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# Automating Six Sigma Project Selection Through Analytic Network Process

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## Abstract

Selection of the correct projects at the correct time is critical to the success of a Six Sigma program. Poor project selection can cause a host of problems for an organization such as resource waste, low stakeholder engagement, unsustainable results, and lost credibility. During the selection of a lean six sigma project, a mix of qualitative and quantitative data with high levels of uncertainty are utilized to study the effectiveness of projects and choose the best option that aligns with organization strategy and maximizes the impact and resource savings in the company. In this process, diverse range of conflicting and interdependent criteria are used to select the most appropriate options that match best with requirements and needs of the organization involved. This paper explores the possibilities of using analytic network process (ANP) and utilizing the collected data for selecting the most appropriate six sigma project to reduce warranty costs. The proposed framework enables automated decision-making process, quantify subjective opinions of stakeholders, and enable efficient modeling of feedback loops in the system. It also shows promising results to decrease decision biases, increase system adaptability, and enhance transparency of the process.

## Keywords
Six sigma, Decision Making, Analytic Network Process (ANP)

## 1.Introduction
Structured problem solving in its various forms such as Six Sigma, Shainin Red X and Kepner Tregoe Problem Analysis can be an effective tool for an organization's continuous improvement efforts to reduce warranty costs. Regardless of the method used to achieve the end result, eliminating the cause of a technical launch issue, optimizing a system or process to reduce variation in process or in outputs, reducing warranty occurrences for a particular failure mode or improving any other quality or efficiency metric all have a positive impact on the bottom line of a company or organization. Assuming unlimited resources, an organization could address all identified issues by any means at their disposal. However, all companies have resource limitations in terms of talent, time, and budget and they need to choose the best corrective actions that match best with their goals and available resources. In majority of Six Sigma processes, the decision makers need to rank and prioritize existing problems based on the actual value that their

resolution brings to the organization. The amount of effort required to fix a technical issue does not automatically reflect its importance to the company's overall performance or financial outcomes. Some problems may demand significant engineering work yet offer minimal strategic benefit, while others—perhaps smaller or simpler—can create substantial impact when addressed. In other words, not all problems carry equal weight and deserve the same level of investment as project owners. Effective decision making in this stage requires careful investigation of the identified problems to distinguish the most valuable efforts and projects that advance organizations' objectives and their competitiveness in the market.

Six sigma is an efficient technique to utilize the existing data in the organization to choose the best corrective actions that can eliminate defects and minimize variability in the product qualities. Six sigma mostly focus on five main categories of define, measure, analyze, improve, and control deciding on potential improvements of the system. Both qualitative and quantitative data collected from processes and experts are utilized to analyze existing challenges and select the projects that increase value added of the processes for the organization. In automotive industry, warranty data can be one of the best sources to identify failures and patterns of product failures, customer complaints, and high frequency technical defects.

This research proposes a structured framework based on analytic network process (ANP) to utilize the warranty data collected from customer services of an automotive company to identify the best corrective actions and select and rank them based on the extracted conflicting criteria. The rest of the paper is organized as follows: Section 2 lists existing challenges and explains the current problem in the lean six sigma project selection, while Section 3 reviews the existing literature. Section 4 presents the proposed methodology, followed by its numerical results in Section 5. Finally, the paper concludes with a summary of the research and directions for future work.

## 1.1 Objectives

To monitor technical capabilities and continue to grow, an organization needs to monitor multiple number of metrics and benchmark its state with other world class organizations and competitors in similar fields and industries. Some common manufacturing internally measured indices include first time capability, jobs per hour, and internal audit compliance percentages. There are also external metrics such as units sold per quarter, percentage of market share, warranty spend per quarter or per unit sold, failure occurrences, and return trips for repair. All these internal and external metrics are selected to identify areas of potential problems and specific failure modes. Any identified failure mode will have a consequence in the marketplace, and its corresponding negative financial impact will be reflected as a loss of sales revenue or loss in customer enthusiasm. Customer satisfaction is one of the important factors that can be measured through complaints and surveys received, and it can be directly translated into a loss of brand strength or negative impact on reputation. The data collected from customers and operations is analyzed to find emerging issues and areas for improvement for a given organization.

