Facilities

Assessment of inoperability from unplanned maintenance in building management

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Received 3 September 2025
Revised 5 January 2026
4 March 2026
Accepted 8 March 2026

Abstract

Purpose – Unplanned maintenance (UPM) decisions in building management are often made at the component level without explicitly considering component interdependencies and their role in cascading disruptions. This study aims to develop and validate a data-driven methodology to assess component inoperability and support maintenance prioritization in facility management (FM).

Design/methodology/approach – A three-phase methodology is proposed using historical work-order data from North American universities. Phase 1 assesses subsystem inoperability from UPM risk profiles and maps probabilities to five ordinal inoperability levels. Phase 2 derives component interdependencies from work-order descriptions using quantitative content analysis and social network analysis (in-strength and out-strength centralities). Phase 3 integrates subsystem inoperability and component centrality in a decision-making algorithm to assign component inoperability levels, followed by AutoML-based classification validation.

Findings – The methodology was demonstrated on HVAC-related UPM data, including 11,399 work orders (WOs) and 32 components across four subsystems. Distribution systems emerged as the most vulnerable subsystem, and components such as steel dampers, supply fans and air handlers were identified as critical in the interdependency network. The AutoML validation selected an Extra Trees classifier as the best-performing model and achieved 95.47% accuracy on unseen data, supporting the consistency of the assigned component inoperability levels.

Originality/value – This study provides a structured method that combines subsystem risk assessment, component interdependency analysis and an interpretable decision-making algorithm for component

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Emerald Publishing Limited
0263-2772
DOI 10.1108/F-06-2025-0096

inoperability evaluation. The approach advances FM practice by enabling prioritization of UPM actions based on both subsystem risk and component network role rather than isolated work-order frequency alone.

Keywords Component inoperability, Component interdependency, Unplanned maintenance, Risk assessment, Social network analysis, Data-driven approach, Facility management

Paper type Research paper

1. Introduction

Modern building facilities are comprised of complex networks of various components. Understanding the diverse building assets requires in-depth knowledge of relationships among systems, subsystems and their components. Yoon *et al.* (2021) provided the reliability model of deferred maintenance (DeM) backlogs in maintenance budget allocation and emphasized the importance of considering the system, subsystem and components collectively in maintenance decision-making. Zhou *et al.* (2009) discussed a model-based fault detection and diagnosis strategy for systems and suggested that the failure (i.e. inoperability – the inability to function as intended) of a single component can propagate throughout the building, causing systemic disruptions. Faqih and Zayed (2021) found that, although failure of one component can trigger cascading failures across others in their review of nine building component rating models, those models nonetheless failed to account for component interdependencies. This suggests that there is a lack of comprehensive research on component inoperability interdependencies in facility management (FM), particularly for UPM decision-making. Although prior studies have examined maintenance prioritization and building component interdependencies, existing approaches still largely evaluate components in isolation (Gashi *et al.*, 2023; Pampana *et al.*, 2025). As a result, facility managers often lack a practical and standardized method to determine which components are critical in UPM situations when both subsystem vulnerability and interdependency effects must be considered simultaneously.

To address this gap, this study proposes a standardized, data-driven methodology for evaluating component inoperability using historical work-order data. The approach integrates subsystem-level UPM risk and component interdependency information into an interpretable decision-support framework, and its utility is further supported through data-driven validation. The objectives of this study are to assess subsystem inoperability in UPM activities; to derive component interdependencies through component relationship assessment; and to develop a decision-making algorithm for evaluating component inoperability based on the subsystem inoperability and component relationship assessments. This methodology is designed to support practical UPM prioritization using historical work-order data and to be adaptable across organizations with different maintenance contexts.

2. Background and related studies

2.1 Asset management systems in facility management

Effective building asset management requires a strategic and systematic approach of tracking, maintaining and optimizing physical assets within the facility and organization. Gavrikova *et al.* (2020) reviewed existing asset management studies and highlighted that the majority of the research relies on case-specific theoretical grounds and approaches. Herath *et al.* (2023) examined maintenance performance in public-school infrastructure and found that, despite high maintenance funding, existing asset management models lack awareness of optimal funding levels and cost-effectiveness. Pampana *et al.* (2022) investigated the planned preventive maintenance strategies used by facility managers to minimize inoperability and found them to be suboptimal. This finding suggests that facilities management (FM) may benefit from a more comprehensive grasp on the functionality of building components.

FM commonly uses asset classification systems such as UniFormat, OmniClass and MasterFormat for organizing assets hierarchically from major systems to individual components. Pampana *et al.* (2024) derived the FMUCO coding system, which identifies and organizes added components, thereby supporting interdependency analysis and inoperability assessment.

