.
 - ✓ Peak electricity demand (PED): Assesses the pressure on the grid during high-demand periods.
 - ✓ Grid reliability (GR): Evaluates the grid's capacity to maintain stability under varying loads.
 - ✓ Renewable energy availability (REA): Quantifies the share of renewables in the energy mix, contributing to grid resilience.

These variables form the foundation of the conceptual framework, which maps the conditional dependencies between them. For instance, an increase in EAR is likely to impact PED and may necessitate enhancements in CSD and GR.

- Step 3: Data collection. Data were gathered from diverse sources, including historical EV sales, charging station data, electricity demand and grid performance and expert opinions.
- Step 4: BN construction. We use *Graphviz*, and Python's *Pandas* library to implement our model. The construction process involved model structuring that translating the conceptual framework into a Directed Acyclic Graph (DAG) where nodes represent variables and edges depict probabilistic dependencies. Defining conditional probability distributions (CPD) where we choice to utilize historical data and expert input to parameterize the model. For example, the dependency of PED on EAR and CSD was modeled using maximum likelihood estimation methods. The final BN model enabled scenario simulations and facilitated probabilistic reasoning to evaluate different integration strategies.
- **Step 5: Scenario simulation.** The model was tested under various scenarios to explore the potential outcomes of different policy and infrastructure strategies:
 - ✓ **Optimistic scenario:** Simulating high renewable energy integration and accelerated infrastructure development.
 - ✓ **Pessimistic scenario:** Considering slow EV adoption and minimal infrastructure improvements.
 - ✓ **Baseline Scenario:** Reflecting current trends with moderate growth across variables.

For each scenario, the model generated probabilistic forecasts, highlighting critical risk areas and opportunities for strategic interventions.

- Step 7: Results interpretation. The final step involved interpreting the results through three steps First, sensitivity Analysis: evaluating how changes in one variable (e.g., EV adoption rate) influence others (e.g., peak electricity demand and grid reliability). Secondly, identifying key drivers: determining which factors most significantly affect grid stability

and infrastructure adequacy. Finally, the insights gained provided a decision-making framework for policymakers, offering evidence-based recommendations to optimize EV integration strategies in Tunisia.

This methodological approach combines quantitative data analysis with probabilistic modeling, offering a robust framework to address the uncertainties and complexities of EV integration. The use of Bayesian Networks not only enhances the understanding of critical dependencies but also supports informed policy-making by simulating potential future scenarios.

Result and discussion

This section presents the results obtained from our BN in the context of electric vehicle (EV) integration in Tunisia.

Definition of variables

For our model, we have defined the following variables, as already mentioned above:

- EV adoption rate (EAR): The rate at which electric vehicles are adopted.
- Charging station density (CSD): The density of available charging stations.
- Peak electricity demand (PED): The maximum electricity demand during peak periods.
- Grid reliability (GR): The stability and reliability of the electrical grid.
- Renewable energy availability (REA): The availability of renewable energy sources.

Dependency relationships

- EV adoption rate (EAR) → Charging station density (CSD): As the adoption rate of electric vehicles (EVs) increases, there is a growing need for an expanded charging infrastructure. A higher EAR encourages investments in charging stations to meet the demand of new EV users, directly influencing the density of charging stations available.
- EV adoption rate (EAR) → Peak electricity demand (PED): The widespread use of EVs increases the overall electricity consumption, particularly during charging periods. As more people adopt EVs, the pressure on the electrical grid rises, leading to potential spikes in peak electricity demand.
- Charging station density (CSD) → Grid reliability (GR): While a well-distributed network of charging stations improves accessibility for EV users, it can also pose challenges to the grid's stability. An increased density of charging stations, especially if not strategically managed, might lead to sudden and localized surges in electricity demand, impacting grid reliability.
- Peak electricity demand (PED) → Grid reliability (GR): High peak electricity demand can strain the grid, particularly if demand surges exceed the grid's capacity. Managing this demand is crucial to maintaining grid stability, as excessive loads can lead to disruptions or reduced grid reliability.