In a large organization, different departments have their own major problems, but they are not equal contributors to the company's overall performance. Comparing problems and challenges of different departments becomes more difficult when the data sources are different and come from different formats. This can create discrepancies between scoring the same problem across multiple departments. One problem may score high on one metric while it achieves lower score on another metric and comparing metrics on different scales is highly subjective and depends on the judgement of subject matter experts. Even with expertise, the urgency of addressing a problem and the complexity of solving it can be unclear. Because urgency, complexity, and problem type all draw on resources differently, organizations struggle to decide how to allocate resources to the issues that truly matter.

Even with knowledge and experience it is not easy to identify the urgency of a project, and it can involve set of complex decision processes to identify which to address to solve a given problem. Factors such as urgency, complexity and the nature of the problem have varying draws on resources and the way that an organization overcomes this uncertainty requires precise investigation of resources to solve the highest priority problems.

Even in the case of a single metric such as warranty, multiple information sources can impact on the overall cost of warranty. The warranty documentation process itself becomes an issue in terms of the volume of data generated through warranty claims. Moreover, redundancies in the system and discrepancies in data types (text, categorical data, quantifiable data) and digital systems to interact to process and pay claims all introduce additional challenges related to manual errors and misinformation. All these constraints can delay the time to identify and react to a problem or lead to resources working on a problem that doesn't really exist. Each step in warranty system is a source of information with different data types, text narratives, dollar amounts, and claim rates for example. There are multiple interacting factors and criteria that need to be considered in this process. Failures to capture complex relations between problem sources and their relations with given criteria can worsen the problem and lead to failures in decision process.

The selection process for a Six Sigma project can be characterized as a multi-criteria decision-making (MCDM) problem (Kumar et al. 2008, Yousefi and Hadi-Vencheh 2016. The complexity in the decision process lies in spanning the different data types and sources used to evaluate the multidimension areas of finance, operations, customer-service, and strategic elements of a company. Even in the face of large amounts of data there often is a large gap in the proposed academic methods proposed in scientific literature and what is used in practice throughout industry. Often companies favor subjective or unstructured methods to approach this task, according to a survey by Kornfeld and Kara (2013). However, a subjective approach leaves the possibility of a disconnect between project selection and benefits to company performance (Kornfeld and Kara 2013). On the other hand, there are hidden complexities between the involved factors in the analysis that creates interdependencies between them and make the decision making even more challenging. Therefore, the decision makers need a structured framework to investigate various aspects in a more systematic way and identify the best choices given the potential outcomes that each choice will bring to the table.

## 2. Literature Review

Multi-Criteria Decision Making (MCDM) constitutes a fundamental field of study and applied methodology utilized for solving complex selection problems, such as the crucial prioritization of Six Sigma (SS) or Lean Six Sigma (LSS) projects ( Odeyinka et al. 2024; Wang et al. 2014; Wen et al. 2018; Yousefi and Hadi-Vencheh 2016). These systematic approaches employ mathematical models and simulations to assist decision-makers in evaluating competitive alternatives based on a comprehensive set of defined criteria, often integrating both qualitative expert judgments and quantitative metrics (Alyamani and Long 2020; Alyamani et al. 2021; Odeyinka et al. 2024; Pakdil et al. 2021; Wen et al. 2018; Yousefi and Hadi-Vencheh 2016). The decision process is characterized by complexity, stemming from the need to manage multiple, often conflicting, organizational objectives within uncertain environments, necessitating methods capable of accommodating the ambiguity inherent in expert opinions and unquantifiable measures (Alyamani et al. 2021; Pakdil et al. 2021). MCDM methods are thus instrumental for generating dependable and logical outcomes that translate qualitative preferences into rigorous quantitative comparisons, aiming to prioritize alternatives that best align with strategic goals (Swarnakar et al. 2023). Prominent techniques frequently employed Analytic Hierarchy Process (AHP), often adapted as Fuzzy AHP (FAHP), Data Envelopment Analysis (DEA), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and the relatively newer Best-Worst Method (BWM to account for inherent vagueness and identify the best choice in a more systematic approach (Alyamani and Long 2020; Swarnakar et al. 2023; Vinodh and Swarnakar 2015; Wen et al. 2018). Given the intricate nature of real-world problems, many researchers advocate for or implement hybrid MCDM models, such as combinations involving DEMATEL and ANP to address interdependencies between criteria and enhance the consistency and reliability of the selection process (Pacagnella Junior et al. 2024, Ortíz et al. 2015).