2.2 Building asset interdependencies

In building facilities, systems and subsystems function collectively to maintain operations (Atef and Bristow, 2019). Each system comprises multiple components – grouped into subsystems – that operate interdependently rather than in isolation. For example, in HVAC distribution systems, components such as air filters, air handlers, supply fans, dampers, exhausts and humidifiers are closely linked. Ahmad *et al.* (2016) demonstrated interdependencies among air-handler systems: fan speed regulates airflow and efficiency; clogged filters elevate fan load; coil degradation reduces comfort and increases energy consumption; and damper malfunction disrupts distribution, enabling failures to cascade and compromise overall HVAC performance. Wang *et al.* (2026) proposed a component-based machine learning framework that predicts indoor airflow and temperature fields by aggregating latent representations of individual inlet components. Chen *et al.* (2024) showed that structural dependencies in multi-component systems are often overlooked, even though maintenance on one component may require disassembly of others, increasing downtime and cost if such relationships are ignored. Gashi *et al.* (2023) highlighted that many data-driven approaches still adopt a single-component perspective, despite evidence that accounting for interdependencies among components can improve deterioration modeling and predictive performance; however, these methods are typically developed in sensor-rich industrial predictive maintenance settings rather than CMMS-based FM contexts. Together, these studies underscore the need for a standardized, data-driven methodology applicable across all subsystems in the built environment.

2.3 Data-driven analysis

2.3.1 Maintenance priority. Maintenance priority systematically determines the sequence and urgency of FM tasks. Besiktepe *et al.* (2020) reviewed several prioritization-related studies and identified a lack of comprehensive criteria in building maintenance decision-making. Chong *et al.* (2019) identified 58 factors for maintenance prioritization, with the top-five being condition, cost, occurrence, severity and usage importance. Au-Yong *et al.* (2019) found a significant gap between perceived and actual maintenance prioritization among facilities professionals in high-rise residential buildings.

Yoon (2018) proposed the Total-Package prioritization framework, using the facility condition index (FCI), facility condition assessment (FCA), MR&R (maintenance, repair and replacement) and Bayesian networks to prioritize subsystems from DeM backlogs. Moretti and Re Cecconi (2019) developed a “Maintenance Priority Index” combining FCI, asset service life, owner preference and component criticality indices. Cheng *et al.* (2020) proposed a predictive maintenance framework using sensor data from BIM and IoT, using neural networks and support vector machines (SVMs) to estimate the condition and priority of mechanical components. These data-driven studies largely rely on BIM, IoT sensors and detailed condition indices – limiting their broader applicability in FM. Kaliszewski *et al.* (2025) argue that effective maintenance decision-making must move beyond isolated component-level needs and instead account for the relationships among interacting system elements within a broader performance context.

2.3.2 Social network analysis. Social network analysis (SNA) is a method used to examine and visualize the relationships and interactions among individuals, groups or entities within a network (Pryke, 2012). SNA elucidates network structure, dynamics and influence patterns, enabling researchers to characterize social phenomena and information flow through centrality metrics. Key SNA tools include degree, strength, closeness, betweenness and eigenvector centralities (Bringmann *et al.*, 2019). Chakrabarti *et al.* (2022) used closeness, betweenness and eigenvector centralities to determine housing prices in real estate. Alexandre *et al.* (2021) used degree, closeness and betweenness centralities to assess systemic risks in financial networks. Vargas *et al.* (2018) used strength, closeness and harmonic centralities to link student collaboration networks to academic performance, finding strength centrality correlated with homework scores. Lee *et al.* (2018) clarified SNA metric interpretations in project management and non-social networks, highlighting its value in strategic planning and efficiency. Together, these studies demonstrate the value of SNA for identifying influential entities, mapping relationships and interpreting network dynamics across fields, while adjacency matrices further support the visualization of network structures and interdependencies in complex systems.

3. Methodology

The objective of this study is to evaluate building component relationships and component inoperability in unplanned maintenance (UPM) activities. Figure 1 illustrates the proposed three-phase methodology:

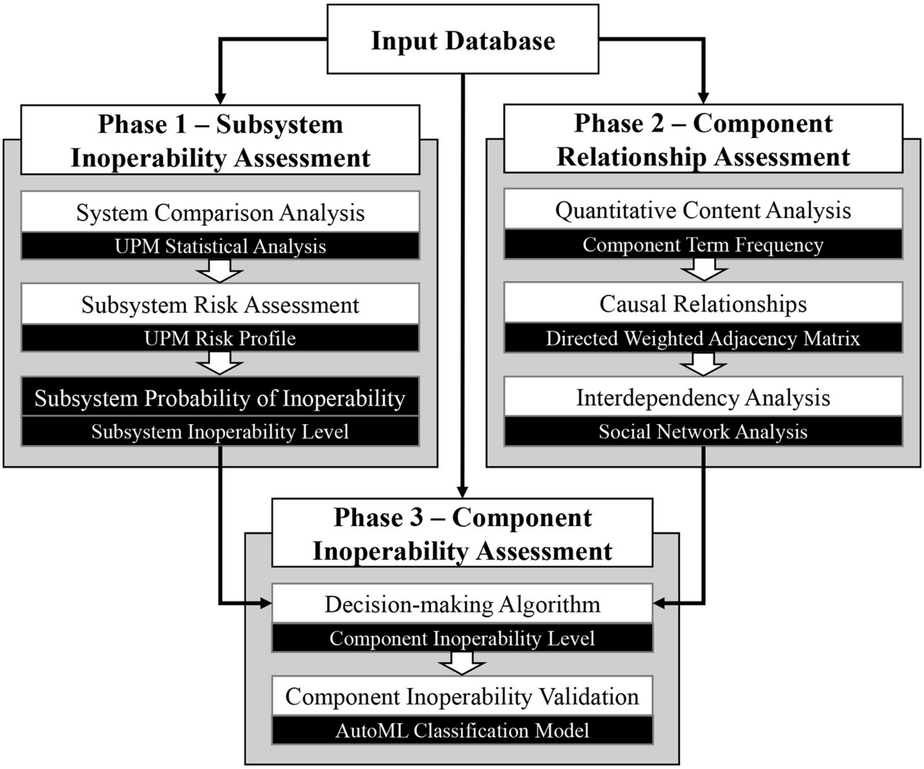

Figure 1. Proposed methodology
Source: Author's own work

(1) subsystem inoperability assessment;

(2) component relationship assessment; and

(3) component inoperability assessment.