- Renewable energy availability (REA) → Grid reliability (GR): Integrating renewable energy sources, such as solar or wind power, can enhance grid reliability by providing a cleaner and potentially more stable supply of electricity. However, since renewable sources can be intermittent, their availability plays a critical role in balancing supply and demand and maintaining a stable grid.
- Charging station density (CSD) → Peak electricity demand (PED): The placement and number of charging stations influence when and where electricity demand will peak. A higher density of charging stations, especially in concentrated areas, might create localized increases in demand, which must be managed to avoid grid instability.

The BN construction

To construct our BN, we utilized Graphviz, an open-source software widely recognized for its capabilities in graph visualization. This tool facilitated the creation of the following BN representation:

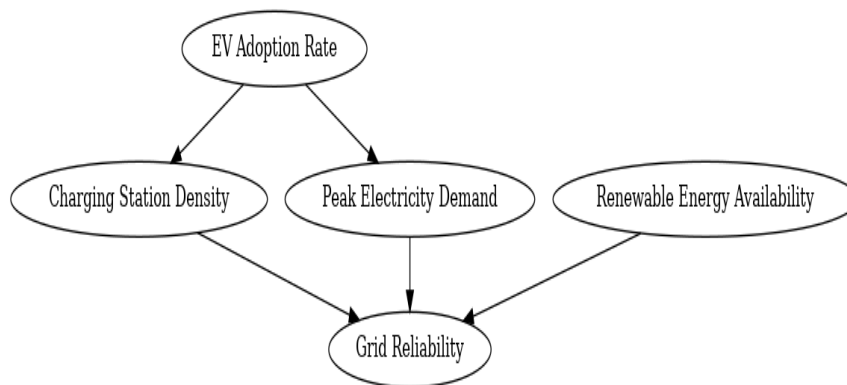


Fig. 1. : BN

The BN illustrated in figure 1 provides a graphical representation of the relationships between the key variables influencing EV integration within Tunisia's transportation and energy systems. To complement this structure, the conditional probability table (CPT) offers a quantitative perspective by detailing the probabilities associated with different states of the variables, given their parent nodes. Following an inference calculation process using *Python's Pandas* and *Graphviz* libraries, we generated the following probability table.

TABLE I. : CPT OF GR GIVEN CSD, PED, AND REA

CSD	PED	REA	GR	Probability
Low	Low	Low	High	0.80
Low	Medium	Low	Medium	0.60
Medium	Medium	Medium	Medium	0.50
Medium	High	Medium	Low	0.30
High	High	High	Low	0.20
High	Very High	High	Very Low	0.10
Very High	Very High	Medium	Low	0.25
Very High	Very High	High	Medium	0.40

This table highlights the critical factors directly influencing grid reliability and sustainable EV integration, namely: EAR, CSD, PED, and REA. It illustrates how grid stability is influenced by charging station density, peak electricity demand, and renewable energy availability. It provides valuable insights into the probability of achieving different levels of grid reliability under varying conditions of these interdependent variables.

- High GR is most likely with low demand and low charging density:

When both CSD and PED are at a low level, and REA is also low, the grid exhibits a high reliability with a probability of 80%. This scenario suggests that lower adoption of electric vehicles and limited charging infrastructure place minimal stress on the grid, even with low renewable energy input.

- Medium reliability under balanced scenarios:

Medium grid reliability is observed in two distinct situations. When CSD is low and PED is medium, despite low REA, indicating that moderate electricity demand can still be managed effectively if the charging infrastructure remains insufficient. The probability here is 60%. Alternatively, when CSD and PED are at very high levels but REA is high, the probability of medium grid reliability rises to 40%. This reveals that robust renewable energy integration can help offset the grid stress caused by widespread EV adoption and intensive charging infrastructure.

- Low grid reliability during high demand and medium renewables:

In scenarios where CSD and PED are both medium, and REA is also medium, grid reliability drops to a medium level with a 50% probability. This balance indicates that while the grid can manage moderate loads, any increase in demand or reduction in renewable energy could disrupt stability. Additionally, when CSD is very high, PED is very high, and REA is medium, grid reliability remains low with a 25% probability, highlighting the grid's vulnerability under extreme demand conditions with only moderate renewable support.