In traditional multi-criteria decision-making, the AHP structures problems into linear, unidirectional hierarchies (Ergin and Alkan 2023). However, modern urban and industrial systems—such as subway construction safety, flood risk management, and sustainable supply chains—require the network-based approach provided by the ANP to accurately reflect mutual influences between criteria (Bai et al. 2025, Li et al. 2020, Ma et al. 2025, Wu 2022). While the ANP is uniquely equipped to prioritize elements in these complex networks, its practical application is often stalled by the "elicitation bottleneck", where even moderately sized models require as many as 500 to 550 expert judgments to determine relative influence (Sava et al. 2022). When information sources change daily, the traditional requirement for manual re-elicitation becomes an inefficient strategy that risks judgment fatigue and logical inconsistency (Sava et al. 2022).

## 3. Methods

In this research, Analytic Network Process (ANP) is selected as a suitable approach to analyze the urgencies of the existing projects to take effective action to reduce warranty claims. The ANP is a generalization of the Analytic Hierarchy Process (AHP), used in multi-criteria decision-making (MCDM) (Ishizaka and Mu 2023). The ANP approach models the decision framework as a network which allows the network to weigh interrelationships between decision elements, decision criteria, and alternatives that are often present in practice (Kim et al. 2025). In the AHP structure, decisions are made through a system of hierarchical relationships, whereas in ANP the network connects clusters, and the nodes inside those clusters to influence the decision-making process allowing it to solve more complex problems (Ishizaka and Mu 2023; Jin and Goodrum 2024; Kim et al. 2025; Lakhouit et al. 2025; Neumüller et al. 2015). The ANP methodology entails model construction, comparing the relative influence of criteria and alternatives using pairwise comparisons, forming an unweighted Supermatrix to capture these rankings, and constructing a Limit Supermatrix for final prioritization of the available alternatives (Kamali Mohammadzadeh et al. 2025; Liu and Mu 2023; Shirinkalam et al. 2025; Toth et al 2022). ANP is useful for making complex decisions, typically structured using the Benefits, Opportunities, Costs, and Risks (BOCR), to efficiently assess the positive and negative consequences of a decision (Figure 1).