The database used in this study comprises comprehensive maintenance data from North American universities, enabling data-driven assessments through its various attributes (Pampana *et al.*, 2024). Phase 1 involves assessing the inoperability of the subsystem using UPM data from the database. In Phase 2, the interdependencies between components are established through quantitative content analysis (QCA) and SNA. The results – subsystem inoperability levels obtained from Phase 1 and centrality values computed in Phase 2 – are combined in Phase 3 to develop a decision-making algorithm for component inoperability assessment, followed by the validation of the component inoperability levels using various variables from the database.

3.1 Phase 1 – inoperability assessment

The inoperability assessment used CMMS historical work-order data from eight universities with associated building information. The database includes diverse discrete and continuous variables required for analyzing component interdependencies. For consistency and comparability across institutions, this study used data from 2015 to 2019, which represented the most complete and commonly available time period across the participating universities (Pampana *et al.*, 2025). The data set also includes case-level contextual variables such as location, building size and type, built year and condition-related indicators, which provide the general case background for the present analysis (Pampana *et al.*, 2024).

3.1.1 System comparison analysis. System comparison analysis was conducted on the database, with a particular focus on UPM WOs and labor hours, to investigate critical systems (Pampana *et al.*, 2022). The data-driven study presented the annual average trend based on five years of data. Top three vulnerable systems with the highest maintenance work were HVAC, plumbing and electrical systems. HVAC was identified as the most critical system with the highest labor hours for UPM. Accordingly, this study focused on HVAC to evaluate the methodology's effectiveness in real-world facility maintenance.

3.1.2 Subsystem risk assessment. This subsection uses subsystem inoperability probabilities derived from the previously established HVAC UPM risk profile reported by (Pampana *et al.*, 2022) as an input to the present methodology. The risk profile was developed using historical work-order occurrence data and provides subsystem-level inoperability probabilities associated with annual UPM occurrences. In the present study, these probabilities are used to represent the relative vulnerability of HVAC subsystems and to support subsequent component-level inoperability assessment. Figure 2 presents the HVAC risk profile, where the *x*-axis shows annual work order (WO) occurrences and the *y*-axis shows inoperability probability, following negative binomial distributions based on higher AIC and BIC values.

Figure 2 shows subsystem inoperability probabilities derived from the *y*-axis of the UPM risk profile. Five HVAC subsystems were analyzed, with yearly probabilities of UPM WOs calculated per occurrence. At 15 occurrences, "Heating" had a 20.79% inoperability probability; "Cooling," 12.38%; "Distribution," 53.7%; "Terminal Units," 29.84%; and "Controls," 65.67%. Controls and distribution subsystems generated more WOs than heating, cooling and terminal units. The top-two subsystems by probability were compared: distribution systems with 15 components emerged as the most critical, making it a prime candidate for interdependency analysis.

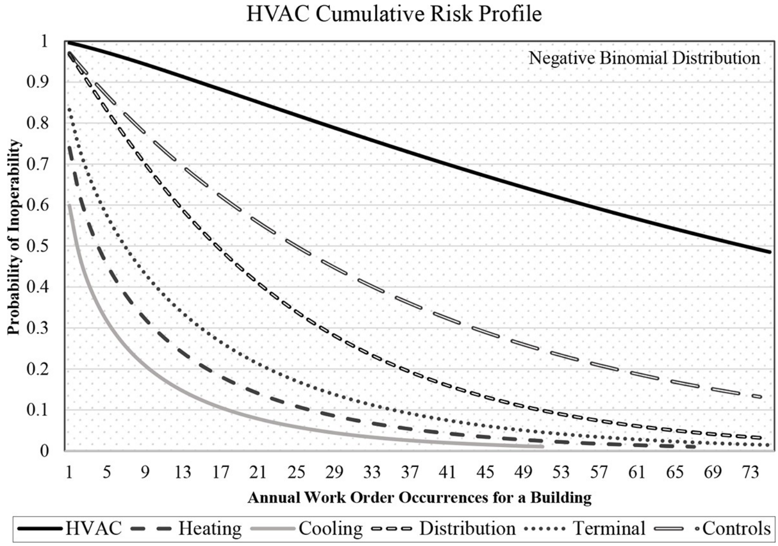

Figure 2. HVAC UPM risk profile
Source: Author's own work

The subsystem probability of inoperability, derived from risk assessment, is categorized into five levels, each 20% apart: Level 1 (0%–20%) to Level 5 (80%–100%). Level 5 indicates the highest criticality, while Level 1 is the lowest.