- Very low grid reliability in extreme scenarios:

The grid is most at risk when CSD and PED reach their highest levels and REA is also high. Under these conditions, the grid reliability drops to very low, with a 10% probability. This critical finding emphasizes that even strong renewable energy availability may not be sufficient to stabilize the grid if the charging infrastructure is overextended and demand peaks simultaneously.

In conclusion, the CPT for grid reliability underscores the delicate balance required to maintain grid stability during the integration of electric vehicles. While renewable energy can play a mitigating role, strategic planning around charging station density and management of peak electricity demand is crucial. These insights could guide decision-makers and infrastructure planners in optimizing EV integration strategies to guarantee grid performance.

Scenarios simulation

The BN model developed in this study provided valuable insights into the complex relationships between EV adoption, charging infrastructure deployment, and grid stability under various scenarios. By simulating different conditions, we were able to assess the potential risks and opportunities associated with Tunisia's transition to electric mobility.

- Optimistic scenario:

In the optimistic scenario, characterized by a high EV adoption rate, accelerated deployment of charging infrastructure, and robust integration of renewable energy sources, the BN model projected a balanced grid load. The probability of grid overload remained below 10%, demonstrating that strategic planning and proactive infrastructure development could effectively mitigate risks to grid stability. This scenario underscores the importance of aligning EV growth with investments in both renewable energy and grid reinforcement.

- Pessimistic scenario:

The pessimistic scenario simulated a situation with low infrastructure deployment but high EV adoption. Under these conditions, the model revealed significant risks to grid stability, with the probability of grid reliability issues exceeding 40%. The lack of adequate charging infrastructure, coupled with rising electricity demand from EVs, created a strain on grid resources. These findings highlight the dangers of uncoordinated growth, where the pace of EV adoption outstrips the development of critical support infrastructure.

- **Baseline scenario:**

The baseline scenario, reflecting current trends in Tunisia, showed moderate grid pressure. The model estimated a 25% likelihood of grid stability issues under existing conditions. While this scenario presents manageable risks, it emphasizes the need for proactive measures to prevent future bottlenecks. The findings suggest that maintaining grid stability will require not only expanding the charging network but also enhancing grid capacity and integrating renewable energy sources more effectively.

Discussion

The comparative analysis of these scenarios indicates that grid reliability is highly sensitive to the balance between EV adoption, charging infrastructure deployment, and renewable energy availability. The model's probabilistic approach allowed for a nuanced understanding of how changes in one variable could propagate through the system, influencing grid stability. In practice, decision-makers should prioritize a coordinated strategy that includes:

- **Investment in charging infrastructure:** Increasing the density of charging stations to match EV growth.
- **Grid capacity reinforcement:** Implementing technologies that enhance grid resilience, particularly during peak demand periods.
- **Support for renewable integration:** Promoting renewable energy projects to ensure a stable and sustainable electricity supply.

These insights provide a data-driven foundation for developing policies and strategies that will facilitate the smooth integration of EVs into Tunisia's transportation and energy systems while maintaining grid stability.

Conclusion

This study developed a BN model to assess the integration of EV into Tunisia's transportation and energy systems. By analyzing the interactions between EV adoption rates, charging infrastructure deployment, and grid stability, the model provided critical insights under various scenarios. The findings demonstrate that a strategic and well-coordinated approach is essential to balance EV growth with the necessary infrastructure and energy grid enhancements. The optimistic scenario highlighted the benefits of aligning EV adoption with renewable energy integration and robust grid management, showing a minimal risk of grid instability. However, the pessimistic scenario underscored the dangers of uncoordinated growth, where the grid reliability risk exceeded 40%, emphasizing the need for careful planning and investment. The baseline scenario, with a 25% likelihood of grid stability issues, reinforced the importance of proactive measures to avoid future challenges. By leveraging probabilistic reasoning, the proposed BN model supports informed decision-making to ensure a fluid and resilient transition toward electric mobility in Tunisia. Future studies could expand on this work by integrating more dynamic variables, such as policy changes and consumer behavior, to further refine strategic planning in this rapidly evolving sector.

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