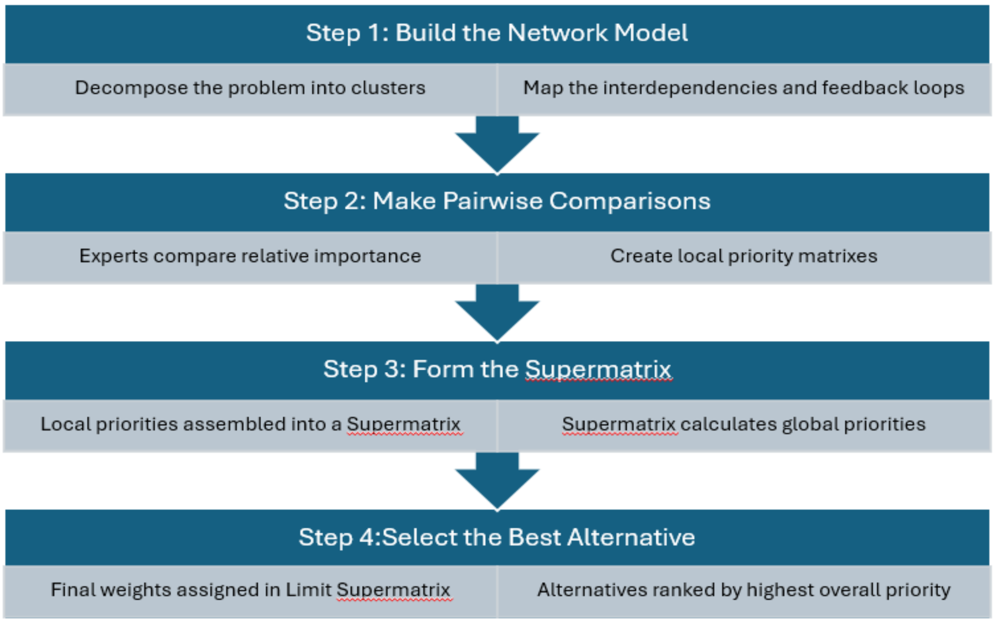



Figure 1. Analytic Process Network process flow

The decision problem is formulated using ANP to capture interdependencies among project selection factors, attribute-level feedback, and alternative-driven influences that cannot be represented using a strictly hierarchical structure. The ANP network, shown in Fig. 2, consists of interconnected clusters representing the goal of selecting one of the three project alternatives, evaluation factors, associated attributes, and alternatives, with bidirectional links denoting feedback and interdependence. The factors and attributes considered in the model, including product phase, problem severity, and cost-related measures—are defined and summarized in Table 1.

The three alternatives are three different six sigma projects representing three different scenarios. Alternative A is an engine repair which is the costliest repair considered but occurs infrequently. Alternative B is a visual defect of a gap between interior panels rather than flush; this is the least costly repair but occurs frequently so many end customers would experience the problem. Alternative C is a problem where the screen intended to display the image from the rear-view camera goes blank when the vehicle is put into reverse, also a costly repair but not as costly as Alternative A. Like Alternative A the occurrence of Alternative C is low, however it also carries the burden of regulatory compliance if it does not function.

Based on the network structure in Figure 2, the corresponding pairwise comparison matrices were built and then submitted to subject matter experts for ranking. The pairwise comparison rankings are translated into a Weighted Supermatrix as displayed in Table 2. This represents the weights without all connections and feedback weights. The addition of these interconnections results in the creation of the Limit Supermatrix, which is used for the problem rankings.