3.2 Phase 2 – component relationship assessment

Phase 2 includes QCA, component causal relationships and interdependency analysis to derive centrality measurements for subsystem components as the final output.

3.2.1 Quantitative content analysis and causal relationships. QCA is a systematic method for examining and quantifying communication content. A core element of QCA is term frequency (TF), which counts the occurrences of specific words or phrases either manually or automatically (Silge and Robinson, 2017). Analyzing TF helps reveal patterns, themes or relationships, and it enables meaningful insights to be drawn from large text data sets. In this study, QCA is used to examine component interdependencies by identifying interaction counts within subsystem WO descriptions.

Building on this, the identified interactions are further analyzed to infer causal relationships, which explain cause-and-effect links between variables (Pearl, 2009). For instance, Faqih and Zayed (2021) found that the failure of one component can trigger cascading failures in others, highlighting the need to capture such causal links. To model these relationships quantitatively, a directed weighted adjacency matrix is used – an analytical structure that captures both the direction and strength of influence among components. This transition from frequency-based interaction to structured causality forms a foundation for the next phase of interdependency analysis.

3.2.2 Interdependency analysis. Interdependency analysis assesses how components within a subsystem influence one another using SNA. Strength Centrality quantifies node importance in SNA, based on the total weight of connections. It extends degree centrality to weighted networks by considering both the number and strength of connections (Saxena and Iyengar, 2020). Strength centrality has two variants: in-strength and out-strength (Bringmann *et al.*, 2019). The in-strength of a node is calculated as the sum of the weights of all incoming links to that node from other nodes in the network, whereas the out-strength is the sum of the weights of all outgoing links from that node to other nodes, as shown in the equations (1) and (2):

$$In - Strength \ (i) = \sum_{j=1}^{n} w_{j \to i} \tag{1}$$

$$Out - Strength \ (i) = \sum_{j=1}^{n} w_{i \to j} \tag{2}$$

where i denotes the focal node, j denotes any other nodes, w is the weight of the direct link and n is the total number of nodes.

Pampana *et al.* (2025) used causal network analysis to show that strength centrality outperforms degree centrality in quantifying building component interdependencies. In this study, out-strength centrality represents the "prominent actor," – a component causing inoperability – while in-strength centrality represents the "affected actor," who is influenced by others.

3.3 Phase 3 – component inoperability assessment

Phase 1 and Phase 2 yield two key outputs: subsystem inoperability level, indicating issue severity, and centrality measurements, reflecting each component's position in the subsystem's causal network. In Phase 3, a decision-making algorithm is developed based on these empirical findings.

3.3.1 Decision-making algorithm – component inoperability level. This research provides a decision-making algorithm for evaluating component inoperability shown in Figure 3. The algorithm was developed as an interpretable rule-based framework that integrates subsystem-level vulnerability with component-level interdependency characteristics. In this study, the subsystem inoperability level serves as the baseline indicator of the relative criticality of the subsystem in which the component operates, while out-strength and in-strength centralities represent the extent to which a component influences other components and is affected by them, respectively. By combining these two inputs, the algorithm provides a consistent basis for assigning component inoperability levels for UPM decision support.

The algorithm begins by identifying the component and subsystem from the WO. The input is the subsystem's inoperability level (1 = least critical, 5 = most critical), and the output is the component's inoperability level, also on a 1–5 scale (low to high risk). It then evaluates component interdependencies using two decision nodes that compare out-strength (prominent actor) and in-strength (affected actor) centralities against the subsystem's average. Each decision yields a "Yes" if the centrality is greater than or equal to the average, indicating high prominence or high impact. A "No" indicates low prominence or low impact. Based on these outcomes, the algorithm applies four assessment conditions. If a component resulted in "Low Prominence and High Affected," or "High Prominence and Low Affected," its component inoperability level is set equal to the subsystem inoperability level. If it has "High Prominence and High Affected," the level is increased by one. Conversely, if it has "Low Prominence and Low Affected," the level is decreased by one. The algorithm concludes once the component's inoperability level is assigned. The prerequisites for this algorithm are the subsystem inoperability level and the centrality values from the subsystem inoperability assessment and component relationship assessment.

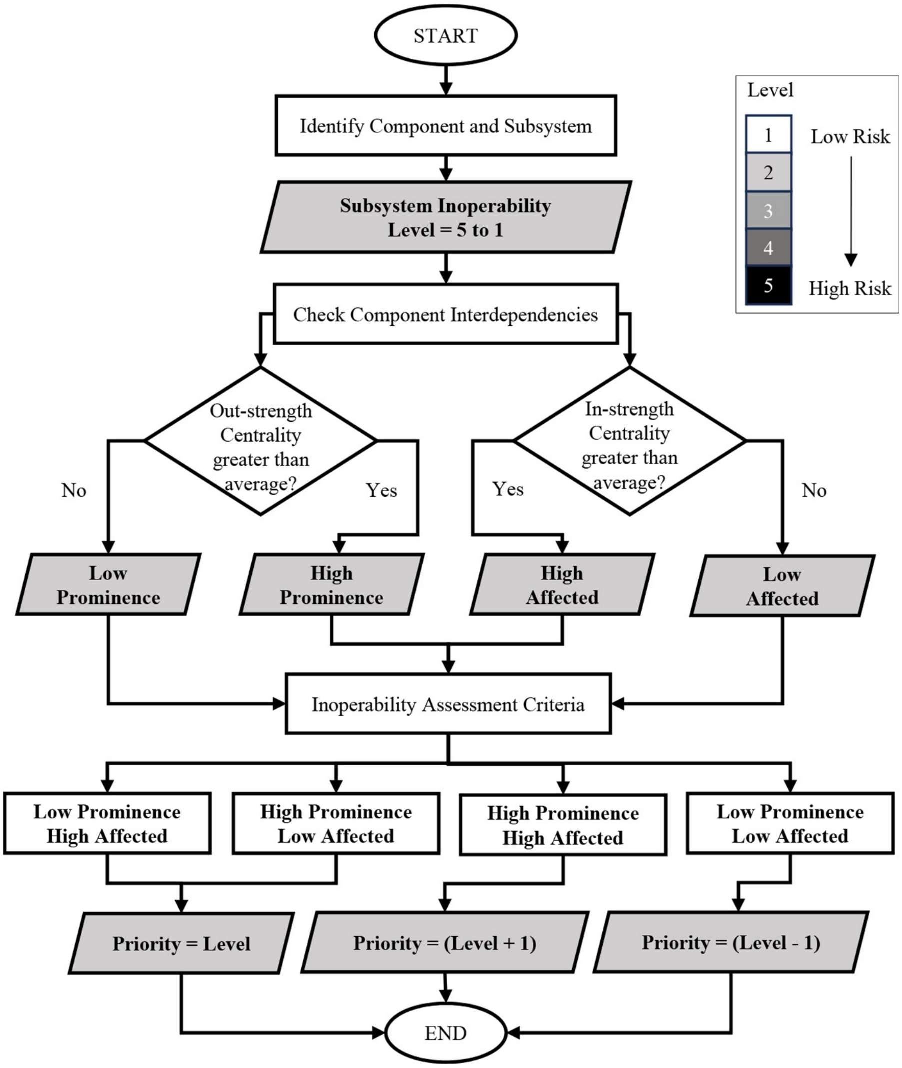

Figure 3. Decision-making algorithm for component inoperability
Source: Author's own work

As illustrated in Figure 3, the decision-making criteria are crucial for any decision-maker to achieve the component's inoperability level.

3.3.2 Component inoperability validation. Component inoperability validation aims to examine whether the inoperability levels generated by the decision-making algorithm are supported by observable maintenance-related patterns in the data set. The input database includes attributes from UPM WOs, such as duration, labor hours, labor cost and temperature data. A supervised machine learning classification model is applied using these variables, along with two additional variables from Phase 2, to assess the consistency of the assigned component inoperability levels. Figure 4 indicates the schematic process of component inoperability validation.

As illustrated in Figure 4, five independent variables from the input data set are used. WO duration is a discrete variable (in days), while labor hours and cost are continuous. Minimum and maximum temperatures, also continuous, reflect weather on the WO date (OpenWeather, 2021) and are converted to Kelvin to eliminate negative values. Two additional predictors – in-strength and out-strength centralities – from Phase 2 are included. The dependent variable, component inoperability level (from Phase 3), is ordinal with five risk levels from low to high.

The class distribution across these five levels is imbalanced, which can reduce classification accuracy. To address this, over-sampling (duplicating minority class records) and under-sampling (truncating majority class records) are applied. In both methods, either the largest or smallest class becomes the baseline. Mohammed *et al.* (2020) found over-sampling generally outperforms under-sampling. An AutoML tool is used to identify the best-performing classification model.

3.3.2.1 AutoML classification model. Automated machine learning (AutoML) handles data preprocessing, feature selection, hyperparameter tuning and model selection in a single pipeline, making it easy to compare many classifiers efficiently (He *et al.*, 2021). For instance, Jeon and Cai (2021) used AutoML on wearable electroencephalogram signals to improve virtual construction-site safety, achieving 95.1% accuracy by pinpointing the specific channel-frequency combinations most indicative of hazard perception. Classifier robustness was assessed via accuracy, precision, recall and F1-score. AutoML helps identify the best-performing model, validating classification models using the selected independent variables.

For AutoML-based validation, the classification data set included records from four HVAC subsystems – heating; cooling; terminal and package units; and distribution. The