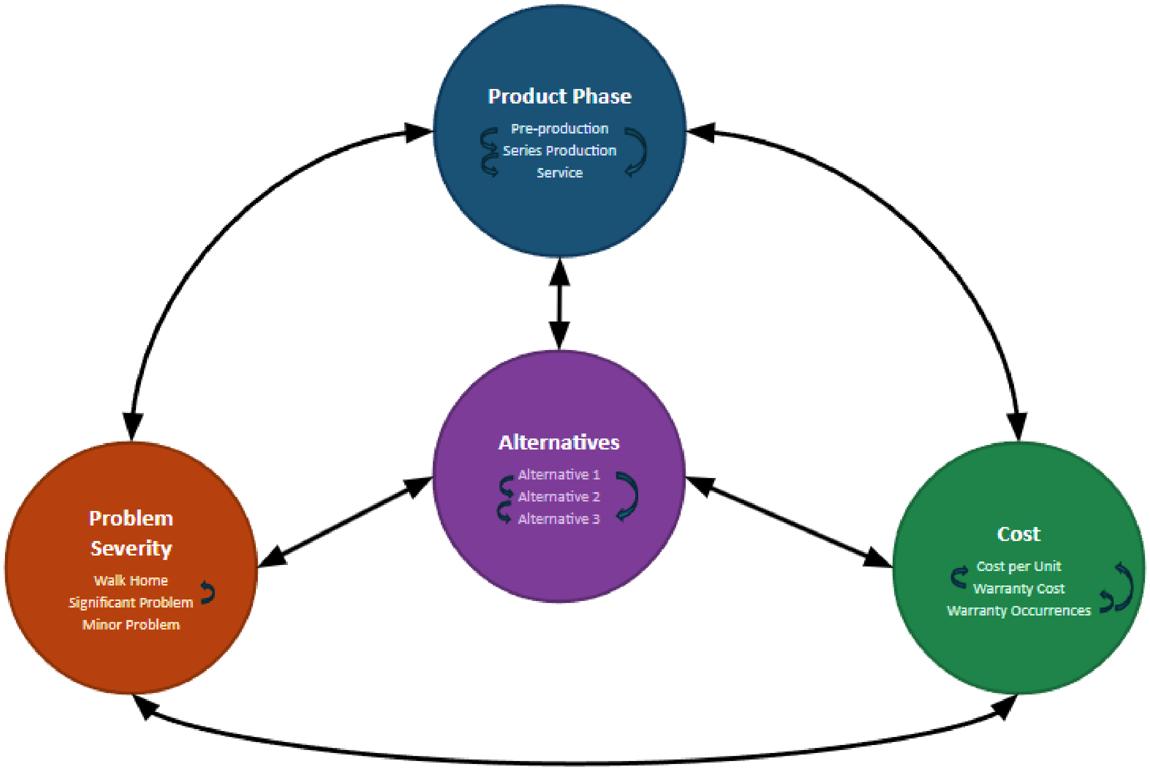



Figure 2. ANP Structure Diagram for project selection showing interdependent criteria, attribute-level feedback, and alternative-to-criteria influence.

Table 1. Definition of Clusters, Nodes, and Descriptions

| Cluster | Nodes | Description |
|---|---|---|
| Product Phase | Pre-Production | Development and pilot phase in which units are built for testing and are not saleable. Problems identified are largely contained and do not reach end consumers, but quantitative assessment is limited due to low sample sizes. |
| Product Phase | Series Production | Products are actively manufactured and sold to customers under normal operating conditions. |
| Product Phase | Service | Post-production phase in which manufacturing has ended but certain warranty and regulatory obligations remain, often related to compliance-critical components. |
| Severity | Walk Home | Failures that render the product unusable and leave the customer stranded. |
| Severity | Significant | Defects perceived by customers as critical to satisfaction and likely to influence purchasing decisions. |
| Severity | Minor | Issues that may be detected by discerning customers but are unlikely to be considered significant by most users. |
| Cost | Number of Occurrences | Frequency with which a repair is performed, normalized by the number of units produced. |
| Cost | Cost per Unit Sold | Repair cost normalized by the number of units sold. |
| Cost | Warranty Cost | Cost of warranty repair by failure type. |
| Alternatives | A | Engine cam failure; 5 c/1000; $1800 repair; Service phase; Walk Home severity. |
| Alternatives | B | Driver door sill plate gap; 2.0 c/1000; $200 repair; Pre-production phase; Significant severity. |

| Cluster | Nodes | Description |
|---|---|---|
| Alternatives | C | Backup camera blank screen; 0.5 c/1000; $1100 repair; |