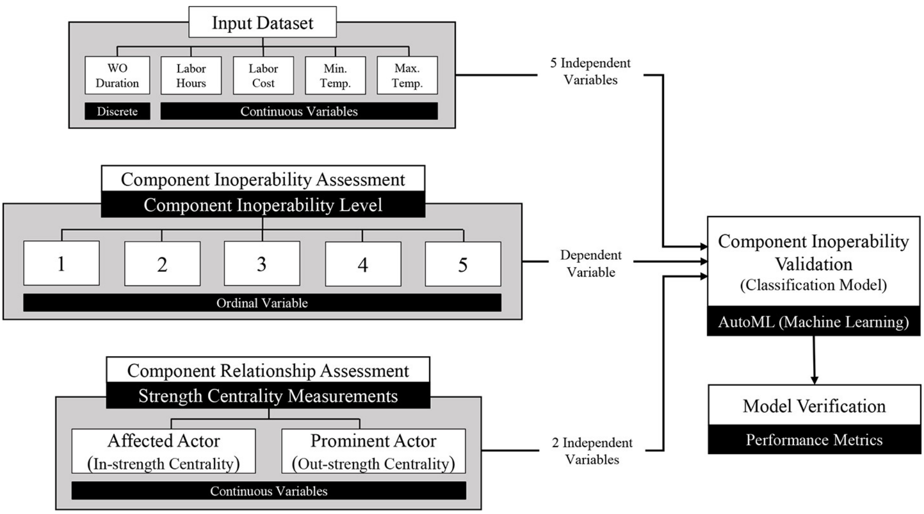

Figure 4. Schematic process of component inoperability validation
Source: Author's own work

original class distribution of component inoperability levels was imbalanced: Level 1 (7,248), Level 2 (2,912), Level 3 (997), Level 4 (214) and Level 5 (28). To reduce bias toward majority classes during model development, oversampling was applied, resulting in 7,248 data points in each class. For model development, the data were first split 90/10 into seen and unseen sets. The seen data were then further divided 70/30 into training and testing sets. The five component inoperability levels served as the dependent variable, and seven variables were used as predictors. AutoML was implemented using the open-source Python library "PyCaret" (Ali, 2020), with candidate classifiers trained on the training data, tested on the testing data and finally validated on the unseen data. Model performance was evaluated using accuracy, precision, recall and F1-score.

4. Results and discussions

This study's results encompass three phases –subsystem inoperability assessment; component relationship assessment; and component inoperability assessment. Phase 1 and Phase 2 results were used in Phase 3 for the decision-making algorithm followed by its validation.

4.1 Phase 1 results

4.1.1 Subsystem probability of inoperability. The subsystem inoperability probabilities derived from the UPM risk profile represent the annual likelihood of work-order occurrence. At the fifth occurrence, the probabilities are 45.33% for heating, 31.58% for cooling, 82.97% for distribution, 52.27% for terminal units and 86.67% for controls. These values are classified into five 20% intervals to assign the subsystem inoperability level, thereby establishing subsystem-level vulnerability differences within HVAC systems and providing the baseline for subsequent component-level inoperability assessment.

4.2 Phase 2 results

To aid interpretation of the Phase 2 outputs, Table 1 defines the key parameters used to compute the network-based measures.

4.2.1 Component term frequency. The WO description data from the input database were used in QCA to evaluate component TF. To ensure robustness, only components with at least 200 WOs were included (Pampana *et al.*, 2025). Distribution systems with ten components met this criterion best among four HVAC subsystems for demonstration. Individual data sets were created for each component to analyze their interactions. Each component was examined for interactions with the other nine components in cases of inoperability. For instance, among 3,987 air handler WOs, "fan," appeared in 347 and "air filter" in 128 WO descriptions.

Term frequencies of affected actor interactions were calculated for four HVAC subsystems: distribution, heating, cooling and terminal and package units. The controls subsystem, with only four components, was excluded. When prominent actor descriptions included multiple components, each affected actor was counted once per WO. For an adjacency matrix, diagonal values are zero. TF is normalized by dividing it by the total WOs of the prominent actor, producing interaction strengths. These values are then used to construct a directed weighted adjacency matrix for further analysis.

4.2.2 Directed weighted adjacency matrix. In this study, a causal relationship is established when a parent WO (e.g. "air handler") references other components (e.g. "supply fan" or "air filter") in its description, indicating inoperability. To build a directed weighted adjacency matrix, the number of times one component appears in another's WO descriptions is calculated. The component with the description is a prominent actor, and the one

Table 1. Definition of key parameters used in the study

Parameters	Description/definition
HVAC subsystems	Heating, cooling, distribution and terminal and package units
Number of work orders	Only components with ≥200 UPM work orders were included
Prominent actor	Component whose work-order descriptions are analyzed
Affected actor	Component found (interaction) in the prominent actor work order
Prominent actor work order	A UPM work order logged under the prominent actor; its description may reference other components (affected actors)
Out-strength centrality	Sum of weights of the outgoing links (from prominent actor)
In-strength centrality	Sum of weights of the incoming links (to affected actor)
Subsystem inoperability level	Risk-based level assigned to subsystems based on risk-profiles

Source(s): Author’s own work

mentioned is an affected actor. Interaction strength is calculated as the frequency of an affected actor’s occurrences in the prominent actor’s descriptions, divided by the prominent actor’s total WOs.

The adjacency matrix for distribution systems was created using normalized strengths. If no interaction exists in either direction, the edge weight is zero. This matrix can then be used to compute centrality measures. Table 2 presents the directed weighted adjacency matrix for the distribution subsystem and its component relationships. The normalized strength of 347 fan interactions in the 3,987 air handler WOs is calculated by dividing 347 by 3,987 to give 0.0870 (second row under Fan). Strength calculations reveal causal relationships between components, producing a directed weighted adjacency matrix.

As shown in Table 2, the supply fan, steel damper and air handler played key roles in evaluating causality. Most components contributed to these relationships, highlighting interdependencies within the subsystem network.

4.2.3 Social network analysis results. In-strength and out-strength centralities were computed from the directed, weighted adjacency matrix of ten distribution-system components to identify prominent and affected actors, using the Python library “NetworkX” (Hagberg *et al.*, 2008). Table 3 presents the centrality measurements for distribution system components. The top prominent actors are the steel damper, air filter and supply fan, while the most affected are the supply fan, air handler and fan.

As shown in Table 3, the steel damper is the most prominent (causing inoperability), while the supply fan is the most affected. Centrality values were similarly calculated for the heating, cooling and terminal and package unit subsystems. These measurements will be used in the decision-making algorithm and serve as predictors in the Phase 3 classification model. These results also show that component relationships can be systematically identified from work-order data, extending prior studies that emphasize interdependency but do not operationalize it for FM decision support.

4.3 Phase 3 results

4.3.1 Component inoperability level. To test the decision-making algorithm, 32 components from four HVAC subsystems were used. A data set of 11,399 WOs was evaluated to determine component inoperability levels, which also supports classification model validation. Table 4 lists the components along with their inoperability criteria attributes. Components with “Level 5” subsystem inoperability include the air handler, exhaust fan, fan, humidifier, steel damper, supply fan, ventilator, air conditioner, fan coil unit and unit heater.

Table 2. Distribution systems directed weighted adjacency matrix

Components	AFT	AHD	DCW	EXH	FAN	HUM	SDM	SUF	VAV	VEN
Air filter (AFT)	0.0000	0.0593	0.0218	0.0010	0.0049	0.0010	0.0000	0.2611	0.0000	0.0504
Air handler (AHD)	0.0321	0.0000	0.0005	0.0028	0.0870	0.0060	0.0083	0.0168	0.0000	0.0008
Duct work (DCW)	0.0021	0.0063	0.0000	0.0211	0.0042	0.0021	0.0063	0.0169	0.0021	0.0021
Exhaust fan (EXH)	0.0021	0.0097	0.0142	0.0000	0.0024	0.0003	0.0097	0.0041	0.0009	0.0035
Fan (FAN)	0.0013	0.0034	0.0004	0.0077	0.0000	0.0000	0.0000	0.0107	0.0000	0.0017
Humidifier (HUM)	0.0000	0.0278	0.0000	0.0000	0.0000	0.0000	0.0000	0.0013	0.0000	0.0000
Steel damper (SDM)	0.0107	0.1095	0.0093	0.0881	0.0841	0.0000	0.0000	0.2136	0.0214	0.0360
Supply fan (SUF)	0.0013	0.0683	0.0020	0.0046	0.0512	0.0020	0.0046	0.0000	0.0000	0.0512
Variable air volume (VAV)	0.0000	0.0032	0.0255	0.0159	0.0064	0.0000	0.0032	0.0159	0.0000	0.0032
Ventilator (VEN)	0.0027	0.0034	0.0113	0.0094	0.0185	0.0002	0.0012	0.0044	0.0007	0.0000

Source(s): Author’s own work

Table 3. Centrality measurements for distribution systems components

No.	Component name	Component code	Centrality measures for directed graphs	
			Out-strength (prominent actor)	In-strength (affected actor)
1	Air filter	D3040AFT	0.3996	0.0523
2	Air handler	D3040AHD	0.1543	0.2911
3	Duct work	D3040DCW	0.0634	0.0850
4	Exhaust fan	D3040EXH	0.0469	0.1506
5	Fan	D3040FAN	0.0252	0.2588
6	Humidifier	D3040HUM	0.0291	0.0116
7	Steel damper	D3040SDM	0.5728	0.0334
8	Supply fan	D3040SUF	0.1853	0.5449
9	VAV box	D3040VAV	0.0732	0.0251
10	Ventilator	D3040VEN	0.0520	0.1490

Source(s): Author’s own work

of these, the air handler, fan, steel damper, supply fan and fan coil unit also received “Level 5” component inoperability. An “N/A” status indicates the component shares the same inoperability level as its subsystem.

Table 4 presents the highest subsystem inoperability levels and their corresponding component inoperability levels. Components marked for demotion can be prioritized based on resource availability. Notably, the supply fan consistently received a promotion, identifying it as the most critical component. Overall, distribution systems emerged as the most vulnerable subsystem for critical unplanned WOs. These results indicate that the decision-making algorithm provides a practical basis for differentiating component-level inoperability in UPM by combining subsystem vulnerability with component network position.

4.3.2 AutoML classification model. Following over-sampling and model training, AutoML-based classification was conducted, and Table 5 summarizes the performance of the top five models across the training, testing and unseen data sets.

Interestingly, the top five models selected by AutoML were tree-based classifiers, known for their interpretability through visual tree structures. The highest performance was achieved by the Extra Trees Classifier, with 92.67% accuracy and recall, 92.6% precision and a 92.61% F1-score. The model was then tested on the remaining 30% of seen data, achieving 93.74% accuracy. As expected, model performance improved on seen data. To validate these results, the trained model was tested on the 10% unseen data. The Extra Trees Classifier was identified as the best model by AutoML with 95.47% accuracy. These results support the component inoperability levels derived by our decision-making algorithm and lend credibility to the five ordinal risk levels. This approach provides facility managers with a data-driven framework for prioritizing UPM maintenance.