## 4.Data Collection

The pairwise comparison rankings are collected from multiple subject matter experts from the organization master blackbelt group inside the quality department and entered the python matrixes in the ANP network. A pairwise comparison matrix was constructed to define the interdependencies between clusters. Each cluster has a pairwise comparison matrix for the nodes inside of it to rank the interdependence between nodes. And finally, each node has a pairwise comparison matrix to evaluate each node with each alternative. The following Figure 3 is a representation of the data collected after it was entered into the python ANP pairwise comparison matrices.

```
--- Cluster-Level Comparison Matrices ---

Comparisons relative to Cluster: Phase
array([[1.        , 3.        , 3.        , 5.        ],
       [0.33333333, 1.        , 1.        , 3.        ],
       [0.33333333, 1.        , 1.        , 3.        ],
       [0.2       , 0.33333333, 0.33333333, 1.        ]])

Comparisons relative to Cluster: Severity
array([[1.        , 3.        , 3.        , 5.        ],
       [0.33333333, 1.        , 1.        , 3.        ],
       [0.33333333, 1.        , 1.        , 3.        ],
       [0.2       , 0.33333333, 0.33333333, 1.        ]])

Comparisons relative to Cluster: Cost
array([[1.        , 3.        , 3.        , 5.        ],
       [0.33333333, 1.        , 1.        , 3.        ],
       [0.33333333, 1.        , 1.        , 3.        ],
       [0.2       , 0.33333333, 0.33333333, 1.        ]])
```

```
--- Node-Level Comparison Matrices (Projects relative to Criteria) ---

Project A comparisons for Phase nodes:
array([[1.        , 9.        , 4.        ],
       [0.11111111, 1.        , 1.        ],
       [0.25      , 1.        , 1.        ]])

Project A comparisons for Severity nodes:
array([[1.        , 7.        , 5.        ],
       [0.14285714, 1.        , 7.        ],
       [0.2       , 0.14285714, 1.        ]])

Project A comparisons for Cost nodes:
array([[1. , 1. , 1. ],
       [1. , 1. , 5. ],
       [1. , 0.2, 1. ]])
```

```
Project B comparisons for Phase nodes:
array([[1.        , 9.        , 4.        ],
       [0.11111111, 1.        , 1.        ],
       [0.25      , 1.        , 1.        ]])

Project B comparisons for Severity nodes:
array([[1.        , 7.        , 5.        ],
       [0.14285714, 1.        , 7.        ],
       [0.2       , 0.14285714, 1.        ]])

Project B comparisons for Cost nodes:
array([[1. , 1. , 1. ],
       [1. , 1. , 5. ],
       [1. , 0.2, 1. ]])

Project C comparisons for Phase nodes:
array([[1.        , 9.        , 4.        ],
       [0.11111111, 1.        , 1.        ],
       [0.25      , 1.        , 1.        ]])

Project C comparisons for Severity nodes:
array([[1.        , 7.        , 5.        ],
       [0.14285714, 1.        , 7.        ],
       [0.2       , 0.14285714, 1.        ]])

Project C comparisons for Cost nodes:
array([[1. , 1. , 1. ],
       [1. , 1. , 5. ],
       [1. , 0.2, 1. ]])
```

Figure 3. Paired comparison matrices from python

Once the data is entered into the python ANP matrices, pyANP uses the weights from the matrices to first build an unweighted matrix and are then translated into a Weighted Supermatrix as displayed in Table 2. This represents the weights without all connections and feedback weights. The addition of these interconnections and feedback loops from the alternatives to the ranking clusters results in the creation of the Limit Supermatrix, which is used for the problem rankings. These calculations and matrices are all done in python using standard imbedded pyANP commands (Table 3).

Table 2. Weighted Supermatrix

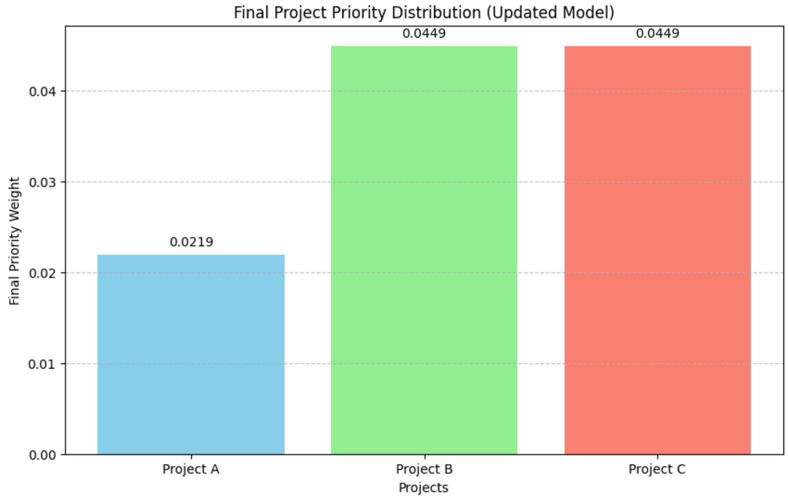
| | Project A | Project B | Project C | Preproduction | Series Production | Service | Walk-Home | Significant Problem | Minor Problem | Cost per Unit | Warranty Cost | Warranty Occurrences |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Project A** | 0.000000 | 0.000000 | 0.000000 | 0.078091 | 0.0 | 0.0 | 0.078091 | 0.0 | 0.0 | 0.078091 | 0.0 | 0.0 |
| **Project B** | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| **Project C** | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| **Preproduction** | 0.249430 | 0.249430 | 0.249430 | 0.522245 | 0.0 | 0.0 | 0.522245 | 0.0 | 0.0 | 0.522245 | 0.0 | 0.0 |
| **Series Production** | 0.036316 | 0.036316 | 0.036316 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| **Service** | 0.047588 | 0.047588 | 0.047588 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| **Walk-Home** | 0.238237 | 0.238237 | 0.238237 | 0.199832 | 0.0 | 0.0 | 0.199832 | 0.0 | 0.0 | 0.199832 | 0.0 | 0.0 |
| **Significant Problem** | 0.072831 | 0.072831 | 0.072831 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| **Minor Problem** | 0.022265 | 0.022265 | 0.022265 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| **Cost per Unit** | 0.101170 | 0.101170 | 0.101170 | 0.199832 | 0.0 | 0.0 | 0.199832 | 0.0 | 0.0 | 0.199832 | 0.0 | 0.0 |
| **Warranty Cost** | 0.172999 | 0.172999 | 0.172999 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| **Warranty Occurrences** | 0.059165 | 0.059165 | 0.059165 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |

Table 3. Limit Supermatrix

| | Project A | Project B | Project C | Preproduction | Series Production | Service | Walk-Home | Significant Problem | Minor Problem | Cost per Unit | Warranty Cost | Warranty Occurrences |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Project A** | 0.021927 | 0.021927 | 0.021927 | 0.021927 | 0.021927 | 0.021927 | 0.021927 | 0.021927 | 0.021927 | 0.021927 | 0.021927 | 0.021927 |
| **Project B** | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 |
| **Project C** | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 | 0.044893 |
| **Preproduction** | 0.467780 | 0.467780 | 0.467780 | 0.467780 | 0.467780 | 0.467780 | 0.467780 | 0.467780 | 0.467780 | 0.467780 | 0.467780 | 0.467780 |
| **Series Production** | 0.004057 | 0.004057 | 0.004057 | 0.004057 | 0.004057 | 0.004057 | 0.004057 | 0.004057 | 0.004057 | 0.004057 | 0.004057 | 0.004057 |
| **Service** | 0.005316 | 0.005316 | 0.005316 | 0.005316 | 0.005316 | 0.005316 | 0.005316 | 0.005316 | 0.005316 | 0.005316 | 0.005316 | 0.005316 |
| **Walk-Home** | 0.194944 | 0.194944 | 0.194944 | 0.194944 | 0.194944 | 0.194944 | 0.194944 | 0.194944 | 0.194944 | 0.194944 | 0.194944 | 0.194944 |
| **Significant Problem** | 0.008136 | 0.008136 | 0.008136 | 0.008136 | 0.008136 | 0.008136 | 0.008136 | 0.008136 | 0.008136 | 0.008136 | 0.008136 | 0.008136 |
| **Minor Problem** | 0.002487 | 0.002487 | 0.002487 | 0.002487 | 0.002487 | 0.002487 | 0.002487 | 0.002487 | 0.002487 | 0.002487 | 0.002487 | 0.002487 |
| **Cost per Unit** | 0.179631 | 0.179631 | 0.179631 | 0.179631 | 0.179631 | 0.179631 | 0.179631 | 0.179631 | 0.179631 | 0.179631 | 0.179631 | 0.179631 |
| **Warranty Cost** | 0.019326 | 0.019326 | 0.019326 | 0.019326 | 0.019326 | 0.019326 | 0.019326 | 0.019326 | 0.019326 | 0.019326 | 0.019326 | 0.019326 |
| **Warranty Occurrences** | 0.006609 | 0.006609 | 0.006609 | 0.006609 | 0.006609 | 0.006609 | 0.006609 | 0.006609 | 0.006609 | 0.006609 | 0.006609 | 0.006609 |

From the Limit Supermatrix, the final priorities are assigned to each of the three alternatives given for this problem. Equal weight was given to alternative B and C, over alternative A. The priorities are shown in Table 4.