5. Conclusions and contributions

This study presents a data-driven methodology for assessing building component inoperability in the context of UPM. By using CMMS work-order data together with content analysis, SNA and machine learning, the study demonstrates how subsystem vulnerability and component relationships can be integrated to support component-level maintenance prioritization.

A central contribution of this work is the explicit incorporation of component interdependencies into maintenance decision-making. Unlike conventional approaches that often evaluate components independently, the proposed methodology links subsystem inoperability assessment with component centrality to identify components with greater

Table 4. Inoperability criteria attributes of HVAC components

Subsystem	Component code	Component description	Highest subsystem inoperability level	Corresponding component inoperability level	Level status
Heating generation systems	D3020BOI	Boiler	3	2	Demotion
	D3020CRP	Circulation pump	4	4	N/A
	D3020CRS	Condensate receiver station	3	3	N/A
	D3020HEX	Heat exchanger	4	4	N/A
	D3020PAF	Pipe and fittings	4	4	N/A
	D3020PRV	Pressure reducer valve	4	3	Demotion
	D3020RFW	Radiator	4	4	N/A
	D3020STB	Steam boiler	4	3	Demotion
	D3020STR	Stream trap	3	3	N/A
	D3020VND	Valve, non-drain	4	3	Demotion
Cooling generation systems	D3030CHP	Chilled water primary pump	3	2	Demotion
	D3030CHR	Chiller	3	3	N/A
	D3030CHW	Chilled water-cooling system	3	3	N/A
	D3030CON	Condenser	3	2	Demotion
	D3030COT	Cooling tower	3	2	Demotion
	D3030CRP	Circulation pump	3	2	Demotion
	D3030PAF	Pipe and fittings	3	3	N/A
Distribution systems	D3040AFT	Air filters	4	4	N/A
	D3040AHD	Air handler	5	5	N/A
	D3040DCW	Ductwork	4	3	Demotion
	D3040EXH	Exhaust fan	5	4	Demotion
	D3040FAN	Fan	5	5	N/A
	D3040HUM	Humidifier	5	4	Demotion
	D3040SDM	Steel damper	5	5	N/A
	D3040SUF	Supply fan	5	5	Promotion
	D3040VAV	Variable air volume box	2	1	Demotion
	D3040VEN	Ventilator	5	4	Demotion
Terminal and package units	D3050ACO	Air conditioner	5	4	Demotion
	D3050FCU	Fan coil unit	5	5	N/A
	D3050HTP	Heat pump	4	3	Demotion
	D3050SCC	Secondary coil	4	4	N/A
	D3050UNH	Unit heater	5	4	Demotion

Source(s): Author's own work

Table 5. Classification performance of classifiers

Data	Model	Accuracy	Recall	Precision	F1-score
Training	Extra trees classifier	0.9267	0.9267	0.926	0.9261
	Random Forest classifier	0.9203	0.9203	0.9195	0.9192
	Decision tree classifier	0.8974	0.8974	0.8969	0.8944
	Extreme gradient boosting	0.8686	0.8686	0.8661	0.8668
	Light gradient boosting machine	0.8346	0.8346	0.831	0.8319
Testing	Extra trees classifier	0.9374	0.9374	0.9370	0.9369
Unseen	Extra trees classifier	0.9547	0.9547	0.9544	0.9545

Source(s): Author's own work

disruption potential. The results show that subsystem-level vulnerability can be differentiated using UPM risk profiles, component relationships can be systematically identified from work-order data, and combining these inputs enables practical assignment of component-level inoperability. In the HVAC distribution subsystem, for example, components such as the steel damper and supply fan emerged as influential contributors to subsystem inoperability.

The decision-making model developed in this study enables more accurate forecasting of maintenance needs and supports the transition from reactive to proactive maintenance strategies. In practice, facilities managers can apply the workflow to unplanned-maintenance WOs to identify high-risk subsystems, rank influential components via strength centrality, and assign inoperability levels to prioritize interventions. This supports strategic FM by focusing limited labor and repair budgets on components most associated with cascading disruptions. By assigning risk-based inoperability levels to components, the model facilitates data-informed scheduling, reduces emergency repair costs and enhances building performance and resilience.

The findings are demonstrated using historical CMMS work-order data from university facilities and selected HVAC systems/components, providing a focused and consistent basis for methodological development and application. Beyond its immediate application in university facilities, this methodology holds broad potential across diverse infrastructure domains. It can be adapted for prioritizing maintenance of transportation assets such as roads and bridges or critical systems in health care, manufacturing and utility sectors. As such, this research supports long-term asset management strategies and large-scale budget planning.

In summary, the study offers both theoretical and practical advancements in FM. It establishes a foundation for future work on component-level risk modeling and lays the groundwork for scalable, intelligent maintenance systems that align with the goals of operational efficiency, cost reduction and infrastructure sustainability. Future research can build on this foundation by applying the methodology to diverse data sets, extending it to additional building systems, and evaluating its performance across broader operational settings.

Data availability

Some or all data, models or code that support the findings of this study are available from the corresponding author upon reasonable request.

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