Table 4. Final Priorities




## 5. Results and Discussion

The pairwise comparison matrices captured the evaluations of each of the subject matter experts effectively enough to assess the three alternatives which were somewhat similar in phase nodes but differed in the cost and severity nodes. Details about each alternative are given in Table 1. The fact that alternative B has a much higher occurrence rate than the other two would logically push it to the top of the list. Although the cost of repairing the problem is lower than the others, the number of consumers impacted is much higher and would have a potential for negative impact on customer satisfaction.

The subjectivity of an engine failure was overshadowed by the occurrence frequency and the cost per repair nodes, which may seem counterintuitive. However, in the context of a large corporation, other factors carry equal or greater weight with respect to the health of the corporation. In this case although the occurrence rates between alternative A and C are similar and the cost to repair alternative A is greater, alternative C carries the burden of government regulation compliance. The risk of noncompliance carries greater weight in the decision-making process due to the possibility of vehicle recall which makes the importance of alternative C outweigh alternative A. By using a set of pre-established criteria to analyze the three alternatives, subjective project selection gives way to a more unbiased selection. This is witnessed in the final priorities assigned to each project in Table 4. Although Project A has the highest cost per repair, Project B and C were both assigned higher priorities, which would indicate that the company's resources would be better spent addressing Project B or C.

## 6. Conclusion

The application of ANP to the multicriteria decision making problem of Six Sigma project selection proves to be an effective and unbiased method to deploy resources in the areas most needed. By addressing the highest priority areas, an organization can ensure its resources are used efficiently and effectively which will transfer to the financial bottom line through the metrics that are improved by the project work.

While the ANP provides a robust framework for modeling complex interrelationships and mutual influences within decision systems, its implementation as a high-frequency, ongoing analysis tool remains constrained by significant methodological and practical challenges. A primary concern is the substantial burden placed on domain experts, as the requisite pairwise comparisons are inherently time-consuming and labor-intensive. Empirical evidence suggests that even moderately complex evaluation structures can require as many as 500 distinct judgments, a requirement that frequently induces cognitive fatigue and leads to subsequent inconsistencies. Methodologically, the traditional ANP framework is designed for a one-time synthesis of preferences, making the initiation of a novel decision-making process for each daily information update an inherently inefficient strategy. Furthermore, because low-dimensional perturbations capture only partial effects of criteria changes, a multi-dimensional stability analysis is necessary to understand the evolutionary behavior of preferences without constant manual re-elicitation. The static nature of conventional ANP models further inhibits their utility in dynamic environments, as they lack the temporal state-updating mechanisms characteristic of more adaptive methodologies like Dynamic Bayesian Networks. High-frequency data streams also introduce risks associated with incomplete or non-existent information, as traditional ANP typically treats datasets containing missing values as invalid, thereby discarding potentially useful data and yielding non-objective assessment results. Consequently, the sustained application of ANP in environments with volatile information sources necessitates the integration of automated feature extraction and information supplementation techniques, such as soft sets or machine learning surrogates, to mitigate these computational and expert-related bottlenecks.

For the ANP to function as an ongoing process, it must transition toward automated data acquisition and dynamic state updating. Researchers increasingly advocate for platforms based on knowledge graphs and digital twin technologies that integrate real-time sensor data (e.g., IoT sensors in healthcare or construction) with the ANP's structural priorities. In such a framework, LLMs serve as the connective tissue, feeding a continuous stream of data into the limit supermatrix for automatic recalculation. This enables a "closed loop" mechanism involving "disturbance identification, rapid response, and proactive recovery", ensuring that the decision model remains resilient to daily fluctuations in external environments. Future research should continue to explore unsupervised feature learning (e.g., autoencoders) to further reduce noise and subjective bias, ultimately realizing a fully adaptive, data-driven governance system for complex industrial and environmental risks. As well, methods to continue to fine tune the weighting in the ANP system are opportunities for continual improvement.

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